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Lucas CHANCEL

Insoutenables inégalités ? Essais sur les inégalités mondiales de revenu et de pollution

Directeur de thèse : Thomas Piketty

Jury

Rapporteurs:	Branko Milanovic	*City University New York*
	Thomas Sterner	*University of Gothenburg*
Directeur:	Thomas Piketty	*EHESS - Ecole d'Economie de Paris*
Examinateurs:	Yann Algan	*Sciences Po Paris*
	Michael Förster	*OCDE*
	Julia Steinberger	*Leeds University*

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Lucas CHANCEL

Unsustainable inequalities?
Essays on global income and pollution inequality

Thesis advisor : Thomas Piketty

Jury

Reviewers:	Branko Milanovic	*City University New York*
	Thomas Sterner	*University of Gothenburg*
Director:	Thomas Piketty	*EHESS - Paris School of Economics*
Examinators:	Yann Algan	*Sciences Po Paris*
	Michael Förster	*OECD*
	Julia Steinberger	*Leeds University*

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INTRODUCTION & SUMMARY

On the measurement of economic and environmental inequality

Rising economic inequality and the rapid exhaustion of natural resources are two of the most pressing challenges for human societies in the 21st century (UN, 2015). In order to prevent major social and environmental disruptions, it is essential to address current economic inequality trends and at the same time reduce human pressure on the environment. This double objective is however not straightforward, given that inequality reduction may increase pollution, and conversely, environmental policies may have undesirable impacts on inequality (Chancel, 2017).

A necessary condition to properly address both challenges is to measure them accurately. While inequality has attracted a lot of attention in the recent global debate (Piketty, 2014), we still know little about its global dynamics. Environmental degradation has also been widely documented: temperature rise due to anthropogenic greenhouse gases (GHG) (IPCC, 2014), erosion of biodiversity at an alarming rate (Cardinale et al., 2012), acidification of oceans or the rise in their level (Hoegh-Guldberg and Bruno, 2010), among other types of environmental disorders, are regularly discussed in public debates and in the academia. However, the distributional implications of these trends are too often overlooked. Not all world citizens contribute in the same way to pollution, nor everyone is impacted in the same way by it, or by environmental policies aiming to tackle environmental degradation (Martinez-Allier, 2002). In many ways, unsustainability is the new frontier of social and economic inequality. *What do we really know of global economic and environmental inequality dynamics? How does economic inequality interact with environmental inequality?* These questions are at the center of this thesis.

Tackling unsustainable and unequal development patterns will require more than accurate measurement. *How can better data on global income and environmental* *inequality help shape effective responses to economic and environmental inequality? Which fiscal, infrastructure and educational policies or regulations should be implemented to reduce inequality and pollution levels?* This work also seeks to reflect upon the role of inequality data in public debates and policymaking.

More than sixty years ago, Simon Kuznets, one of the inventors of GDP and of modern National Accounting, invited the economics profession to go beyond the measurement and the study of growth and to focus how growth is distributed across individuals. In order to do so, Kuznets (1955) called for a "shift from market economics to political and social economy". Unfortunately, this call has been largely unheard by generations of students and researchers in economics. Thanks to the work of Tony Atkinson, Thomas Piketty, Emmanuel Saez, Facundo Alvaredo and others (Atkinson and Morrison, 1978, Piketty, 2001, 2003; Piketty and Saez 2003; Alvaredo et al., 2013), the systematic study of the distribution of national income, gained importance over the past decades. The reconciliation of micro data with macroeconomic totals, to produce systematic Distributional National Accounts (see Alvaredo et al., 2016), however remains an enterprise in its infancy today. Lack of transparency on income and wealth distributional data is still the norm in many countries. This data gap facilitates tax evasion and fraud, makes it impossible for governments to design proper responses to inequality and contributes to undermine citizens' support in democratic institutions (Alvaredo et al., 2018).

In many ways, disciplines focusing on the impacts of human activity on the environment, as well as on the impact of environmental degradation on human beings, have also been more interested in averages and totals, rather than the distribution of impacts across individuals. An illustrative example is the Intergovernmental Panel on Climate Change, which synthesizes every five years or so, research of the global scientific community on the matter. Partly because of the structure of climate negotiations, partly because of the lack of existing individual level data, discussions on climate inequality in IPCC publications are still essentially based on national or regional averages (IPCC, 1990, 1995, 2001, 2007, 2014). Over the course of time, the

IPCC gradually included analyses related to environmental inequality between individuals (rather than countries or regions), but at the same time repeatedly highlighted the lack of systematic individual level data on the matter[1]. In climate negotiations, climate justice is still understood as a between-country issue, despite the fact that within-country emissions inequality is taking over between-country emissions inequality, as it will be discussed in chapter 4.

Lack of research on individual level environmental inequality resulted in a policy world deprived of data, concepts and tools to develop environmental policies in line with social realities (Chancel, 2017; Combet and Hourcade, 2017; Sterner, 2011). In 2009-10 for instance, when the French government tried to implement a carbon tax, it did not have the tools to properly assess the distributional impacts of a measure which eventually lost the support of public opinion[2]. The perception that environmental policy can have regressive impacts is strong and can sometimes prevent the implementation of environmental policy[3]. Anticipating such impacts in the design of environmental policies requires sound data, but the systematic measurement of environmental inequality dynamics between individuals is also in its early stages.

Ultimately, the two processes, i.e. production of Distributional National Accounts and production of Distributional Environmental Accounts on the other, must meet so as to create Distributional Economic and Environmental Accounts. The Stiglitz, Sen and Fitoussi Commission (2009) has formulated recommendations which go in this direction. National and international statistical institutions have engaged in this path,

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[1] See for instance the 3rd Assessment Report of 2001 which stressed that "there is a severe need for studies that consider the distributional impacts within developing countries. In addition, nearly all the studies lack the detail necessary to consider impacts in socioeconomic dimensions other than income. As a result, important costs to various groups within the general population may be overlooked. Important costs may also be hidden by aggregation." (IPCC, 2001). Progress has been made in the 5th Assessment Report, but the authors still warn that "cases of observed impacts often rely on qualitative data and at times lack methodological clarity in terms of detection and attribution [of the impacts]." (IPCC, 2014)

[2] The government did not have a micro-simulation model to assess the distributional impacts of environmental its environmental tax policies at the time. Many factors explain the failure of the French 2009-10 carbon tax (Senit, 2012; Combet and Hourcade, 2017) but surely the absence of tools to properly assess the measure and anticipate criticisms was an important limitation.

[3] One of the main justifications voiced by the U.S. President when he withdrew from the Paris Climate agreement was that climate protection hurts U.S. blue-collar workers.

but the work ahead will be long. In particular, it will require a series of methodological and conceptual innovations to guarantee in homogeneity of series and concepts over time and space. This work provides a modest contribution to this long-run collective endeavor by applying frontier methodologies to track systematically income and carbon inequality in a way that seeks to serve policymaking.

Structure of the thesis

This manuscript is structured in a didactic order, rather than in a chronological one. That is, the structure does not follow the order of publication of the different papers that constitute the thesis but rather follows an order that better reflects the logic at stake in the research process that guided this body of work.

In order to track the global dynamics of income inequality, it is necessary to start with the construction of systematic national level income inequality estimates and then build a global distribution of income (Chapters I and II). In order to produce global pollution inequality series, given current data limitations, one must first analyze the links between income and pollution within countries and using this information, as well as the knowledge one has acquired about global income inequality dynamics, construct a distribution of emissions between world individuals (Chapters III and IV). How to move from measurement to policy? The first four chapters all contain, at least to some extent, a discussion on the policy relevance of the trends observed but Chapters V and VI specifically focus on this question, at the national level and global level respectively. A more detailed summary of the different chapters is given below.

Chapter I, entitled “Indian income inequality dynamics, 1922-2015: From British Raj to Billionaire Raj?” [4], discusses the methodological issues at stake when reconstructing historical income inequality series in a country as populated as India, but with very scarce data. The chapter shows that despite many important data

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[4] This chapter is based on *“Indian income inequality dynamics, 1922-2015: From British Raj to Billionaire Raj?”* co-authored with Thomas Piketty and published as a WID.world Working Paper 2017/11.

limitations, one can combine tax data, surveys and national accounts in a systematic manner to reconstruct income inequality estimates robust to a wide range of alternative strategies. In the case of India, the results are striking as they reveal that income inequality is currently at its highest level since the creation of the Indian Income tax in 1922. The top 1% capture more than 22% of national income today, up from 6% in the mid-1980s, when the top 1% captured about 6% of total income.

Chapter II, entitled "Building a global income distribution brick by brick" [5], builds on chapter I (and many other similar endeavors carried out by my colleagues at the WIL) to construct a global distribution of income based on a systematic combination of tax, survey data and national accounts. Our results are notable as some go against preconceived ideas on globalization and its impacts on economic inequality. In particular, we show that the global top 1% captured twice as much global income growth as the bottom 50% since 1980. We demonstrate that inequality increased, rather than decreased between world individuals since 1980, despite strong growth in the emerging world. In other words, rising inequality within countries was stronger than the effect of reduced inequality between countries since 1980. Looking into the future, the chapter also reveals that under "Business as Usual", global inequality is likely to further rise (despite strong growth in emerging regions) contrary to what has been argued in academic and public debates on the matter. The Appendices to the chapter present the details of the method and reveal that our results are robust alternative strategies to account for missing data at the country level.

How to move from global income inequality to global environmental inequality? A first step is to understand the role of income and non-income drivers of individual pollution levels within countries. This is the work that is discussed in **Chapter III**,

[5] This chapter is based on chapters 2.1 and 5.1 of the "World Inequality Report 2018" co-authored with Facundo Alvaredo, Thomas Piketty, Emmanuel Saez and Gabriel Zucman, published by Harvard University Press, 2018. I served as general coordinator of the report and lead author of these chapters. The technical appendix of the chapter is based on "Building a global distribution of income brick by brick", co-authored with Amory Gethin, published as a WID.world Working Paper 2017/5.

entitled "Are younger generations higher carbon emitters than their elders?" [6], which focuses on the determinants of individual level CO_2 emissions and discusses the role of income, technology and date of birth in CO_2 emissions differentials across individuals. I show that the French baby-boom generation emitted relatively more CO_2 than their parents and their children, throughout their lifetime (about 20% more direct CO_2 emissions than average). This is due to a combination of income, technological lock-in and cultural effects.

Chapter IV, entitled "Carbon and inequality: From Kyoto to Paris" [7], builds on the results obtained in the previous chapters to construct a global distribution of carbon emissions. At the time of writing this chapter, global income inequality estimates presented in Chapter II were not available, so we had to rely on work done by other researchers to obtain global income series (Lakner and Milanovic, 2015). These were corrected with tax data and then used to reconstruct a global carbon emissions database. We show that the top 10% emitters account for about 45% of global emissions today and that twenty years ago, global inequality of carbon emissions was essentially a between-country inequality phenomena. Today, the situation is being reversed as within-country emissions inequality accounts for as much of global emissions inequality as the between-country dimension. On the basis of our results, we propose schemes to better share contributions to climate adaptation funds. The history of climate negotiations shows the extreme difficulty to implement any kinds of allocation rules to share a climate burden. But recent data (UNEP, 2017) also shows the limits of the approach of voluntary pledges (which still do not add-up, in terms of finance or mitigation) and hence the interest in this kind of allocation exercise.

[6] This chapter is based on "*Are younger generations higher carbon emitters than their elders?*", published in Ecological Economics, vol. 100, 2014.

[7] This chapter is based on "*Carbon and inequality: from Kyoto to Paris. Trends in the global inequality of carbon emissions (1998-2013) & Prospects for an equitable adaptation fund* ", co-authored with Thomas Piketty and published as a WID.world Working Paper 2015/7.

Chapter V, entitled "The French 'frais réels' scheme: an unfair and unsustainable tax loophole?" [8], brings the lens back to the national level and reveals how current tax systems can be improved to be better aligned with environmental protection and social objectives. In this chapter, we focus on a French tax loophole (the "Frais réels" scheme) and assess its environmental and distributional impacts. We show that the top 20% richest individuals capture about half of the gains associated to the scheme, which can also be seen as a pollution subsidy. This work is also instructive as its initial publication contributed to a partial reform of the measure.

Chapter VI, entitled "Assessing the potential of Sustainable Development Goals"[9] discusses the potential of the Sustainable Development Goals (SDG) framework (developed by the United Nations in 2015), to turn the global inequality debate into policy action. The SDG framework places inequality reduction at its center and recognizes the systemic impact of inequality on a wide range of social and environmental issues. In this chapter, we assess whether countries passed SDG Target 10.1 (requiring that the income of the bottom 40% of a country's population grows faster than national average) and discuss the use of such a target in the realm of public debate and policy. We show that such a metric can be used for peer pressure, peer review and mutual learning across countries.

[8] This chapter is based on *"Les frais reels: une niche fiscale inéquitable et anti-écologique?"*, co-authored with Mathieu Saujot and published as an IDDRI Working Paper 2012/19.

[9] This chapter is based on a paper entitled "*Reducing Inequalities within Countries : Assessing the Potential of the Sustainable Development Goals*", co-authored with Tancrède Voituriez and Alex Hough and published in Global Policy, Vol. 9(1), 2018.

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Part I

Income inequality

CHAPTER 1

Indian income inequality, 1922-2015: From British Raj to Billionaire Raj?

Abstract. We combine household surveys and national accounts, as well as recently released tax data in a systematic way to track the dynamics of Indian income inequality from 1922 to 2015. According to our benchmark estimates, the share of national income accruing to the top 1% is at its highest since the creation of the Indian Income tax act in 1922. The top 1% of earners captured less than 21% of total income in the late 1930s, before dropping to 6% in the early 1980s and rising to 22% in the recent period. Over the 1951-1980 period, the bottom 50% group captured 28% of total growth and incomes of this group grew faster than the average, while the top 0.1% incomes decreased. Over the 1980-2014 period, the situation was reversed; the top 0.1% of earners captured a higher share of total growth than the bottom 50% (12% vs. 11%), while the top 1% received a higher share of total growth than the middle 40% (29% vs. 23%). These findings suggest that much can be done to promote more inclusive growth in India. Our results also appear to be robust to a range of alternative assumptions seeking to address numerous data limitations. Most importantly, we stress the need for more democratic transparency on income and wealth statistics to avoid another "black decade" similar to the 2000s, during which India entered the digital age but stopped publishing tax statistics. Such data sources are key to track the long run evolution of inequality and to allow an informed democratic debate on inequality.

This chapter is based on "Indian Income inequality, 1922-2015: From British Raj to Billionaire Raj?", WID.world Working Paper 2017/11, co-authored with T. Piketty.

1 Introduction

India introduced an individual income tax with the Income Tax Act of 1922, under the British colonial administration. From this date, up to the turn of the 20th century, the Indian Income Tax Department produced income tax tabulations, making it possible to track the long-run evolution of top incomes in a systematic manner. Using this data, Banerjee and Piketty (2005) showed that the share of fiscal income accruing to the top 1% earners shrank substantially from the mid-1950s to the mid-1980s, from about 13% of fiscal income, to less than 5% in the early 1980s. The trend was reversed in the mid-1980s, when pro-business, market deregulation policies were implemented. The share of fiscal held of the top 1% doubled from approximately 5% to 10% in 2000.

According to National Accounts estimates, post-2000 income growth has been substantially higher than in the previous decades. Average annual real income growth was below 2% in the 1960 and 1970s, it reached 2.5% in the 1980s and 2% in the 1990s[10]. Since 2000s it is of 4.7% on average (Figure 1). Little is known however on the distributional impacts of economic policies in India after 2000 in part because the Income Tax Department stopped publishing income tax statistics in 2000, and also because self-reported survey data does not provide adequate information concerning the top of the distribution (fiscal data is not perfect either, but it delivers higher and more plausible income levels for the top). In 2016, the Income Tax Department released tax tabulations for recent years (2011-12, 2012-13 and 2013-14), making it possible to revise and update previously published top income estimates and better inform public

[10] Appendix A1 presents real per adult annual growth rates using GDP from United Nations National Accounts Database (used in this paper) and the World Bank Database.

debates on growth and income inequality. We find that the bottom 50% group grew at a substantially lower rate than average growth (Figure 1a) since the 1980s. Middle 40% grew at a slower rate than the average (Figure 1b). On the contrary, top 10% and top 1% grew substantially faster than the average since 1980 (Figure 1c).

The first objective of this paper is to mobilize this newly released set of tax data in order to track the evolution of income inequality from 1922 to 2015. The second objective is to go beyond top income shares and produce estimates of income dynamics throughout the entire distribution using concepts that are consistent with National Accounts (following, as much as possible, the Distributional National Accounts Methodology, see Alvaredo et al., 2016).

Figure 1a - National income growth in India: full population vs. bottom 50% income group, 1951-2015

Figure 1b - National income growth in India: full population vs. middle 40% income group, 1951-2015

Figure 1c - National income growth in India: full population vs. top 1% and top 10% income groups, 1951-2015

To do so, we combine in a systematic manner household survey, fiscal and national accounts data. Such an exercise is fraught with methodological and conceptual difficulties given the lack of consistent historical income inequality data in India. Indeed, the tax data available only covers the very top of the distribution of Indian earners (around 7% of total population in fiscal year 2014-15). In addition, the National Sample Survey Organization (NSSO) household surveys measure consumption rather than income. We repeatedly stress that there are strong limitations to available data sources, and that more democratic transparency on income and wealth statistics is highly needed in India. That said, we find that our key results are robust to a large set of alternative assumptions made to address data gaps. The present paper should be viewed as an exercise in transparency: we propose a method to combine the different available sources (in particular national accounts, tax and survey data) in the most possible transparent way, and we very much hope that new data sources will become available in the future so that more refined estimates can be constructed. All our computer codes are available on-line so that everybody can use them and contribute to improve the methods.

The rest of this paper is organized as follows. Section 1 discusses the Indian income inequality data gap of the past two decades, section 2 describes our data sources and methodology, section 3 presents our key findings, section 4 briefly discusses their policy relevance and section 5 concludes.

2 Entering the digital age without inequality data

i. Economic policy shifts since the 1980s

Over the past thirty years, the Indian economy went through profound evolutions. In the late seventies, India was recognized as a highly regulated economy with socialist planning. From the 1980s onwards, a large set of liberalization and deregulation reforms were implemented. In this context, it is unfortunate that Indian authorities stopped in 2000 publishing income tax tabulations, which represent a key source of data to track consistently the evolution of top incomes.

Under Prime Minister Jawaharlal Nehru (in power from 1947 to 1964), India was a statist, centrally directed and regulated economy. Transport, agriculture and construction sectors were owned and administered by the Central Government, commodity prices were regulated and the country had important trade barriers. Nehru's followers, including Indira Gandhi's (1966-77 and 1980-1984) prolonged these policies and implemented a highly progressive tax system. In the early 1970s, the top marginal income tax rate reached record high levels (up to 97.5%).

From the mid 1980s onwards, liberalization and trade openness became recurrent themes among Indian policymakers. The Seventh Plan (1985-1990), led by Rajiv Gandhi (1984-1989), promoted the relaxation of market regulation, with increased external borrowing and increased imports. The tax system was also gradually transformed, with top marginal income tax rates falling to 50% in the mid-1980s. In the late 1980s, when India faced a balance of payment crisis, it called for International Monetary Fund assistance. Financial support was conditioned to structural reforms which pushed forward the deregulation and liberalization agenda.

What came to be known as the first set of economic reforms (1991-2000) placed the promotion of the private sector at the heart of economic policies, via denationalizations, disinvestment of the public sector, deregulation (dereservation and delicencing of public companies and industries)[11]. These reforms were implemented both by the Congress government of N. Rao (1991-1996) and its successors, including the conservative Janata Party government of A. Vajpayee (1998-2004). The reforms were prolonged after 2000, under the 10th and subsequent five-year plans. These plans

[11] Economic policies also seeked to rationalize the public sector, its branches now had to pursue the objectives of profitability and efficiency. The opening of imports, exchange rate floating regime and banking, capital market opening were also implemented.

ended government fixation of petrol, sugar or fertilizer prices and led to further privatizations, in the agricultural sector in particular.

The impacts of these reforms in terms of growth has been praised by public authorities. Real per adult national income growth, which has more sense from the point of view of individual incomes than commonly used GDP[12], significantly increased after the reforms. It was 0.7% in the 1970s, 2.5% in the 1980s, 2.0% in the 1990s and 4.7% since 2000 (Figure 1). However, little is known on the distributional characteristics of post-2000 growth.

ii. The income inequality data gap

Public debate over liberalization policies largely focused on their macroeconomic impacts (Ramaswami, Kotwal, Wadhwa, 2011) and on the impacts on poverty, with a substantial reduction in poverty rates[13] (World Bank, 2017; Deaton & Dreze, 2002; Deaton & Kozel, 2005). How the Indian economy fared in terms of inequality has been arguably less discussed. This can partly be explained by a lack of consistent data on the distribution of incomes or wealth for the recent period.

Some evidence suggesting a rise in income inequality in India after the turn of the century can however be found in NSSO surveys and in openly-available data sources. Figure 2 presents the share of total consumption attributable to the top 20% of consumers, available online from the World Bank and United Nations WIDER World Income Inequality Database (UN-WIDER WIID). The data shows a decrease in top quintile consumption share from the fifties to the seventies from around 43% to 40% and an increase thereafter (in line with Banerjee and Piketty findings) to close to 44%.

[12] Net national income is equal to GDP minus depreciation of fixed capital plus net foreign incomes.
[13] The share of Indians under the $1.9 poverty line went from 45.9% in 1993 to 21.2% in 2011 (PovcalNet, 2017)

There are important irregularities with the data, but the overall "U-shape" trend seems relatively consistent[14].

Figure 2 - Top 20% consumption share from NSSO surveys

The shortcomings of household survey data in monitoring the evolution of inequality are well known; because of underreporting and undersampling issues, surveys fail to properly capture inequality dynamics at the top of the distribution (Atkinson and Piketty, 2007, 2010). What is more, NSSO surveys only focus on consumption rather than income and the distributional dynamics of these two concepts can differ notably. In addition, the relatively limited magnitude of the changes observed in NSSO data calls for care in the interpretation of such results. Consumption data available through surveys constitutes part of the evidence, but are not sufficient to inform debates on Indian inequality.

Other data sources, such as Forbes' Indian Rich lists, suggest an important increase in the wealth of the richest Indians after 2000 (see Figure 3). The wealth of the richest Indians reported in Forbes' India Rich List, amounted to less than 2% of National income in the 1990sn, but increased substantially throughout the 2000s, reaching 10% in 2015 and with a peak of 27% before the 2008-9 financial crisis. Such data suggests a rise in wealth inequality levels throughout the post-2000 period, but does not enable a consistent analysis of income inequality over the long run. This is

[14] As discussed below, income surveys sources are available for 2005 and later years; in particular data from the National Council for Applied Economic Research (NCAER) and from the Inter University Consortium for Applied Political and Social Sciences Research (ICPSR). These data sources however do not enable comparison before and after 2000.

confirmed by simple simulations using a fixed normalized wealth distribution and taking into account rising average nominal wealth over the period (unfortunately Indian wealth data is very limited so it is difficult to go further).

Figure 3 - Wealth of richest Indians in Forbes' Rich List, 1988-2015

The recent release of income tax tabulations by the Indian Income Tax Department for the post 2011 period does, however, allow for a more consistent analysis of the dynamics of income in India since the turn of the century.

3 Data sources and Methodology

We present the data used to produce series on the evolution of income for the entire distribution from 1951-52 to 2014-15 (period covered by both household surveys and tax data, as well as national accounts) and for the evolution of incomes of the top 1% share and above from 1922-23 to 2014-15 (period covered by tax data and national accounts only, with no survey data prior to 1951).

i. Description of the different data sources

Tax data

The Indian Income Tax Department released tax tabulations for the fiscal years 1922-1923 to 1998-1999, and interrupted the publication in 2000. After several public calls for more democratic transparency over Indian inequality data[15], the ITA released tax tabulation for fiscal years 2011-12 to 2014-15. All these tabulations report the number of taxpayers and the gross and returned income for a large number of income brackets[16]. Gross income corresponds to pre-tax income before certain deductions are applied to compute returned income[17]. Tax units are defined as individuals or Hindu Undivided Families (HUF, family clusters allowed to file their income jointly). The number of HUF represented roughly 20 % of tax returns in the interwar period, 5% in 1990 and less than 2.5% in 2011.[18]

The exact reason why the Income Tax Department stopped publishing data in 2000 remains unknown. One potential explanation for this is the change in the sampling method employed in the late 1990s, with a resulting loss in the precision of estimates. Indeed, official tax tabulations were based on the entire population until the early 1990s - or based on stratified samples with sampling rates close to 100 percent for top incomes

[15] See for instance http://www.bbc.com/news/world-asia-india-36186116

[16] According to the Income Tax Department, a number of tax payers paid their taxes but did not file returns in fiscal years 2011-12 to 2014-15. These represent an additional 25% taxpayers. In order to take into account these "non-filers" taxpayers, we tested alternative assumptions: i) non-filers are scattered across all brackets, in the same way as filers, ii) non-filers fall in the lowest taxable bracket, iii) non-filers fall in the four lowest income brackets. We find that these alternative assumptions have very limited impact on our final results. Minor corrections were done to raw tax data and mainly pertain to the clubbing of brackets in some years as the average income was incompatible with the bracket they were categorized. In such rare cases, we club erroneous brackets in the lower bracket. Year 1997 was removed altogether, as data is erroneous.

[17] Deductions are defined at chapter VI of the Income Tax Act. They include premiums of annuity plans, equity fund investments, medical or health insurance, certain forms of donations, etc. Focusing on gross income is more accurate in terms of pre-tax income and is also less impacted by changes in the definitions of deductions. Income losses (such as business income losses) have to be adjusted while computing Gross Total Income as per Income Tax law. Note that imputed rent for owner occupied dwellings were included in Income tax computations before 1986 and removed afterwards. More precisely, post 1986 tax data excludes imputed rent for first residence, but not for secondary residences.

[18] One should note that the Indian income tax data is entirely based upon individual income. This corresponds to equal-split income (ie. income shared among spouses) only if we assume that tax-payers are either single or married to other tax-payers falling in the same bracket, which strictly speaking cannot be true. This implies that our estimates tend to over-estimate inequality as compared to the equal-split benchmark. The equal-split benchmark however tends to under-estimate inequality as compared to an individualistic benchmark (a benchmark in which one assumes no sharing of income among spouses). If and when we access to micro-level Indian tax data, we will be able to refine this analysis and compute separate equal-split and individualistic series.

as is the case in most OECD countries, but seem to be based on uniform samples of all tax returns after this period and up to 2000 (Banerjee and Piketty, 2005). The latter method led to less precise results[19]. Another potential explanation for the halt in tax reporting could just be the lack of interest in income statistics and inequality (which given the rise in top income shares observed from mid 1980s to 2000 seems rather surprising).

Interestingly enough, the number of income tax payers in India has increased substantially over the past decades. Less than 0.5% of the population filed tax returns up to the 1950s, between 0.2 and 1% over the period between 1960 to 1990, before a substantial increase thereafter; from 1% to close to 3% in the late 1990s and 7% in the latest period (Figure 4). This increase over twenty years is impressive. Yet, comparatively, the current figure is similar to the levels observed in France and in the USA in the late 1910s, and much lower than the levels observed in the interwar period (about 10-15%) and in the decades following World War 2 (50% or more) in these two countries (Piketty, 2001; Piketty and Saez, 2003). With revenues from income tax equivalent to approximately 2% of GDP, India receives more revenue than China (1%), but significantly less than other emerging countries such as Brazil and Russia (4%), and South Africa and the OECD countries (9%) (OECD, 2017).

Figure 4 – Proportion of income-tax taxpayers in India, 1922-2015

[19] For year 1997, see Appendix A2.

NSSO consumption data

The NSSO, led by the Ministry of Statistics and Program Implementation started an all-India consumer household expenditure survey (AIHS) after its independence in 1947. The first round of the AIHS was carried out in 1951 and surveys were then conducted on an annual basis. The size of rounds varies since the quinquennial AIHS has a larger sampling of about 120 000 households and five times less for smaller other rounds. The reach of the quinquennial survey is extensive in terms of consumption items (ranging from daily used food, clothing to durable goods and services such as construction, education and healthcare). NSSO surveys however do not measure individual or household incomes[20], in part because agricultural and business incomes are judged to be volatile and assumed to be much less reliably measured than consumption.

Since the first survey rounds, NSSO produced 30 days reference period estimates. This period is known as the Universal Reference Period. Post-1990, concerns were raised about the sensitivity of the reference period on the estimates and NSSO started publishing alternative reference periods (7 days and 365 days). As Deaton and Kozel (2005) note, shorter recall periods tend to lead to higher consumption estimates. However, experiments carried out with different reference periods by the NSSO working group concerned concluded that there is no clear superiority of a period over another. We thus use the Universal Reference Period. This choice is also motivated by the fact that the 30 days period is the only one that is consistent throughout the entire period of analysis (1951-2014).

[20] The Employment Unemployment Surveys report wages for the working-age population, but other sources of income are not covered.

For recent years (1983 to 2010) we use quinquennial rounds 38 (1983), 43 (1987-88), 50 (1993-94), 55 (1999-2000), 61(2004-05), 66 (2009-10). Micro data at the household level was obtained from the NSSO. For earlier rounds (rounds 3 to 32), for which we could not access micro data files, we use the Poverty and Growth in India Database of the World Bank (Ozler et al., 1996) which provides rural and urban per capita consumption tabulations for a dozen quantile groups for years 1951 to 1978. All rounds and corresponding years used are summarized in Appendix A3, along with the summary statistics of each round. We describe in section 0 the procedure used to infer the full distribution of income from these surveys and how we interpolate missing years.

National Accounts data

From 1950 to the present day, we use GDP data from WID.world, based on National Accounts Statistics (NAS) from 1971 to 2013, on World Bank (after 2013) and on Maddison (2007) from 1950 to 1970[21]. WID.world then performs its own computations to infer Net Foreign Income and Consumption of Fixed Capital (Blanchet and Chancel, 2016). Before 1950, we use historical National Income growth rates from Sivasubramonian (2000).

A well know puzzle in Indian statistics (Deaton and Kozel, 2005; CSO, 2008) pertains to the difference in survey consumption growth rates and national accounts growth rates, particularly during the recent period. Figure 5 shows the total growth rate of Net National Income and Household Final Consumption Expenditure from NAS and personal consumption from NSSO, from 1983 to 2011. According to NAS, national

[21] In the 1990s we observe noticeable differences between real GDP growth estimates obtained from UN SNA and those reported by the World Bank (see Appendix A1).

income grew at 475% and household consumption grew at slightly more than 300%, while NSSO data indicates that household consumption grew at 200%.

Figure 5 – Income and consumption growth rates in India, 1988-2011

Several reasons have been put forward to explain this gap, including (i) population coverage (it is different between NSSO and NAS, since Non Profit Institutions Serving Households and homeless individuals are not covered by NSSO surveys); (ii) valuation and integration of certain types of services in survey questionnaires (it was argued that the treatment of cooked meals served by employers to employees leads to underestimation of the total value of services consumed by households in the NSSO surveys (CSO, 2008) while other services such as financial intermediation that are particularly important among top earners, are not included in survey estimates (Sundaram and Tendulkar, 2005); (iii) imputed rents (while the NAS incorporates imputed rents, NSSO surveys do not[22]); (iv) consistency of National Accounts estimates (Kulshreshtha and Kar, 2005) ; (v) under-reporting and under-sampling of top incomes in survey data (Banerjee and Piketty, 2005). We should stress from the outset that we do not pretend to solve this complex issue. The divergence probably involves several, if not all of the factors above cited. What we seek here is to better estimate the fraction of the difference that can be explained by the absence of top earners in survey data. We do not think that this factor alone can explain the entire gap, as it has been suggested (Lakner and Milanovic, 2015).

[22] When correcting for imputed rents the Central Statistical Organization (2008) finds a large and growing share of total consumption remains unexplained.

IHDS income and consumption survey

The Inter University Consortium for Applied Political and Social Sciences Research (ICPSR), based at the University of Michigan, provides access to the India Human Development Survey (IHDS), conducted in 2004-05 and 2011-12 among more than 40 000 households from rural and urban areas. The survey provides information at the household level on both income and consumption. Consumption related questions were designed so as to match the NSSO questionnaire, using similar item categories and similar referencing periods. The definition of income in the IHDS survey includes all sources of income: labour income (wages and pensions), capital income (rents, interests, dividends, capital gains) as well as mixed (or business) incomes. Government benefits, reported in the survey, are excluded from the analysis for consistency with tax tabulations; our focus is pre-tax income.

The IHDS is one of the very few surveys estimating both consumption and income in India. This is particularly useful as it enables a tentative reconstruction of NSSO unobserved income levels, using IHDS information. We describe this methodology in section 0. IHDS micro data is also openly available via the ICPSR website, which makes it particularly convenient[23].

UN statistics population data

We define the theoretical population of tax payers as the total number of adult individuals in India. We use adult population data from UN Population Prospects (2015) from 1950 to today. UN Population prospects provide 5-year age range annual

[23] We were not able to access the micro files of the National Council for Applied Economic Research's National Survey on Household Income and Expenditure, carried out in 2004-5 and 2011.

population tables, based on national census and their own estimation procedures. The adult population is defined as the number of individuals over age 20. Before 1950, we use total population estimates from Sivasubramonian (2000) and reconstruct the adult population using total population growth rates given by the same author.

ii. Methodology

Estimation of top fiscal incomes

Following Banerjee and Piketty (2005), we first reconstruct top income thresholds and levels, using generalized Pareto interpolation techniques. The main methodological difference with Banerjee and Piketty lies in the use of generalized Pareto interpolation techniques (Blanchet, Fournier and Piketty, 2017) rather than standard Pareto distributions. Generalized Pareto interpolation[24] allows for the recovery of the distribution based on tax tabulations without the need for parametric approximations. This method has demonstrated its ability to produce very precise results and also has the advantage of generating smooth estimates of the distribution, i.e. generating a differentiable quantile function and a continuous density, while other methods introduce kinks around the thresholds used as inputs for the tabulation.

The generalized Pareto interpolation procedure generates 127 generalized percentiles, namely p0p1, p1p2, ..., p99p100, corresponding to 100 fractiles of the distribution. The top fractile is split into 10 deciles (p99.0 p99.1, p99.1 p99.2,..., p99.9p100), its top decile itself split in ten deciles (p99.90 p99.91, p99.91 p99.92, ..., p99.99 p100), the tenth decile again split in ten deciles (p99.990p99.991, p99.991

[24] Available online at www.wid.world/gpinter

p99.992, ..., p99.999p100). The top generalized percentile thus corresponds to the top 0.001% of the population. As shown in Figure 4, tax data in India is only reliable above the p94 threshold for the recent period and above the p99.9 threshold when we go backwards in time.

Estimation of bottom survey incomes

One of the main difficulties of our exercise is related to the fact that NSSO does not include questions on individual and/or household income. Our strategy consists of using observed income-consumption profiles in IHDS data to reconstruct income profiles from NSSO consumption data. We first estimate income and consumption levels for each generalized percentile of the distribution of income and consumption given by IHDS data. For each survey and each percentile of the distribution, we construct observed income-consumption ratios $\alpha_{1p}=y_p/c_p$, with y_p and c_p respectively with a mean income and consumption within quantile *p*. We call this strategy A1. To obtain a theoretical income-consumption profile over percentiles, we take average of years 2004-5 and 2011-12. In practice, the two profiles differ only marginally. We then construct two alternative ratios, α_{2p} and α_{0p}, referred to as strategies A2 and A0 respectively. In strategy A2, we assume that $\alpha_{2p}= 1$ for $\alpha_{1p}\leq 1$ and $\alpha_{2p}=\alpha_{1p}$ otherwise. This second strategy is equal to assuming no negative savings rates among the poor. In strategy A0, we define $\alpha_{0p=(}\alpha_{1p}+\alpha_{2p})/2$ for $\alpha_{1p}\leq 1$. This strategy assumes that there can be negative savings rates, remittances or household transfers, but that the true α_p value lies between strategy A1 and strategy A2. Income consumption ratios for the different strategies are presented in Appendix A4. We find that these different strategies have no effect on the trends we observe and a limited impact on top share estimates, as we show in section .

The choice of these different strategies indeed impacts on the estimated share of total savings in the economy. In strategy A1 total savings are close to 0, which seems too low compared to the current rate of savings in India (about 30%). This figure is close to 5% in strategy A0 and approximately 10% in strategy A2. These values are more or less constant throughout the entire period covered whereas in National accounts they move from about 10% in the 1960s to 30% today. However, using strategy A0 and factoring in top incomes in the analysis allows us to find an aggregate savings rate of the same order of magnitude as those observed today (see Appendix A5).

Interpolating survey and tax data for missing years.

Our objective is to produce yearly estimate for the full distribution from 1951 to 2014. Given that survey or tax data is not available for all years, it is necessary to interpolate tax and/or survey data for a certain number of years. In order to do so, we interpolate missing years using a constant growth rate between known intervals t and $t+N$[25].

As described in section 2.i, two surveys can be used for the estimation of survey income for the years 2004-5 and 2010-11, NSSO and IHDS. However, the trends observed in the surveys are somehow divergent. The ratio of reconstructed NSSO total income to total personal income from national accounts decreases, while the ratio of IHDS total income to total personal income from national accounts is stable. The choice of one or the other source of data has implications on our final inequality statistics: using IHDS income group averages for the estimation of the bottom of the distribution

[25] In practice, for each average income at percentile p of the survey (or tax) distribution, we define $y_{pt+1}=y_{pt}\times g$ where $g=(y_{pt+N}/y_{pt})^{1/N}$, with g the growth rate, y_{pt+1} the average income at percentile p and year t+1.

(strategy B1) yields a lower rise in top income shares than when using the NSSO survey (strategy B2). In fact, using NSSO totals mechanically accentuates the rise in top shares over the period and the strategy B1 is therefore used as our benchmark, as it represents the conservative approach. That said, we cannot rule out strategy B2, if we believe NSSO surveys are consistent throughout the entire period covered. We provide results for strategy B2 in the data appendix.

Between 2000 and 2011, we do not observe any tax statistics, but we do observe survey data in 2004-5 and in 2010-11. Survey data is not satisfactory to track the dynamics of top incomes, but it is better than no data at all. We thus estimate the growth rates of each percentile between 1999 and 2005 on the basis of their evolution observed in the survey distribution. The resulting estimates show the top 10% share evolving in the same direction between 2005 and 2011 in our final results as in the survey. We see this strategy as the best we can have with the available data at hand for this specific sub-period.

Combination of tax and survey data

Several strategies can be used to correct for missing top incomes in survey data. These include the modification of the weights assigned to top earners in household surveys, the addition of extra observations of top earners or the multiplication of income levels at the top (Burkhauser et al, 2016), and each has its own strengths and weaknesses. We think that an acceptable method should be consistent, in producing distributions with plausible statistics, in particular, the shape of inverted Pareto beta coefficients curves should be relatively smooth. The method followed should also be transparent, in so-much as it should provide a statistical outcome that could be anticipated from an economic perspective; survey inequality should in principle increase when we factor in top fiscal incomes. Furthermore, a simple strategy would also be better than a complex one.

Our preferred strategy is to assume that surveys are reliable from the bottom of the distribution up to a certain percentile and that tax data is reliable after another (in line with Piketty et al., 2017). In practice, this amounts to multiplying income of the top percentiles in the survey by a certain factor, given by tax data. More precisely: we suppose that survey data is reliable from p0 to p_1 - this means that between p_0 and p_1, averages and thresholds are given by the distribution of interpolated (estimated) survey income. In our benchmark scenario, which we refer to as strategy C1, p_1=p90. We also test alternative ranges: (i) p_1=p95, which we refer to as strategy C2 and (ii) p_1=p80, referred to as strategy C3. As shown in section 3.5, these different strategies have no impacts on the recent and long-term income trends observed in India and have only a moderate impact on income concentration levels.

We then suppose that tax data is reliable from a certain percentile, p_2, up to the top of the distribution. P_2 is given by the population share lying under the first taxable bracket observed in the tax data. This value varies from p_2=99.9 in the 1950s to p_2=93 in the la2010s. Therefore, our strategy implies that averages and thresholds for all percentiles above p_2 are given by the distribution interpolated from observed tax data. Appendix A5 gives the precise value of p_2 for each year.

Between p_1 and p_2, we test several strategies for the progression of income levels and thresholds at a given point of time. We define a convex junction profile (strategy D1), a linear profile (strategy D2) and a concave profile (strategy D3). We adopt D1 (convex profile) as our benchmark strategy as it corresponds to the profile observed for recent years, for which we have more observed fiscal data at the top; more than 6% of the population against 0.1% for the earlier period (see Appendix A6). We find that these different strategies have negligible impacts on top share results. In fact, the bulk of the correction we apply to survey incomes occurs above p_2, not between p_1 and p_2.

From total fiscal income to national income

Total fiscal income is the total personal income that would be reported by individuals or tax units, if all of them reported their revenues to the tax administration. In the case of India, we do not observe this value because of the limited tax base. One way to recover it, following Atkinson (2007), is to start from the sum of primary incomes obtained by households reported in national accounts and operate a series of deductions and additions towards a definition closer to taxable income. This is the approach followed by Banerjee and Piketty (2005) and appears appropriate given that their focus was restricted to top incomes only. By construction, total fiscal income evolves at the same rate as pre-tax national income under this approach.

The other approach consists of reconstructing total fiscal income via the combination of top fiscal incomes and observed (or estimated) survey income, as we detailed in the previous section. This is equivalent to assuming that tax data give true fiscal incomes for individuals over p_2 and that estimated survey data gives the true fiscal incomes for individuals below p_1. In this approach, reconstructed fiscal income and total national income can evolve at a different pace. Over the years, we observe a growing gap between reconstructed total income from surveys and total national income (see Appendix A7). This divergence is the repercussion of the gap between household consumption surveys and national accounts discussed in section 0. We show in Figure 12 that we can account for a non-negligeable share of this gap after the combination of survey and tax data , but that a large part of the difference remains unexplained.

In order to produce income estimates comparable to other countries, we chose to rescale our fiscal income estimates to match total pre-tax national income from national accounts. In practice, we preserve the distribution obtained from the combination of tax and survey data and simply rescale average and threshold levels of all percentile groups by a yearly factor so that we match total national income.

In further work, we intend to distribute retained earnings to the top of the distribution following the DINA guidelines (Alvaredo et al, 2016). This would most likely increase the level of inequality in the recent period, since the growth of retained earnings is likely to be concentrated among top earners. The amount by which our results would vary presumably remains limited though.

Definition of a benchmark scenario

The combination of our different strategies defines 54 scenarios (3 A scenarios x 2 B scenarios x 3 C scenarios x 3 D scenarios). We stress that most of the combinations of scenarios among these 54 possibilities can be a priori justified, and as such, we provide results for all corresponding series in our data appendix. We see our benchmark scenario (A0B1C1D1) as being at the same time plausible and conservative compared to most of the scenarios tested, as top income shares increase at a slower rate over the recent decades than in most scenarios. Robustness tests are presented in section 3.5.

4 Results

i. Sharp rise in top income shares since the mid-1980s

Our results exhibit a strong rise in top income shares since the mid-1980s. In our benchmark estimation scenario, the share of national income attributable to the top 1% reached 21.3% of national income in 2014-15, up from 6.2% in 1982-1983 (see Figure 6). The top 1% share of national income was at 13% of national income in 1922-23 and increased to 20.7% in 1939-40, at the dawn of World War II. It then dramatically decreased to 10.3% in 1949-50 and further decreased from the late 1960s to the early 1980s.

Figure 6 - Top 1% national income share in India, 1922-2015

As expected, the top 0.1% income share dynamics exhibit a similar pattern in our benchmark scenario (see Figure 7). Top 0.1% earners captured 8.2% of total income in 2014-2015. This only slightly below its pre-independence peak of 1939-40 (8.9%). The top 0.1% then saw a strong drop during World War II (down to 5.5% in 1944-45), followed by a continued reduction up to 1982-83 (when it reached 1.7%). From 1983-84 onwards, the share of national income accruing to the top 0.1% rose almost continuously.

Figure 7 - Top 0.1% national income share in India, 1922-2015

Looking at the 0.01% earners (Figure 8), we also observe a strong increase in their share of national income since the mid 1980s, reaching 3.4% in 2014-2015, up from 0.4% in 1982-83. In 1941-42, the top 0.01% earned 3.8% of total income.

Figure 8 - Top 0.01% national income share in India, 1922-2015

ii. Fall in Middle 40% and bottom 50% shares

We now turn to post-1951 results, which we have for the entire distribution of income. Figure 9 shows the mirror evolution of top 10% share in total income and middle 40% share (i.e. individuals above the bottom 50% earners and below the top 10%). In the mid-fifties, the top 10% and the middle 40% held about 40% of total income each, the share of the middle 40% progressively increased from the mid-fifties to 1982-83, reaching 46% of total income. It then decreased afterwards. At the turn of the Millennium, the top 10% and the middle 40% groups captured exactly the same amount, 40%. However, by 2014-15, the middle 40% share had fallen to a historically low level of 29.2%.

Figure 9 - Top 10% vs. Middle 40% national income shares in India, 1951-2014

The income dynamics of the poorest half of the income distribution exhibit a similar pattern to that of the middle 40% (Figure 10). Bottom 50% share of national income increases from 19% in 1955-56 to 23.6% in 1982-1983, but then decreases sharply and almost continuously thereafter (20.6% in 2000-2001 and 14.9% in 2014-15).

Figure 10 - Bottom 50% income share: 1951-2015

iii. Total growth rates by income group

We now measure total growth rates across the full distribution of incomes over the 1980-2015 period and compare these results to other countries available in the WID.world database, namely China, France and the USA. We also provide global growth estimates for the corresponding global groups.

Table 1 - Total growth rates by income group in India, 1980-2015

Figure 11 – Income growth by percentile in India, 1980-2015: The cobra curve of inequality and growth.

Table 1 and Figure 11 show that income growth rates in India over the 1980-2015 period substantially increase as we progress upwards through the distribution of income. The bottom 50% of earners experiences a growth rate of 90% over the period, while the top 10% saw a 435% increase in their incomes. The equivalent figures for the top 0.01% and top 0.001% were 1699% and 2040%, respectively. Appendix A10 shows the same results on an annual growth rate basis.

Unequal growth dynamics over the period are not specific to India. Income growth rises the higher up the income distribution one proceeds in China, in the USA and in France as well. India's dynamics are, however, striking: it is the country with the highest gap between the growth of the top 1% and growth of the full population (near factor 4 difference in growth rates between these groups). It is also interesting to note that bottom 50% of earners grew 4 times more slowly in in India than in China, whereas the middle 40% Indians grew nearly 8 times more slowly than their Chinese counterparts. Differences between the two countries among top groups are much less pronounced.

While Table 1 is particularly meaningful from the perspective of individual growth dynamics (what individuals observe), it is also useful to balance this with information on the share of total growth captured by different income groups Indeed, high income growth at the individual does not necessarily translate into a high share of total growth captured at the macro level. Table 2 shows that the top 0.1% earners captured more total growth than the bottom 50% (11% vs. 10% of total growth) over the period. The top 0.1% of earners represented less than 800 000 individuals in 2014-15, this is equivalent to a population smaller to Delhi's IT suburb, Gurgaon. It is a sharp contrast with the 397 million individuals that made up the bottom half of the adult population in 2014-15. At the opposite end of the distribution, the top 1% of Indian earners captured 28% of total growth, as much as the bottom 83% of the population. The comparison of these figures with China and other countries is particularly noteworthy. Out of the four countries, India is the country where the middle 40% benefitted from the least from total growth over the period. We discuss this "missing middle class" issue in the next sections of the the paper. The bottom 50% however captured a similar share of total growth in India and in China (respectively 10% and 13%).

Table 2 – Share of total growth captured by income groups, 1980-2015: India, China, the USA, Western Europe.

Table 3 shows income levels and income thresholds for different groups and corresponding adult population size in 2014-2015. Top 1% earners earn on average INR 2.9 million (21 times national average) versus INR 40,700 (0.3 times national average) for the bottom 50% and INR 101,100 (0.6 times national average) for the middle 40%.

Table 3 - Income inequality in India, 2014-15

Table 4 shows the growth rate over different income groups in India for the 1951-1980 period. The situation is reversed as compared to the 1980-2015 period: the higher the group in the distribution of income, the lower the growth rate over the period. Real per adult income of the bottom 50% middle 40% groups grew substantially faster (respectively 87% and 74%) than average income (65%). On the contrary, top 0.1%, top 0.01% and top 0.001% income groups experienced a severe decrease in their real incomes (-26%, -42% and -45% respectively). Appendix Apresents the same data with annualized growth rates.

Table 5 reveals that bottom 50% group captured 28% of total growth over the 1951-1980 period, vs. 49% for the middle 40% and 24% for the top 10%.

Table 4 - Total growth rates by percentile in India, 1951-1980

Table 5 - Share of total growth captured by percentile groups in India, 1951-1980

iv. Growing share of income gap explained by top incomes

We compare the theoretical fiscal income obtained from national accounts[26] to our reconstructed fiscal income and the total income estimated from household surveys. This comparison reveals the share of survey and national accounts discrepancy

[26] Supposed to be 70% of net national income, following Banerjee and Piketty (2005).

discussed in section 0, that can be attributed to the absence of top earners in survey data. We find that our reconstructed fiscal income bridges a growing and non-negligible gap between national accounts surveys data. The share of the gap explained by our reconstructed fiscal income rises from about 0% in 1990 to close to than 40% in 2014-15.

Figure 12 – Importance of missing top incomes in India since 1990: Share of gap between survey income and national accounts explained by missing top incomes

v. Measurement issues and robustness tests

One of the main assumptions underlying our results is that tax data measures the actual income shares of the richest. There are a number of reasons why this may not entirely be true. A potential issue with tax data is that the surge in top incomes may reflect improvements in the Income Tax Department's ability to measure and tax the incomes of the richest. The tax cuts in the early 1990s might have reduced the incentives among the wealthy for evading the income tax. Indeed, there were a number of innovations in tax collection in the 1990s, such as the 1998 introduction of the "one in six rule" that required everyone who satisfied at least one of six criteria (such as owning a car and travel abroad) to file a tax return. We note however that the decline in the top marginal rate was quite moderate during the late 1980 to 2000 period: the top marginal tax rate dropped from 50% in 1987-1988 to less than 40% in 1999-2000 (and only minor evolutions after, see Figure 13). By comparison, the increase in the share of the top 0.01% was huge: it went up from 0.7% in 1987-88 to more than 2% in 1999-2000. If this entire change is to be explained by a shift in tax rates, the implied elasticity would have to be enormous. Another key limitation of the Indian tax series is the ten-year break from 2000 to 2010. We did not find evidence of significant changes in the tax legislation, that could explain the rise in top shares post-2000. We also note that the post-2000 rise does not mark a discontinuity in the series, but comes more as the prolongation of rising top shares trend observed in the 1990s. The trend is also in line with the rise of inequality observed in consumption surveys, in wealth rich lists and recent wealth inequality series (Anand and Thampi, 2016). The release of tax tabulations for the years 2000 to 2010 would allow us to better analyze year-on-year evolutions for this crucial period.

In order to test the robustness of our results to data limitations (including the tax data gap of the 2000s and the growing gap between national accounts and consumption surveys), we present our results along the 54 estimation strategies described in section 2.ii. These 54 scenarios reflect a wide range of alternative assumptions to make up for the lack of consistent data for the entire distribution of income. We find that our main results are robust to all the strategies tested.

Appendix A12a-c show the evolution of the top 1%, 0.1% and 0.01% shares from 1922 to 2014 across the 54 scenarios, along with our benchmark series (thick red line). The results only differ slightly between the different scenarios before 2005. In 1982-83, the top 1% share indicates 5.5% in the lower case scenario vs. 6.6% in the upper case. After 2005, the spread between scenarios is higher: top 1% income shares indicate 20.3% in the lower case scenario and 27.7% in the upper case scenario in 2014-2015. The higher spread after 2005 is essentially due to strategy B assumptions (ie. whether NSSO consumption surveys in 2005 and 2010 are rescaled upwards). Our benchmark strategy consists in rescaling the income levels estimated from NSS upwards - on the basis of IHDS data - to temper the rise in top shares at the end of the period. Considering these assumptions, the trends are remarkably similar across all scenarios, but the true top share values could be higher than what we obtain in our benchmark results.

Results for the middle 40% and the bottom 50% groups are relatively more sensitive to our sets of scenario assumptions, as Appendix A12d and Appendix A12e show. We find a 2.5 p.p. spread on lower case and upper case scenarios for middle 40% shares on average and an average 8 p.p. spread for bottom 50% income shares. This spread is essentially due to assumptions on the savings profiles of lower consumption groups (strategies A0, A1, A2). The A0 scenario reflects a mid-range position between the 0 negative assumption (scenario A2) and the profiles obtained from the IHDS dataset, with arguably excessive negative savings rates[27]. Long run results for bottom 40% and middle 50% groups are consistent across all scenarios: a slight increase from 1951-52 to 1983-84 and and a significant decrease afterwards.

To sum up, we see our set of alternative scenario assumptions as a way to shed light on the gaps in our current knowledge of Indian income inequality. Our results are robust to a wide range of alternative assumptions but we do not pretend that these new series are definitive. More modestly, we hope they can encourage the publication of full series from 2000 to 2010. All computer codes are provided in the data Appendix Aof the paper and can be used to produce alternative strategies, if novel data addressing current gaps were to be released.

5 Discussion

[27] We note particular divergences around between 1978 and 1983 for both middle 40% and bottom 50% shares. This is explained by the fact that from 1978 to 1983, as shown in Appendix A14c, we do not have survey distributional data and we interpolate them on the basis of 1978 and 1983 information. The combination of interpolated survey income levels for these specific years and certain of our strategies - in particular strategy C3 (p_{x1}=80) and D3 (concave junction profile), tend to reduce "next 9%" income levels (ie. individuals above the bottom 90% but below the top 1%) and relatively increase levels of the bottom 90%. These 'extreme' scenarios are the less plausible of the set of assumptions in our view.

i. The mid-1980s turnaround

Our findings confirm and amplify the conclusions of Banerjee and Piketty (2005) on Indian inequality in the long run, namely i) a marked decrease in inequality in the early fourties ii) an even stronger reduction in top income shares in the 1950-70s and iii) a significant increase from the mid-eighties onwards. Current income inequality in India is higher than during pre-independence period. This holds true from the creation of the Income Tax in 1922 to independence in 1947 when comparing the top 1% share of national income, but also for the pre-1922 period. Before 1922, the best available estimates show that the top 0.1% income share varied between 5 and 7% of national income vs. more than 8% today in our benchmark, conservative scenario.

We note that the reduction in top income shares was smaller during the interwar period than the reduction which occurred throughout the 1950-1970s. This seems consistent with the interpretation posited for industrialized countries' (Piketty, 2001; Piketty and Saez, 2003). The shock induced by the Great Depression of the 1930s and the War had relatively lesser impacts in India than in the USA and Europe. In India, strong government control along with an explicit goal to limit the power of the elite[28] seems to have played a key role in reducing top income inequality after independence in 1947. The set of "socialist" policies implemented up to the 1970s included nationalizations, strong market regulation and high tax progressivity.

Railways were nationalized in 1951, air transport in 1953, banking in 1955, 1969[29] and 1980, oil industry in 1974 and 1976 to cite but a few. Along with the transfer of private to public wealth and reduction of capital incomes they implied, nationalizations

[28] An anecdote may reflect this view on fairness which prevailed in Nehruvian politics: when industrialist Tata asked then Prime Minister J. Nerhu about allowing profits in Stata-owned industries, J. Nehru answered, *"Never talk to me about profit, [...], it is a dirty word"* (Das, 2000).
[29] 14 banks were nationalized, representing 70% of the sector.

came along with government setting over pay scales. In the private sector, incomes were constrained by extremely high tax rates: between 1965 and 1973, top marginal tax rates rose from 27% to 97.5%[30]. Such evolutions may have reduced rent-seeking behavior at the top of the distribution via a process of discouragement, which in presence of excessive bargaining power and rent-seeking is the efficient thing to do (Piketty, Saez, Stantcheva, 2014).

Figure 13 – Top marginal income tax rate in India, 1948-2016

As discussed in section 2, from the early 1980s onwards, the Indian economy underwent reverse transformations. The turnaround of income inequality (in 1983-84, see Figure 6 to Figure 10) seems consistent with the implementation of a new economic policy agenda to disengage the public sector and to encourage entrepreneurship as well as foreign investments. The start of the process has been associated with the nomination of Rajiv Gandhi as Prime Minister in 1984.

In terms of tax progressivity, however, the downwards trend in fact started earlier - in the mid-1970s (Figure 13). That said, marginal income tax rate remained at fairly high levels until 1984-85 when Rajiv Gandhi's government reduced the rates from 62% to 50%. Why year 1983-84 marks so abruptly the turning point of our inequality series over the recent period remains a topic of enquiry. Several factors can be at play: anticipations in the 1984-85 change in the top marginal tax rate, and anticipations of a more pro-business environment, could have had a positive impact on top incomes, in line with the rent-seeking theory posited by Piketty, Saez and Stantcheva (2014). Other factors could include the combination of a strong recession in the agricultural sector

[30] These figures include the "super tax" on top incomes.

the previous year (-5% agricultural production due to severe droughts in 1982-1983), which impacted income groups at the bottom. A surge in top earners filing tax returns, because of less stringent tax policies, is not to be excluded and could explain why the change is so abrupt this year. However, the fact that the rise in inequality is prolonged throughout the 1990s and in the recent period shows that this factor is very unlikely to play decisive role in the observed trends.

Available macro series also show that the wage share in the private corporate sector has been declining in India since the early to mid-1980s (in contrast to the 1970s, when the profit share was declining; see Nagaraj (2000) and Tendulkar (2003), which is consistent with the time for the turnaround proposed here.

Our results are also consistent with the evolution of Indian wealth inequality according to All-India Debt and Investment survey data (Anand and Thampi, 2016). Recently released wealth inequality estimates indeed show a sharp increase in wealth concentration from 1991 to 2012, particularly after 2002. The increase in wealth inequality at the top of the distribution is a logical outcome of the highly unequal income growth we report in this paper over the recent period.

ii. Shining India for the rich mostly?

Our results shed light on a particularly striking characteristic of Indian growth over the past three decades: the very moderate rise of the "middle class" - at least defined as individuals above median income and below the top 10% earners. Incomes of the middle 40% grew at 102% over the 1980-2014 period. Compared to industrialized countries' growth rates for this group, the figure is impressive. In the Indian context however, the middle 40% were notably below average growth (187%). Since 1980, the middle 40% group in India captured a much smaller share of total growth (25%) in than its counterparts did in China or Europe (more than 40%) or even the USA (33%). This result should help us better characterize what has been termed as "the rise of India's middle class". From the perspective or our newly income inequality dataset, "Shining India" corresponds to the top 10% of the population (approximately 80 million adult individuals in 2014) rather than the middle 40%. Relatively speaking, the shining decades for the middle 40% group corresponded to the 1951-1980 period, when this group captured a much higher share of total growth (49%) than it did over the past forty years. It is also important to stress that, since the early 1980s, growth has been highly unevenly distributed within the top 10% group. This further reveals the unequal nature of liberalization and deregulation processes. India in fact comes out as a country with one of the highest increase in top 1% income share concentration over the past thirty years.

6 Conclusion

We combine historical and novel tax data with household surveys and national accounts data in order to produce the novel estimates of the full distribution of adult pre-tax income in India, from 1951 to 2015 and for the top 1% of the distribution from 1922 to 2015.

We document a large increase in the level of inequality in India over the recent period and a large increase in the current level as compared to survey-based statistics generally used in public debates. We find that our results are robust to a large set of alternative estimation strategies addressing important data gaps. According to our benchmark estimates, the top 1% income share is at its highest level (22%) since the create of the Income Tax during the British Raj, in 1922. Top income shares and top income levels were sharply reduced in the 1950s to the 1970s at a time when strong market regulations and high fiscal progressivity are implemented. During this period, bottom 50% and middle 40% incomes grew faster than average. The trend reverted in the mid 1980s with the development of pro-business policies.

We certainly do not have the capacity to put an end to debates over the impact of economic reforms on inequality or poverty India. Our contribution is in fact relatively modest; better data series on the distribution of income inequality can and should lead to better informed democratic conversation on the state of the Indian economy. We stress the need for more research dedicated to reconcile micro and macro estimates of income and consumption inequality in India. Efforts following the Distributional National Accounts Guidelines (Alvaredo et al., 2016), published on the WID.world database, seek to go in this direction. Ultimately, meeting this objective will not be possible without the participation and expertise of official statistical agencies, in India and elsewhere.

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Table 1 - Total growth rates by percentile in India, 1980-2015

	Total cumulated per adult real growth (1980-2015)			
Income group (distribution of per-adult pre-tax national income)	**India**	**China**	**USA**	**Western Europe**
Full population	**201 %**	**776 %**	**74 %**	**44 %**
Bottom 50%	90 %	386 %	10 %	34 %
Middle 40%	94 %	733 %	54 %	36 %
Top 10%	435 %	1232 %	139 %	62 %
incl. Top 1%	775 %	1800 %	230 %	74 %
incl. Top 0.1%	1 134 %	2271 %	355 %	79 %
incl. Top 0.01%	1 699 %	2921 %	499 %	90 %
incl. Top 0.001%	2 040 %	3524 %	698 %	124 %

Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Estimates for China, USA, Western Europe are based on WID.world and the World Inequality Report (wir2018.wid.world). Growth rates are net of inflation.

Table 2 – Share of total growth captured by income groups, 1980-2015: India, China, the USA, Western Europe.

Income group (distribution of per-adult pre-tax national income)	**India**	**China**	**USA**	**Western Europe**
Total	*100 %*	*100%*	*100%*	*100%*
Bottom 50%	11.1 %	13.3 %	2.9 %	17.4 %
Middle 40%	22.6 %	43.4 %	33.1 %	36.6 %
Next 9%	66.4 %	28.4 %	31.2 %	29.3 %
Top 1%	29.4 %	14.9 %	33. %	16.8 %
Top 0.1%	12.2 %	6.8 %	17.1 %	6.5 %
Top 0.01%	5.6 %	3.5 %	8.5 %	2.8 %
Top 0.001%	2.8 %	1.5 %	3.9 %	1.3 %

Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: This graph shows the share of national income growth captured by different income groups between 1980 and 2015. Distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Estimates for China, USA, Western Europe are based on WID.world and the World Inequality Report (wir2018.wid.world).

Table 3 - Income inequality in India, 2015

Income group (distribution of per-adult pre-tax national income)	**Number of adults**	**Income share (%)**	**Income threshold**	**Average income**	**Comparison to average (ratio)**
Average	794 305 664	100 %	0	138 426 INR	1
Bottom 50%	397 152 832	14.7 %	0	40 671 INR	.3
Middle 40%	317 722 266	29.2 %	63 728 INR	101 084 INR	.7
Top 10%	79 430 566	56.1 %	195 445 INR	776 567 INR	6
incl. Top 1%	7 943 057	21.3 %	1 303 946 INR	2 954 386 INR	21
incl. Top 0.1%	794 306	8.2 %	4 459 114 INR	11 346 371 INR	82
incl. Top 0.01%	79 431	3.4 %	18 260 916 INR	47 154 896 INR	341
incl. Top 0.001%	7 943	1.4 %	77 801 552 INR	188 558 192 INR	1362

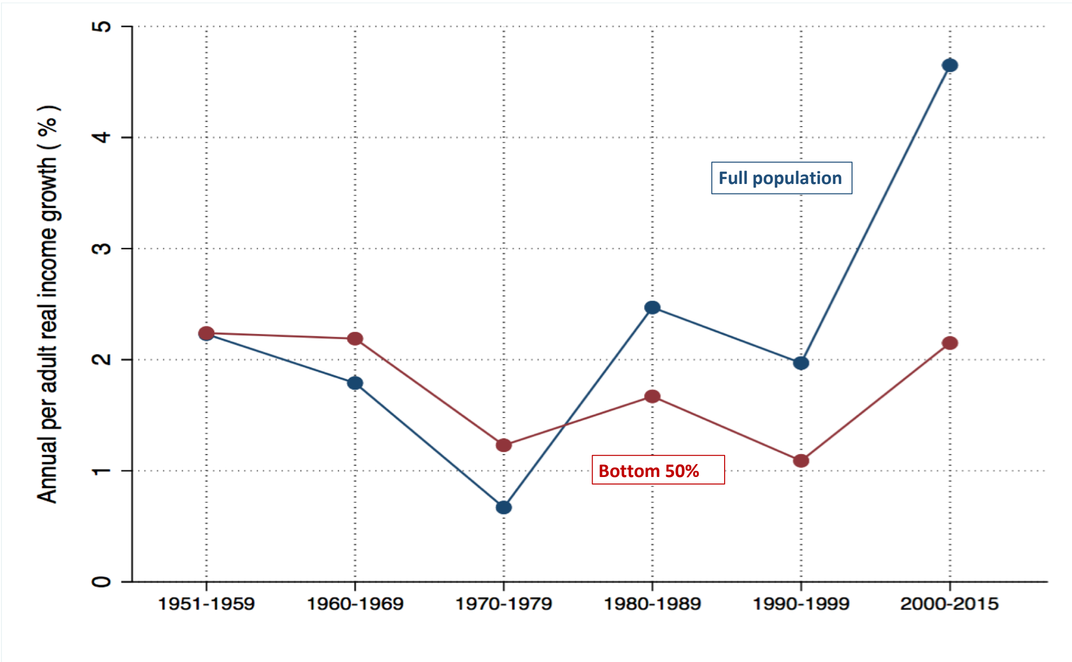
Source: Authors' estimates combining survey, fiscal and national accounts data.
Notes: Distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Population estimates for 2014.

Table 4 - Total growth rates by percentile in India, 1951-1980

Income group (distribution of per-adult pre-tax national income)	**Total real per adult income growth (1951-1980)**
Full population	**65 %**
Bottom 50%	87 %
Middle 40%	74 %
Top 10%	42 %
incl. Top 1%	5 %
incl. Top 0.1%	-26 %
incl. Top 0.01%	-42 %
incl. Top 0.001%	-45 %

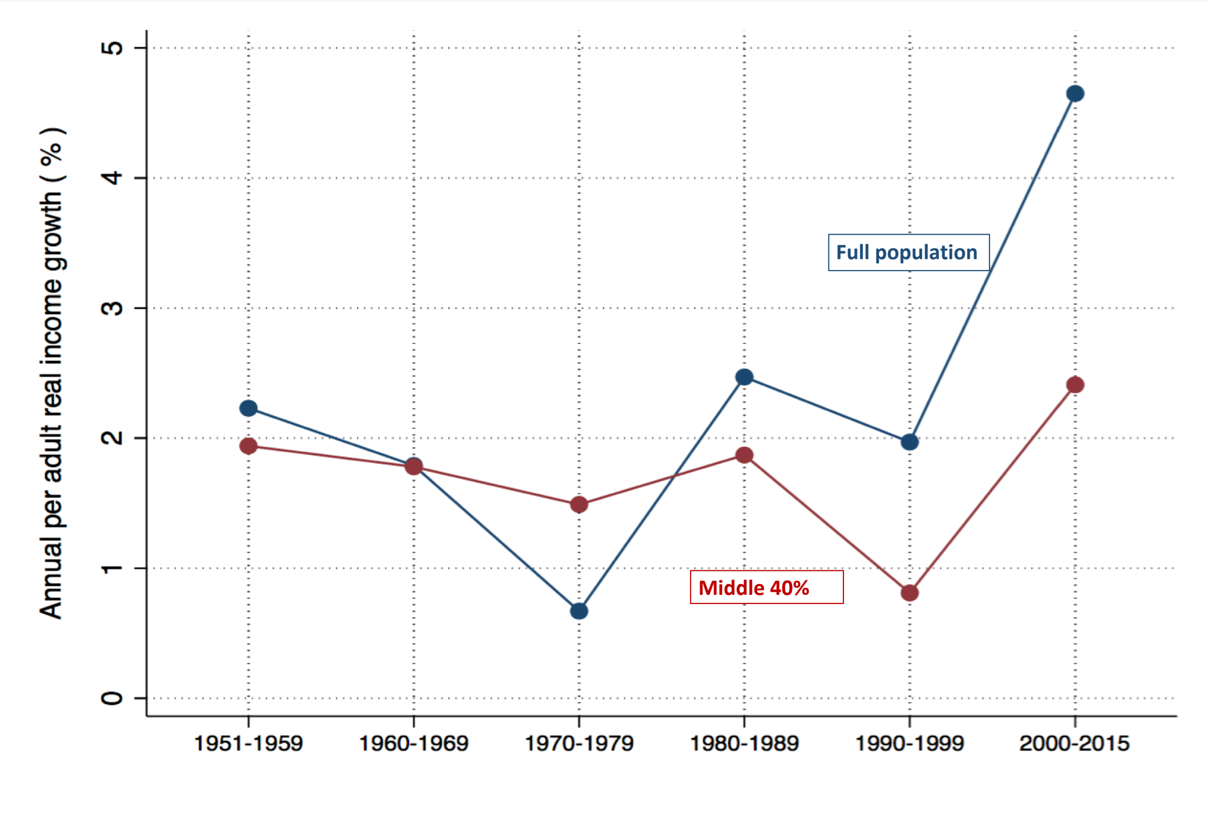
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 1a - National income growth in India: full population vs. bottom 50% income group, 1951-2015



Source: Authors' estimates combining survey, fiscal and national accounts data. Average annual per adult real income growth rate from 1970 to 1979 was 0.67%.

Figure 1b - National income growth in India: full population vs. middle 40% income group, 1951-2015

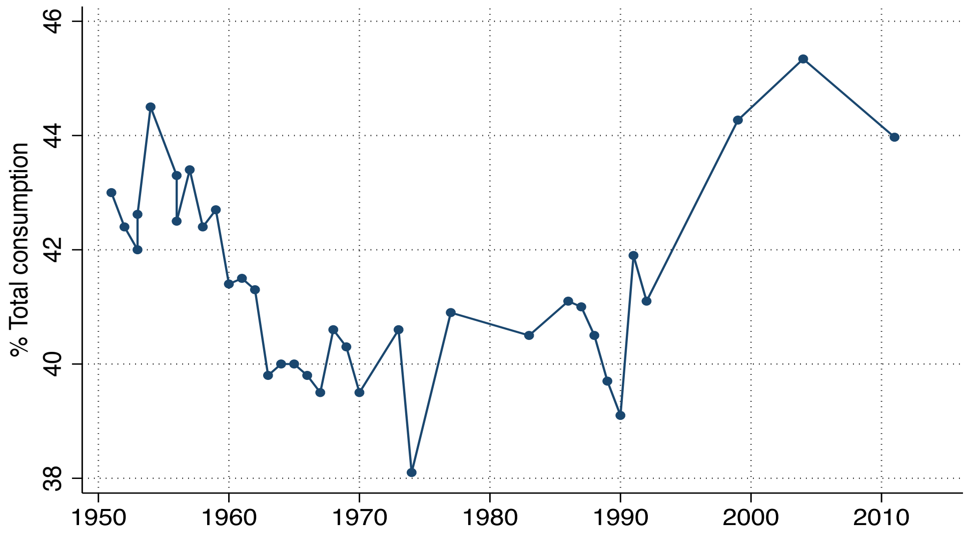


Source: Authors' estimates combining survey, fiscal and national accounts data. Average annual per adult real income growth rate from 1970 to 1979 was 0.67%.

Figure 1c - National income growth in India: full population vs. top 1% and top 10% income groups, 1951-2015

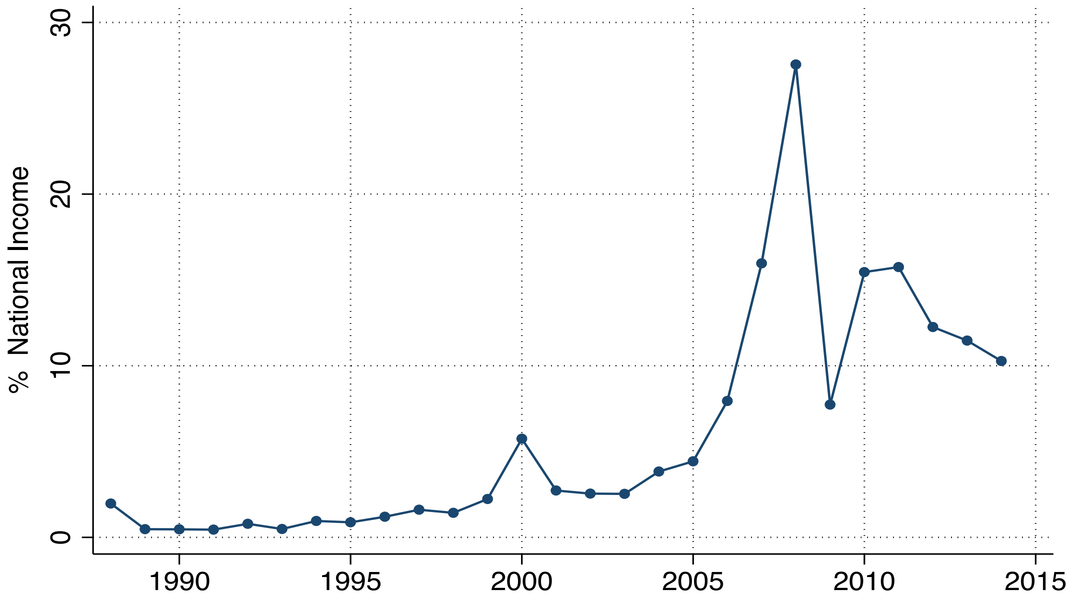
Source: Authors' estimates combining survey, fiscal and national accounts data. Average annual per adult real income growth rate from 1970 to 1979 was 0.67%.

Figure 2 - Top 20% total consumption share reported in household surveys



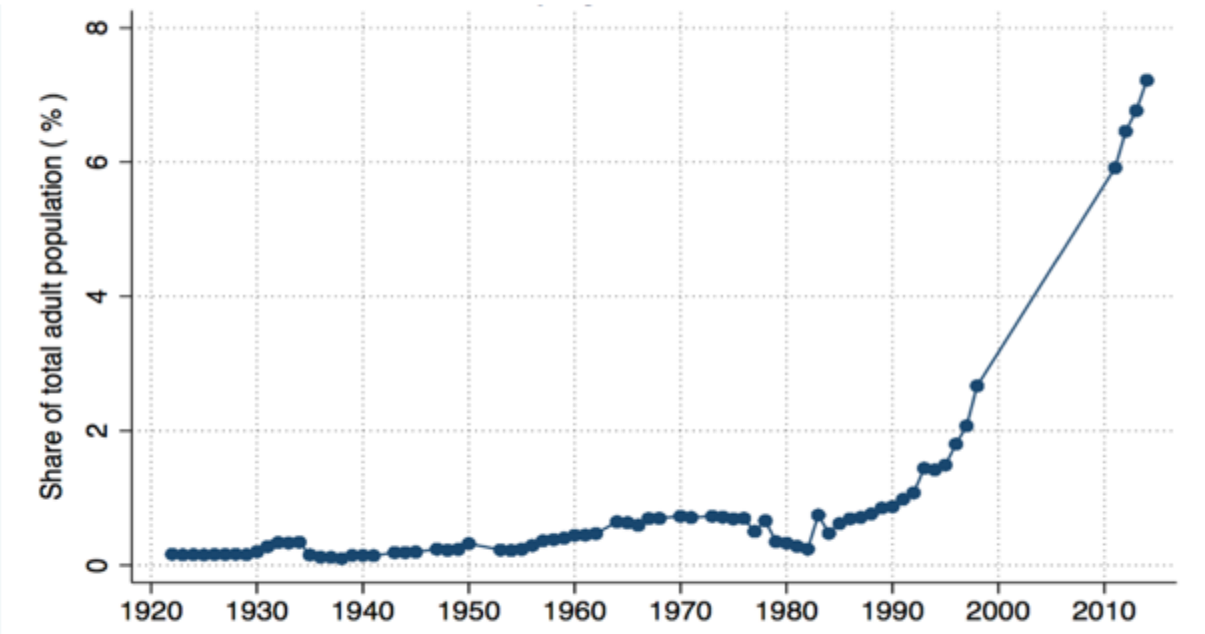
Source: Authors' computations using data from United Nations WIDER Income Inequality Database and World Bank India Database (based upon NSSO surveys).

Figure 3 - Wealth of richest Indians in Forbes' Rich List, 1988-2015



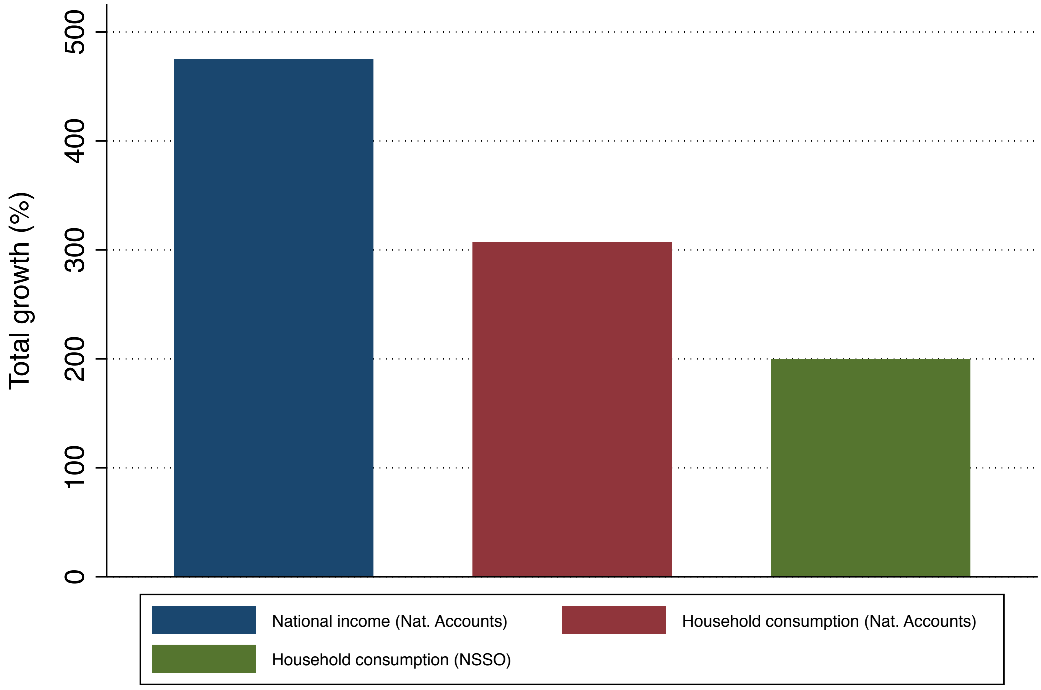
Source: Authors' computations based upon Forbes billionaire rankings and WID.world national income data.

Figure 4 - Proportion of income tax taxpayers in India, 1922-2015



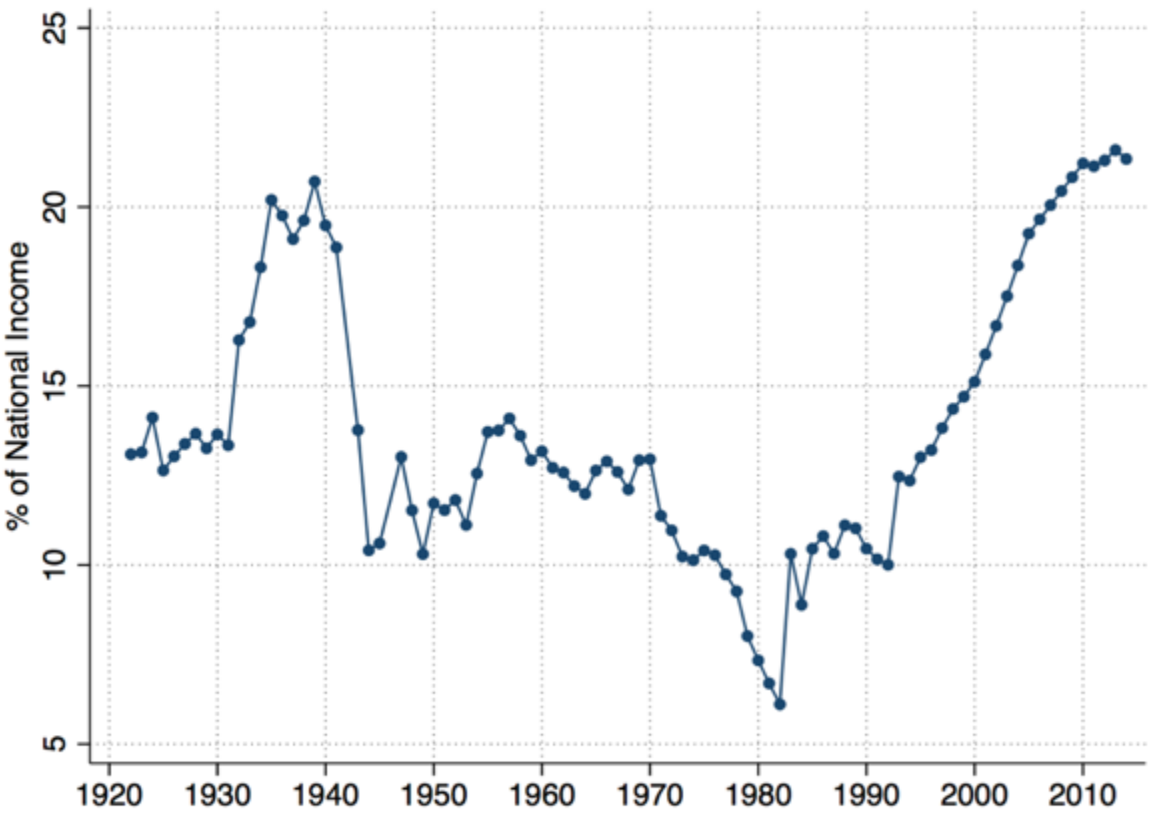
Source: Authors' computations based on Indian Tax Administration statistics, United Nations Population Database and Banerjee and Piketty (2005). Estimates refer to individuals and Hindu Undivided Families only.

Figure 5 – Total income and consumption growth in India, 1988-2011



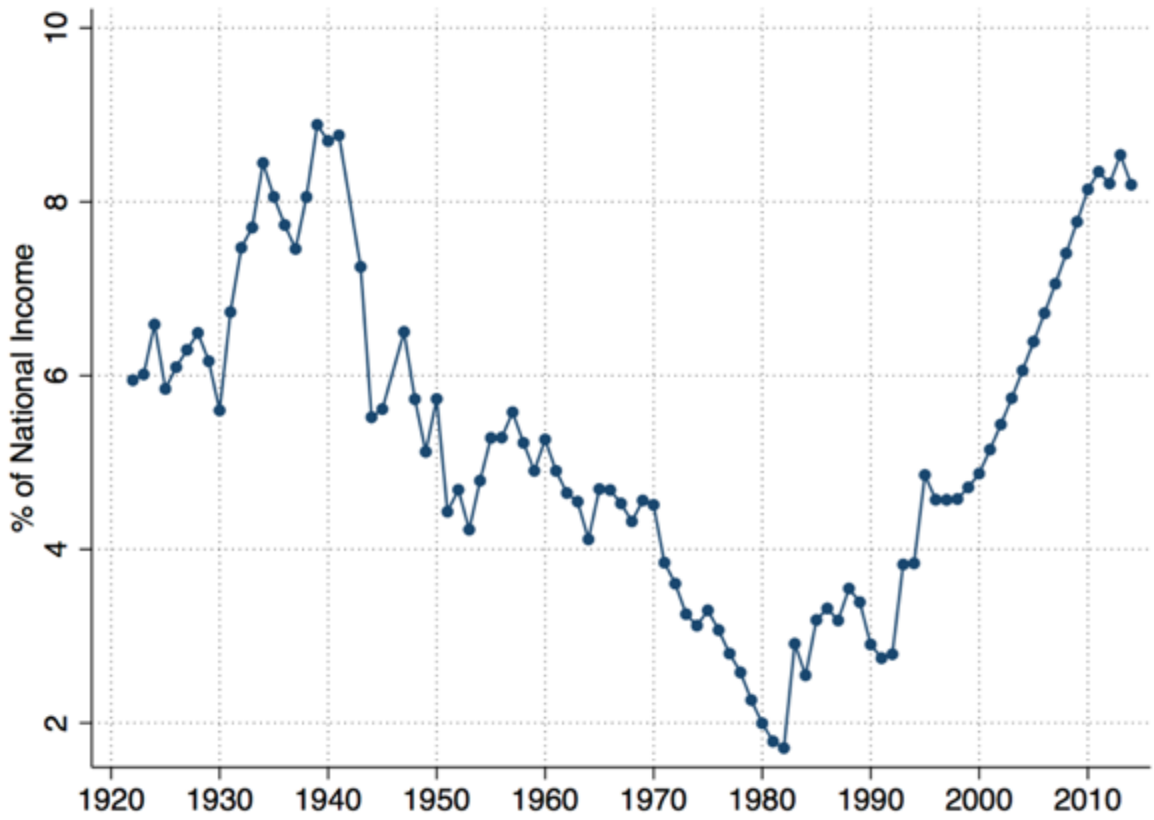
Source: Authors' computations using National Accounts and NSSO data.

Figure 6 - Top 1% national income share in India, 1922-2015



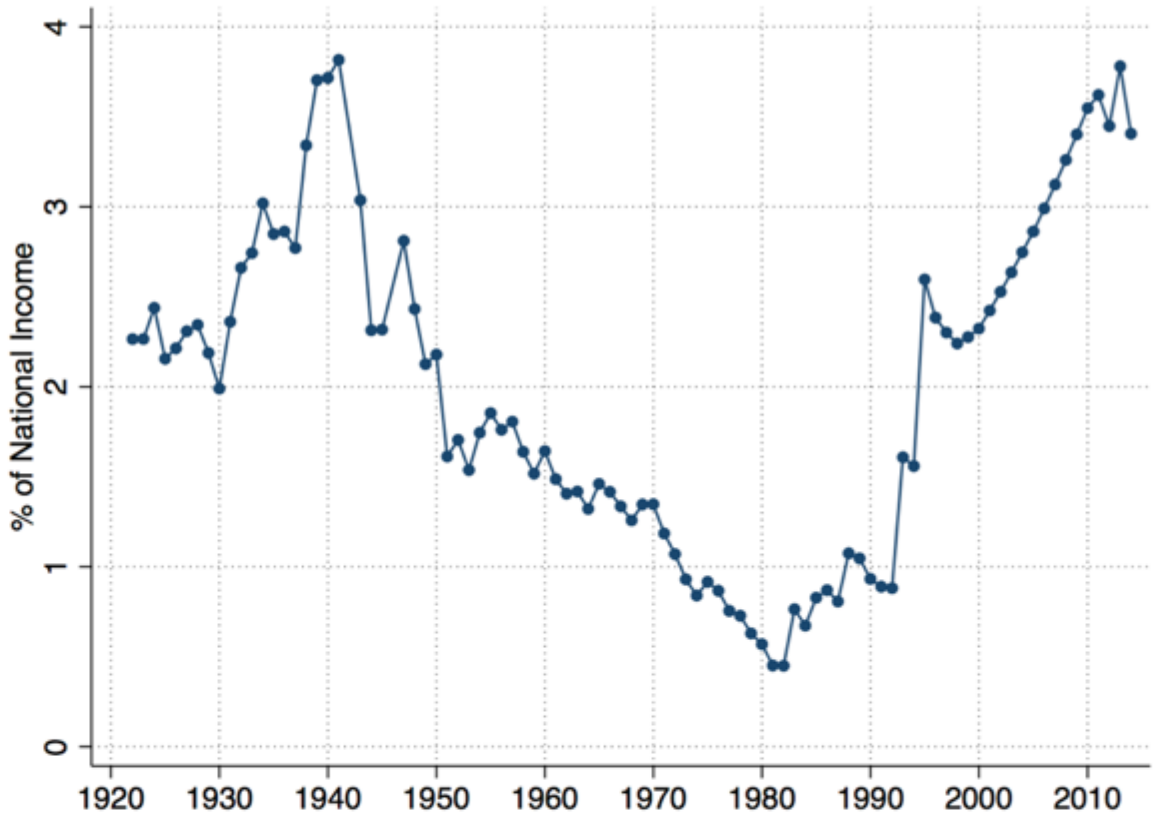
Source: Authors' estimates combining survey, fiscal and national accounts data.
Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 7 - Top 0.1% national income share in India, 1922-2015



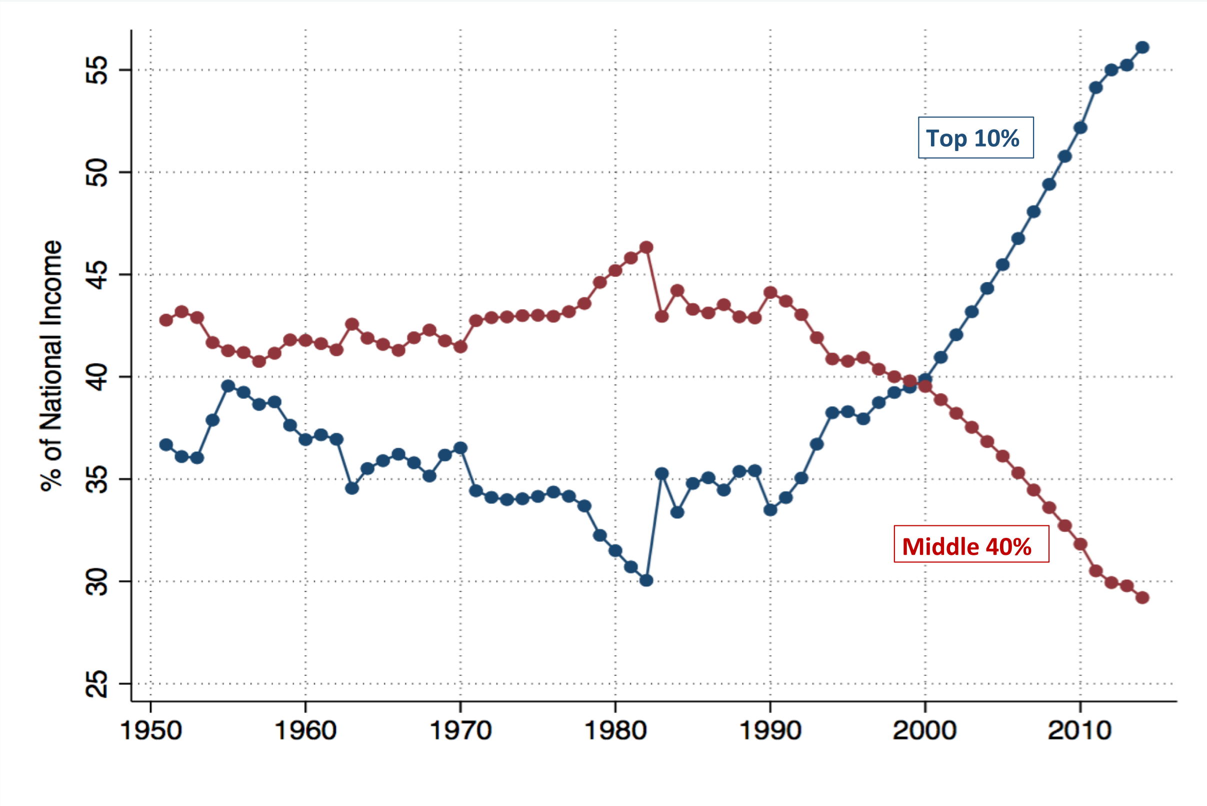
Source: Authors' estimates combining survey, fiscal and national accounts data.
Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 8 - Top 0.01% national income share in India, 1922-2015



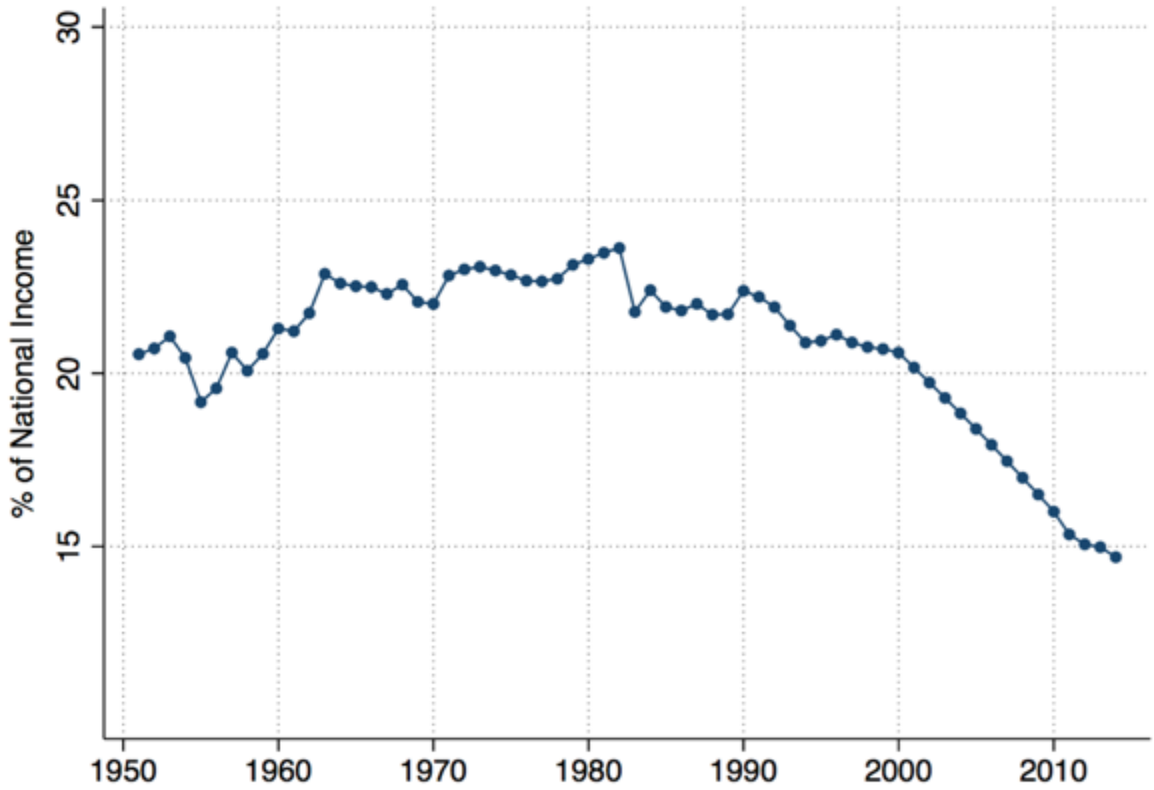
Source: Authors' estimates combining survey, fiscal and national accounts data.
Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 9 - Top 10% vs. Middle 40% national income shares in India, 1951-2015



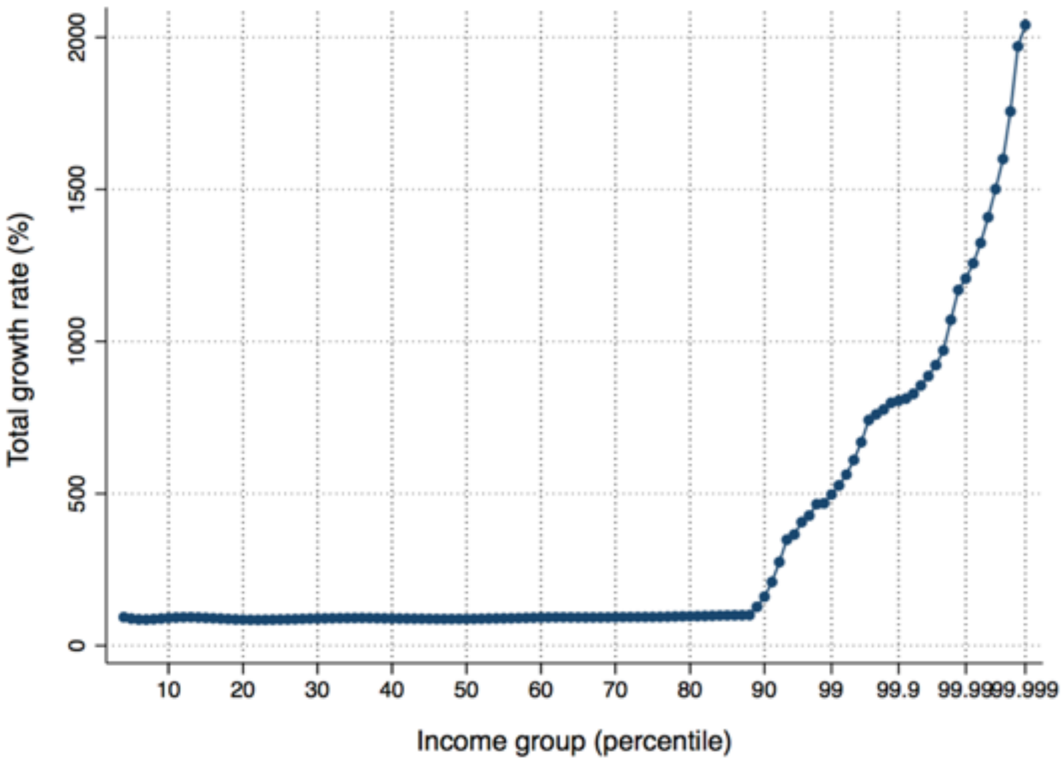
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 10 - Bottom 50% national income share in India, 1951-2015



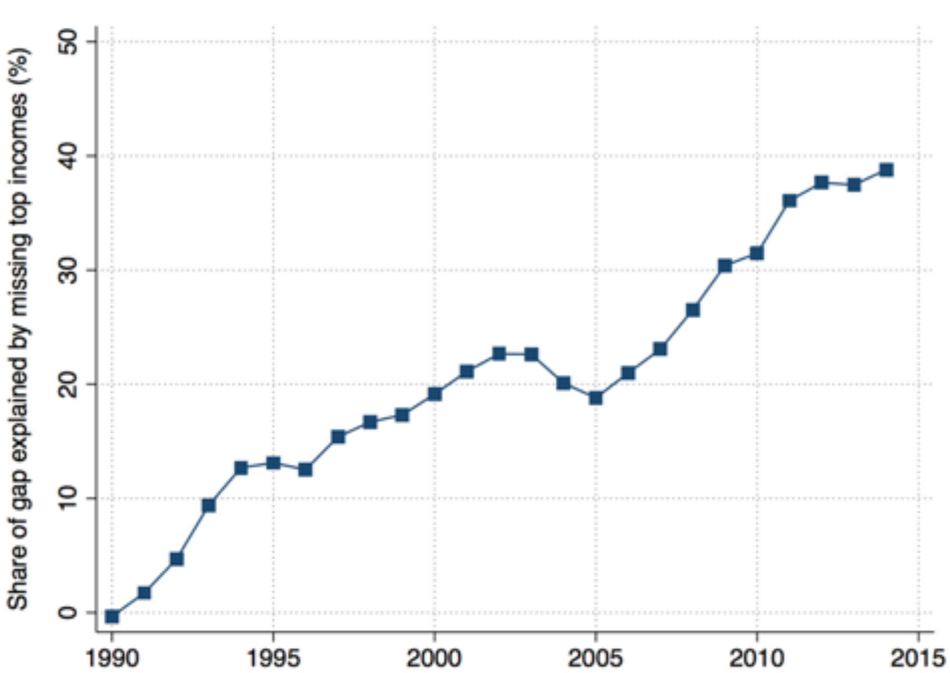
Source: Authors' estimates combining survey, fiscal and national accounts data.
Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1).

Figure 11 – Income growth by percentile in India, 1980-2015: The "cobra curve" of inequality and growth.



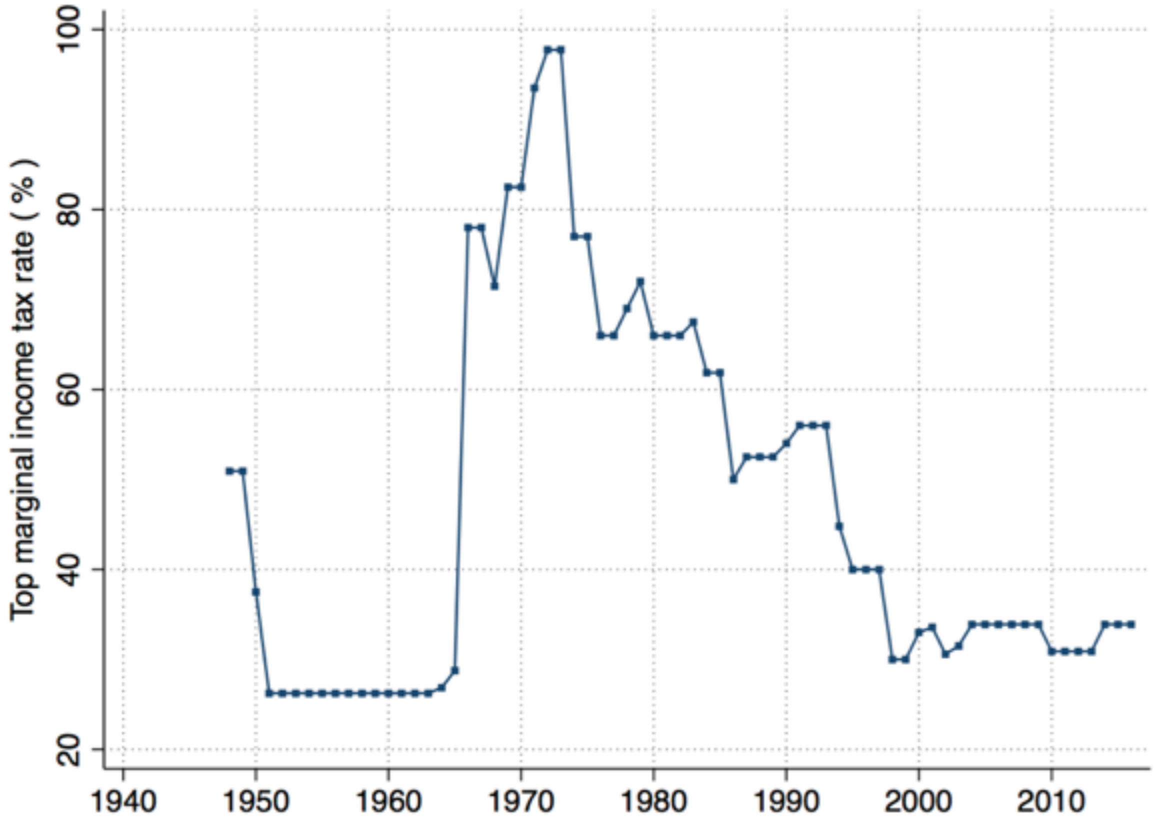
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). The Figure shows that the average per adult real income growth rate between 1980 and 2015 of the top 0.001% income group was 2040%.

Figure 12 – Importance of missing top incomes in India since 1990: Share of gap between survey income and national accounts explained by missing top incomes



Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: This graph shows the share of the gap between (reconstructed) survey income and income from the National accounts, which can be explained by the absence of top incomes in survey data. In practice, we compare the share of the gap between fiscal income from the national accounts (assumed to be 70% of national income), reconstructed survey incomes and reconstructed survey incomes, corrected at the top with tax data. Section 2 provides a description of these concepts.

Figure 13 – Top marginal income tax rate in India, 1948-2016



Source: Authors' estimates based on ITD and Union Budget Speeches. Notes: Figures include super tax on top incomes.

CHAPTER 2

Building a global distribution of income brick by brick

Abstract. The dynamics of global inequality have attracted growing attention in recent years. However, we still know relatively little about how the distribution of global income is evolving. Income inequality is increasing in many countries, but large emerging countries like India and China are catching up and might drive global inequality down. Recent studies of global inequality combine household surveys and provide valuable estimates (Lakner and Milanovic 2016, Liberati 2015, Ortiz and Cummins 2011). Surveys, however, are not uniform across countries, they cannot capture top incomes well, and are not consistent with macroeconomic totals from National Accounts.

In this chapter, we report on new estimates of global inequality. These estimates are based on recent, homogeneous inequality statistics produced for a number of countries in the World Inequality Database (WID.world), consistent with aggregate National Accounts. We find that the global top 1% has captured twice as much total growth than the global bottom 50% between 1980 and 2016. We also analyze different projected trajectories for global inequality in the coming decades and find that optimist assumptions about growth in emerging countries in the future will not be sufficient to reduce global inequality by 2050 if countries continue their own recent inequality trends, highlighting the need for a renewed debate on the set of policies required to generate more equitable growth pathway.

This chapter is based on “The Elephant Curve of Global Inequality and Growth”, American Economic Association Papers & Proceedings, 2018, co-authored with F. Alvaredo, T. Piketty, E. Saez and G. Zucman as well as on parts 2.1, 2.2 and 5.1 of the World Inequality Report 2018, written with the same co-authors. I am grateful to Amory Gethin for extremely valuable research assistance.

1 Introduction: managing data limitations to construct a global income distribution

The dynamics of global inequality have attracted growing attention in recent years. However, we still know relatively little about how the distribution of global income and wealth is evolving. Available studies have largely relied on household surveys (Lakner and Milanovic 2016, Liberati 2015, Ortiz and Cummins 2011, Bourguignon and Morrisson, 2002), a useful source of information, but one that does not accurately track the evolution of inequality at the top of the distribution, that is often hard to compare across time and countries and that is not consistent with macro totals. Global distributions based on survey data thus also inherently suffer from these limitations.

Anand and Segal (2014) provide a first attempt to combine survey data and top income shares available from the WTID (the previous version of WID.world) in order to construct global income inequality estimates. Our work goes in this direction. Up to now, because of national level data limitations, global inequality estimates reasonable geographical coverage of global inequality coverage of the WTID was relatively limited for large emerging countries. Income inequality estimates for income inequality in India or China for instance (a third of the global population) used in global inequality distribution exercises were for instance based on survey data essentially. This chapter thus goes beyond existing work as it is grounded more robust and systematic national level income distributions, in particular in large emerging countries (see Chapter 1) but also in high-income countries.

We stress at the outset that the production of global inequality dynamics is in its infancy and will still require much more work. It is critical that national statistical and tax institutions release income and wealth inequality data in many countries where data are not available currently—in particular, in developing and emerging countries.

Researchers also need to thoroughly harmonize and analyze these data to produce consistent, comparable estimates.

Even if there are uncertainties involved, as discussed in Chapter 1, it is already possible to produce meaningful global income inequality estimates. The WID.world database contains internationally comparable income inequality estimates covering the entire population, from the lowest to the highest income earners, for many countries: the United States, China, India, Russia, Brazil, the Middle East, and the major European countries (such as France, Germany, and the United Kingdom). A great deal can already be inferred by comparing inequality trends in these regions. Using simple assumptions, we have estimated the evolution of incomes in the rest of the world so as to distribute 100% of global income every year since 1980. This exercise should be seen as a first step towards the construction of a fully consistent global distribution of income.

The exploration of global inequality dynamics presented here starts in 1980, for two main reasons. First, 1980 corresponds to a turning point in inequality and redistributive policies in many countries. The early 1980s mark the start of a rising trend in inequality and major policy changes, both in the West (with the elections of Ronald Reagan and Margaret Thatcher, in particular) and in emerging economies (with deregulation policies in China and India). Second, 1980 is the date from which data become available for a large enough number of countries to allow a sound analysis of global dynamics.

The rest of this chapter is organized as follows, we give an overview of the methodology followed to construct our estimates of global income inequality since 1980 and of our projections of global income inequality up to 2050. We then discuss our results on the evolution of global income inequality at the level of world regions and of the world as a whole. Next, we discuss the results of our projections of global income inequality up to 2050 and we conclude.

2 Methodology

The United Nations System of National Accounts (UNSNA) was created after World War II, on the basis of important methodological developments in national accounting which followed the 1929 crisis and during the war (Lepenies, 2016), in particular in the U.S, the U.K, France and the Netherlands[31]. This system was designed to construct a dashboard of aggregate economic statistics enabling policymakers to monitor the evolution of output, prevent crises, better administer the economy and compare their country's performances to that of other nations.

This system was not designed to track the evolution of the distribution of aggregate concepts such as income or savings across individuals. Developments in the systematic measurement of income inequality were essentially carried out separately from the UNSNA framework, even though one of the founding fathers of National Accounts, Simon Kuznets, also made critical innovations in the field of income inequality measurement. Indeed, in his seminal work on the "Share of upper income groups in income and savings", Kuznets (1953), laid the basis for the systematic measurement of top income shares over time using tax data, from 1919 to 1945 in the U.S. Another key innovation was made by Atkinson and Harrison in their "Distribution of personal wealth in Britain" (Atkinson and Harrison, 1978). The authors used estate data to measure wealth inequality dynamics between 1923 and 1972 in Britain.

Building on these methods and refining them, Piketty (2001, 2003), Piketty and Saez (2003), Atkinson and Piketty (2007, 2010), Atkinson et al. (2011) expanded the work to many countries and over a very long time span, in a systematic manner. Methodological developments included the use of income tax data microfiles, which Kuznets didn't have access to. This literature, which has sometimes been called the "Top incomes" literature, was however limited to the study of top fiscal incomes, given that distributional information relied solely on tax data.

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[31] See Kuznets for the U.S. (1934), Stone and Meade (1942) for the U.K., Vincent (1943) for France, Tinbergen for the Netherlands.

More recently, in line with the recommendations of the Commission on the Measurement of Economic Performance and social progress (Stiglitz et al. 2009) who stressed the need to distribute National accounts so as to better measure well-being and economic progress, a methodology was developed to reconcile National Accounts with distributional measures: the Distributional National Accounts Guidelines (Alvaredo et al, 2016).

The Guidelines are consistent with UNSNA concepts and enable their distribution to individuals of a given country. Pioneering applications of the method to high-income countries (with relatively high quality data) were carried out for the U.S. (Piketty et al., 2018a) and France (Garbinti et al., 2018). A pioneering application to the case of a developing country was presented in the chapter *"Indian income Inequality Dynamics, 1922-2015"* of this Thesis (see also Piketty et al. (2018b) for the case of China).

The construction of Distributional National Accounts at the global level, based on national level DINA estimates had not been carried out so far. Beyond the challenges associated to the construction of national level DINA, they pose a series of methodological questions specific to global dimension of the exercise: Which method should be used to account for countries and regions with missing distributional data? In order to aggregate countries into a global distribution, should one use PPP or Market Exchange Rates? If one uses PPPs, how to account for changes in PPP over time? How to account for the missing income problem (the fact that net foreign income does not sum to zero at the global level)?

The main text of this chapter briefly addresses these issues but is essentially focused on the results. A detailed version of the methodology, with more emphasis on the technical aspects of the exercise, is provided in Appendix A and B to this chapter[32]. These appendices also provide results from alternative methodologies to compute global income inequality estimates (highlighting that these methodological choices have

[32] Interested readers should also refer to "Global inequality User Guide" by Lucas Chancel and Amory Gethin (WID.world Technical Note 2017/9).

little impacts on the general conclusions presented in the chapter, which we see as robust).

i. National Income estimates

The first step to produce a global distribution of income is to obtain coherent sources for national income. In order to do so, one faces several limitations. Net national income (NNI) is a key concept to monitor the dynamics of global and domestic economic inequalities. Contrary to gross domestic product (GDP), NNI takes into account net foreign income flows and capital depreciation. Therefore, it better reflects the true evolution of individual incomes in a country and can be more easily connected to personal income. However, while it is possible to find homogenous GDP series for all countries and over a long time period on many macroeconomic data portals (such as the World Bank), there are no published global harmonized NNI series.

At least two main reasons can explain this. First, despite the growing recognition that GDP is a very imperfect measure of progress (Stiglitz et. al, 2009), GDP remains the benchmark indicator for the measure of economic growth and for the comparison of the economic performance of nations. As a result, statistical institutions invest time and resources to maintain global and consistent GDP series in priority, sometimes at the expense of other macroeconomic series. The second reason is methodological: in the United Nations SNA, NNI is a function of GDP. NNI has not always been constructed from GDP: one of the founding father of national accounting, W. Petty, constructed national income via a bottom up method, summing all incomes measured in the economy. With the development of the UNSNA, the measurement of National Income gradually became "top-down", i.e. it is defined as a function of GDP, consumption of fixed capital (CFC) and net foreign income (NFI). In the data provided by countries to the UNSNA, CFC series are missing for several countries and time periods and sometimes indicate possibly erroneous values. It is then necessary to reconstruct robust CFC series before producing NNI series. NFI, estimates, on the other hand, can be found for a relatively large number of countries and years from the International

Monetary Fund (IMF), but these series do not sum to zero at the global level — the so-called "missing income" problem (Zucman, 2013). To ensure global consistency of NFI series to a reasonable extent, reallocation rules must be developed. Such adjustments, estimations and imputations require several hypotheses and an important data cleaning work, given the need to combine different statistical sources for a large number of countries over a relatively long time frame.

Details on the methods followed to construct harmonized Net National Income series used in this Thesis are described in "**Building a global income distribution brick by brick: Appendix A**".

ii. Distributional National Accounts estimates

Consistent estimates on the distribution of national income are not yet available for as many countries and years as for macroeconomic aggregates such as national income. Distributional series are based on a combination of sources including tax receipts, household surveys and national accounts. This chapter partly relies on recent development in generalized Pareto interpolations methods (see Blanchet et al. 2017), which allowed to track more systematically and with more precisions top incomes from tax tabulations.

Income or consumption inequality data is available from household surveys in most countries today. Surveys however are well known to misreport top incomes (Atkinson and Piketty, 2007), they are not consistent with macro totals and hardly comparable across countries. As such, surveys cannot be used to produce national level DINA, and consequently for global level DINA. When harmonized and corrected with fiscal sources, surveys can however be useful to inform on distributional dynamics at the bottom of the distribution. The previous chapter offers an overview of the challenges that the combination of tax and survey data can pose to researchers[33]. In

[33] The combination of tax data and survey data raises a number of methodological issues, which have been discussed in the recent literature (see for instance Burkhauser et al., 2016).

many cases for developing countries, this combination amounts more to a mapping of the numerous types of data inconsistencies and gaps that exist. Provided the data gaps are properly highlighted and interpolation methods made transparent, the resulting series are a much more reliable source of information than survey data alone.

Consistent estimates of national income inequality (for the full population in a given country, that is not only the top groups) are now available for the USA, Western Europe (and in particular France, Germany, the United Kingdom) as well as China, India, Brazil, Russia and the Middle East (see in particular Piketty et al., 2018a; Garbinti et al, 2018.; Piketty et al., 2018b; Morgan, 2017; Novokmet et al., 2017; Alvaredo et al., 2017; Bartels, 2017) These regions represent approximately two thirds of the world adult population and three quarters of global income.

We here seek to distribute the totality of global income, to the totality of the world population. To achieve this, we must distribute the quarter of global income to the third of the global population for which there is currently no consistent income inequality data available. One crucial information we have, however, is total national income in each country. This information is essential, as it already determines a large part of global income inequality among individuals.

We tested different alternative assumptions to distribute national incomes in countries where there are no available Distributional National Accounts (Alvaredo et al. 2016) and found that these had very moderate impacts on the distribution of global income, given the limited share of income and population concerned by these assumptions. In our benchmark results, we assume that countries with missing inequality information had similar levels of inequality as other countries in their region. Take an example, we know the average income level in Malaysia, but not (yet) how national income is distributed to all individuals in this country. We then assumed that the distribution of income in Malaysia was the same, and followed the same trends, as in the region formed by China and India. This is indeed an over simplification, but to some extent this is an acceptable method as alternative assumptions have a limited impact on our general conclusions.

Sub-Saharan Africa is a particular case: we did not have any country with consistent income inequality data over the past decades (whereas in Asia we have consistent estimates for China and India, in Latin America, we have estimates for Brazil, etc.). For Sub-Saharan Africa, we thus relied on household surveys available from the World Bank (these estimates cover 70% of Sub-Saharan Africa's population and yet a higher proportion of the region's income). These surveys were matched with fiscal data available from WID.world so as to provide a better representation of inequality at the top of the social pyramid.

Details on the methods followed to distribute national income within countries, along with results for alternative scenarios, are described in Sections 2-3 of "**Building a global income distribution brick by brick: Appendix B**".

iii. Global inequality projections

Our projections of global income inequality dynamics are based on global income inequality dynamics observed between 1980 and 2016 as well as on the modeling of three forces: within-country income inequality, national level total income growth, and demographics.

Three scenarios are defined to project the evolution of inequality up to 2050. All our scenarios run up to the halfway mark of the twenty-first century; this has us looking out at a time span similar to the one that has passed since 1980—the starting date of our analyses in the previous chapters. Our first scenario represents an evolution based on "business as usual"—that is, the continuation of the within-country inequality trends observed since 1980. The second and third are variants of the business-as-usual scenario. The second scenario illustrates a high within-country inequality trend, whereas the third scenario represents a low within-country inequality trend. All three scenarios have the same between-country inequality evolutions. This means that a given country has the same average income growth rate in all three scenarios. It also has the same population growth rate in all three scenarios. For estimations of future total income and population growth we turned to the OECD 2060 long-term forecasts (OECD, 2017)[34]. We also relied on the United Nations World Population Prospects UNDESA (2017)[35].

In the first scenario, all countries follow the inequality trajectory they have followed since the early 1980s. For instance, we know that the bottom 50% income earners in China captured 13% of total Chinese growth over the 1980–2016 period[36]. We thus assume that bottom 50% Chinese earners will capture 13% of Chinese income growth up to 2050. The second scenario assumes that all countries follow the same inequality trajectory as the United States over the 1980–2016 period. Following the above example, we know that bottom 50% US earners captured 3% of total growth since 1980 in the United States. The second scenario then assumes that within all countries, bottom 50% earners will capture 3% of growth over the 2017–2050 period. In the third scenario, all countries follow the same inequality trajectory as the European Union over the 1980–2016 period—where the bottom 50% captured 14% of total growth since 1980.

Details on the methods followed to distribute national income within countries, along with results for alternative specification to account for missing countries, are described in Section 4 of "**Building a global income distribution brick by brick: Appendix B**".

3 Global income inequality between countries (1950-2016)

[34] Note that the rates we use are voluntarily more optimistic than the rates assumed by the OECD to compute their total global income in 2050 for Africa, Latin America, and Asia. Assuming higher growth rates tends to reduce global inequality. Ours should be seen as a conservative approach to the rise of global inequality in the coming decades.
[35] Note that we use the medium variant of the UN prospects.
[36] These projections may be done at the level of regions rather than of countries, when there are not sufficiently detailed data over the 1980-2016 period.

i. National income is more meaningful than GDP to compare income inequalities between countries

As discussed in the methodology section[37] of this chapter, GDP is, by definition a gross measure: it does not take into account expenses required to replace capital that has been deteriorated or that has become obsolete during the course of production of goods and services in an economy. Machines, computers, roads, and electric systems have to be repaired or replaced every year. This is known as consumption of fixed capital (CFC). Subtracting it from GDP yields the net domestic product, which is a more accurate measure of true economic output than GDP.

Consumption of fixed capital actually varies over time and countries (Table 1). Countries that have an important stock of machines in their overall stock of capital tend to replace higher shares of overall capital. This is generally true for advanced and automatized economies—in particular, for Japan, where consumption of fixed capital is equal to 21% of its GDP (which reduces GDP by close to €8 000 per year and per adult). Consumption of fixed capital is also high in the European Union and the United States (16–17%). On the contrary, economies that possess relatively fewer machines and a higher share of agricultural land in their capital stock tend to have lower CFC values. CFC is equal to 11% of GDP in India, and 12% in Latin America. CFC variations thus modify the levels of global inequality between countries. Such variations tend to reduce global inequality, since the income dedicated to replacing obsolete machines tends to be higher in rich countries than in low-income countries. In the future, we plan to better account for the depreciation of natural capital in these estimates.

Table 1 - Distribution of world national income and gross domestic product, purchasing power parity, 2016

[37] See also "Building a Global Distribution of Income Brick by Brick: Appendix A", at the end of this manuscript.

Table 2 - Distribution of world national income and gross domestic product, market exchange rate, 2016

GDP figures have another important limitation when the need is to compare income inequality between countries and over time. At the global level, net domestic product is equal to net domestic income: by definition, the market value of global production is equal to global income. At the national level, however, incomes generated by the sale of goods and services in a given country do not necessarily remain in that country. This is the case when factories are owned by foreign individuals, for instance. Taking foreign incomes into account tends to increase global inequality between countries rather than reduce it. Rich countries generally own more assets in other parts of the world than poor countries do. Table 1 shows that net foreign income in North America amounts to 0.9% of its GDP (which corresponds to an extra €610 ($670) received by the average North American adult from the rest of the world.[38] Meanwhile, Japan's net foreign income is equal to 3.5% of its GDP (corresponding to €1 460 per year and per adult). Net foreign income within the European Union is slightly negative when measured at PPP values (Table 1) and very slightly positive when measured at market exchange rate values (Table 2). This figure in fact hides strong disparities within the European Union. France and Germany have strongly positive net foreign income (2 to 3% of their GDP), while Ireland and the United Kingdom have negative net foreign incomes (this is largely due to the financial services and foreign companies established there). On the other hand, Latin America annually pays 2.4% of its GDP to the rest of the world. Interestingly, China has a negative net foreign income. It pays close to 0.7% of its GDP to foreign countries, reflecting the fact that the return it receives on its foreign portfolio is lower than the return received by foreign investments in China.

[38] Measured at market exchange rate. At purchasing power parity, the corresponding value is $790.

By definition, at the global level, net foreign income should equal zero: what is paid by some countries must be received by others. However, up to now, international statistical institutions have been unable to report flows of net foreign incomes consistently. At the global level, the sum of reported net foreign incomes has not been zero (Zucman, 2013). This has been termed the “missing income” problem: a share of total income vanishes from global economic statistics, implying non-zero net foreign income at the global level.

This chapter relies on a novel methodology which takes income flows from tax havens into account. Our methodology relies on estimations of offshore wealth measured by Zucman (2013). It should be noted that, when measured at market exchange rates, net foreign income flows should sum to zero (Table 2), but there is no reason for this to happen when incomes are measured at purchasing power parity (Table 1). Taking into account missing net foreign incomes does not radically change global inequality figures but can make a large difference for particular countries. This constitutes a more realistic representation of income inequality between countries than figures generally discussed.

ii. Asian growth contributed to reduce inequality between countries over the past decades

According to our reconstructed Net National Income estimations, at the global level, per-adult monthly income in 2016 is €1 340 ($1 740) at purchasing power parity (PPP) and €990 ($1 090) at market exchange rate (MER). As discussed, PPP and MER are different ways to measure incomes and inequality across countries. Whereas MER reflects market prices, PPP aims to take price differences between countries into account.

National income is about three times higher in North America at PPP (€4 230 or $5 500 per adult per month) than the global average and it is two times higher in the European Union at PPP than the global average (€2 620 or $3 410 per adult per month). Using MER values, gaps between rich countries and the global average are reinforced: United States and Canada are five times richer than the world average whereas the EU is close to three times richer .[39] In China, per-adult income is €1 170 or $1 520 at PPP—that is, slightly lower than world average (€1 340 or $1 740). China as a whole represents 19% of today's global income. This figure is higher than North America (17%) and the European Union (17%). Measured at MER, the Chinese average is, however, equal to €700 or $770, notably lower than the world average (€980 or $1 080). The Chinese share of global income is reduced to 15% versus 27% for US-Canada and 23% for the EU.

Table 3 - Distribution of world national income and gross domestic product, purchasing power parity, 1980

This marks a sharp contrast with the situation in 1980. Thirty-eight years ago, China represented only 3% of global income versus 20% for US-Canada and 28% for the European Union (at purchasing power parity estimates: see Table 3). Indeed, China's impressive real per-adult national income growth rate over the period (831% from 1980 to 2016, versus 106% from 1950 to 1980: see Table 4) highly contributed to reducing between-country inequalities over the world. Another converging force lies in the reduction of income growth rates in Western Europe, as compared to the previous decades (180% per-adult growth between 1950 and 1980 versus 45% afterwards). This deceleration in growth rates was due to the end of the "golden age" of growth in Western Europe but also due to the Great Recession, which led to a decade of lost growth in Europe. Indeed, per-adult income in Western Europe was in 2016 the same as ten years before, before the onset of the financial crisis.

[39] Our figures for the European Union include all countries on the European continent, apart from Russia and Ukraine.

Table 4 - Total national income growth rates, 1950–2016

Despite a reduction of inequality between countries, average national income inequalities remain strong among countries. Developing and emerging countries did not all grow at the same rate as China. India's average monthly per-adult income (€580 or $750) is still only 0.4 times the world average measured at PPP, while sub-Saharan Africa is only 0.3 times the world average (€430 or $560) today. Average North Americans earn close to ten times more than average sub-Saharan Africans.

iii. Diverging forces were also at play in certain parts of the world, such as sub-Saharan Africa and Latin America.

Huge inequalities persist among countries but, in some cases, they actually worsened. Certain low- to middle-income regions are relatively worse off today than four decades ago. Between 1980 and 2016, per-adult incomes in Africa grew more slowly (18%) than the world's average per-adult incomes (54%). This growth trend, marked by a combination of political and economic crises and wars, is not limited to the poorest region of the world. In South America, as well, incomes have grown by only 12% since 1980. As a result, these regions' average incomes fell relative to the world average, from 65% to only 40% of the world average in 1950, versus 140% to less than 100% in Latin America (Figures 1a-b).

Figure 1a - Africa and Asia average incomes to global average, 1950–2016

Figure 1b - China and Latin America average incomes to global average, 1950–2016

4 Global income inequality between individuals (1980-2016)

i. Income inequality between main world regions

We now present our basic findings regarding the evolution of income inequality within the main world regions. Three main findings emerge.

First, we observe rising inequality in most of the world's regions, but with very different magnitudes. More specifically, we display in Figure 2a the evolution of the top 10% income share in Europe (Western and Eastern Europe combined, excluding Ukraine, Belorussia, and Russia), North America (defined as the United States and Canada), China, India, and Russia. The top 10% share has increased in all five of these large world regions since 1980. The top 10% share was around 30–35% in Europe, North America, China, and India in 1980, and only about 20–25% in Russia. If we put these 1980 inequality levels into broader and longer perspective, we find that they were in place since approximately the Second World War, and that these are relatively low inequality levels by historical standards (Piketty, 2014). In effect, despite their many differences, all these world regions went through a relatively egalitarian phase between 1950 and 1980. For simplicity, and for the time being, this relatively low inequality regime can be described as the "post-war egalitarian regime," with obvious important variations between social-democratic, New Deal, socialist, and communist variants to which we will return.

Figure 2a - Top 10% income shares across the world, 1980–2016: Rising inequality almost everywhere, but at different speed

Top 10% income shares then increased in all these regions between 1980 and 2016, but with large variations in magnitude. In Europe, the rise was moderate, with the top

10% share increasing to about 35–40% by 2016. However, in North America, China, India, and even more so in Russia (where the change in policy regime was particularly dramatic), the rise was much more pronounced. In all these regions, the top 10% share rose to about 45–50% of total income in 2016. The fact that the magnitude of rising inequality differs substantially across regions suggests that policies and institutions matter: rising inequality cannot be viewed as a mechanical, deterministic consequence of globalization.

Next, there are exceptions to this general pattern. That is, there are regions—in particular, the Middle East, Brazil (and to some extent Latin America as a whole), and South Africa (and to some extent sub-Saharan Africa as a whole)—where income inequality has remained relatively stable at extremely high levels in recent decades. Unfortunately, data availability is more limited for these three regions, which explains why the series start in 1990, and why we are not able to properly cover all countries in these regions (see Figure 2b).

Figure 2b - Top 10% income shares across the world, 1980–2016: Is world inequality moving toward the high-inequality frontier?

In spite of their many differences, the striking commonality in these three regions is the extreme and persistent level of inequality. The top 10% receives about 55% of total income in Brazil and sub-Saharan Africa, and in the Middle East, the top 10% income share is typically over 60% (see Figure 2c). In effect, for various historical reasons, these three regions never went through the post-war egalitarian regime and have always been at the world's high-inequality frontier.

The third striking finding is that the variations in top-income shares over time and across countries are very large in magnitude, and have a major impact on the income shares and levels of the bottom 50% of the population. It is worth keeping in mind the following orders of magnitude: top 10% income shares vary from 20–25% to

60–65% of total income (see Figures 2a and 2b). If we focus upon very top incomes, we find that top 1% income shares vary from about 5% to 30% (see Figure 2d), just like the share of income going to the bottom 50% of the population (see Figure 2e).

Figure 2c - Top 1% income shares across the world, 2016

Figure 2d - Top 1% income shares across the world, 2016

Figure 2e - Bottom 50% income shares across the world, 1980–2016

In other words, the same aggregate income level can give rise to widely different income levels for the bottom and top groups depending on the distribution of income prevailing in the specific country and time period under consideration. In brief, the distribution matters quite a bit.

What have been the growth trajectories of different income groups in these regions since 1980? Table 5 presents income growth rates in China, Europe, India, Russia, and North America for key groups of the distribution. The full population grew at very different rates in the five regions. Real per-adult, national income growth reached an impressive 831% in China and 223% in India. In Europe, Russia, and North America, income growth was lower than 100% (40%, 34%, and 74%, respectively). Behind these heterogeneous average growth trajectories, the different regions all share a common, striking characteristic.

Table 5 - Global income growth and inequality, 1980–2016

In all these countries, income growth is systematically higher for upper income groups. In China, the bottom 50% earners grew at less than 420% while the top 0.001% grew at more than 3 750%. The gap between the bottom 50% and the top 0.001% is even more important in India (less than 110% versus more than 3 000%). In Russia, the top of the distribution had extreme growth rates; this reflects the shift from a regime in which top incomes were constrained by the communist system towards a market economy with few regulations constraining top incomes. In this global picture, in line with Figure 1, Europe stands as the region with the lowest growth gap between the bottom 50% and the full population, and with the lowest growth gap between the bottom 50% and top 0.001%.

The right-hand column of Table 5 presents income growth rates of different groups at the level of the entire world. These growth rates are obtained once all the individuals of the different regions are pooled together to reconstruct global income groups. Incomes across countries are compared using purchasing power parity (PPP) so that a given income can in principle buy the same bundle of goods and services in all countries. Average global growth is relatively low (60%) compared to emerging countries' growth rates. Interestingly enough, at the world level, growth rates do not rise monotonically with income groups' positions in the distribution. Instead, we observe high growth at the bottom 50% (94%), low growth in the middle 40% (43%), and high growth at the top 1% (more than 100%)—and especially at the top 0.001% (close to 235%).

To better understand the significance of these unequal rates of growth, it is useful to focus on the share of total growth captured by each group over the entire period. Table 6 presents the share of growth per adult captured by each group. Focusing on both metrics is important because the top 1% global income group could have enjoyed a substantial growth rate of more than 100% over the past four decades (meaningful at the individual level), but still represent only a little share of total growth. The top 1% captured 35% of total growth in the US-Canada, and an astonishing 69% in Russia.

Table 6 - Share of growth captured by income groups, 1980–2016

At the global level, the top 1% captured 27% of total growth—that is, twice as much as the share of growth captured by the bottom 50%. The top 0.1% captured about as much growth as the bottom half of the world population. Therefore, the income growth captured by very top global earners since 1980 was very large, even if demographically they are a very small group.

ii. The elephant curve of global inequality and growth

A powerful way to visualize the evolution of global income inequality dynamics is to plot the total growth rate of each income groups. This provides a more precise representation of growth dynamics than Table 5. To properly understand the role played by each region in global inequality dynamics, we follow a step-by-step approach to construct this global growth curve by adding one region after another and discussing each step of the exercise.

We start with the distribution of growth in a region regrouping Europe and North America (Figure 3a). These two regions have a total of 880 million individuals in 2016 (520 million in Europe and 360 million in North America) and represent most of the population of high-income countries. In Euro-America, cumulative per-adult income growth over the 1980–2016 period was +28%, which is relatively low as compared to the global average (+66%). While the bottom 10% income group saw their income decrease over the period, all individuals between percentile 20 and percentile 80 had a growth rate close to the average growth rate. At the very top of the distribution, incomes grew very rapidly; individuals in the top 1% group saw their incomes rise by more than 100% over the time period and those in the top 0.01% and above grew at more than 200%.

How did this translate into shares of growth captured by different groups? The top 1% of earners captured 28% of total growth—that is, as much growth as the bottom 81% of the population. The bottom 50% earners captured 9% of growth, which is less than the top 0.1%, which captured 14% of total growth over the 1980–2016 period.

These values, however, hide large differences in the inequality trajectories followed by Europe and North America). In the former, the top 1% captured as much growth as the bottom 51% of the population, whereas in the latter, the top 1% captured as much growth as the bottom 88% of the population.

Figure 3a - Total income growth by percentile in US-Canada and Western Europe, 1980-2016

The next step is to add the population of India and China to the distribution of Euro-America. The global region now considered represents 3.5 billion individuals in total (including 1.4 billion individuals from China and 1.3 billion from India). Adding India and China remarkably modifies the shape of the global growth curve (Figure 3b).

The first half of the distribution is now marked by a "rising tide" as total income growth rates increase substantially from the bottom of the distribution to the middle. The bottom half of the population records growth rates which go as high as 260%, largely above the global average income growth of 146%. This is due to the fact that Chinese and Indians, who make up the bulk of the bottom half of this global distribution, enjoyed much higher growth rates than their European and North American counterparts. In addition, growth was also very unequally distributed in India and China.

Between percentiles 70 and 99 (individuals above the poorest 70% of the population but below the richest 1%), income growth was substantially lower than the global average, reaching only 40–50%. This corresponds to the lower- and middle-income groups in rich countries which grew at a very low rates. The extreme case of these is the bottom half of the population in the United States, which grew at only 3% over the period considered.

Earlier versions of this graph have been termed "the elephant curve," as the shape of the curve resembles the silhouette of the animal. These new findings confirm the orders of magnitude of global inequality found in earlier results (Lakner and Milanovic, 2016; Anand and Segal, 2014). They also amplify the share of income growth captured at the top of the global income distribution—a figure which couldn't be properly measured before.

Figure 3b - Total income growth by percentile in China, India, US-Canada, and Western Europe, 1980-2016

At the top of the global distribution, incomes grew extremely rapidly—around 200% for the top 0.01% and above 360% for the top 0.001%. Not only were these growth rates important from the perspective of individuals, they also matter a lot in terms of global growth. The top 1% captured 23% of total growth over the period—that is, as much as the bottom 61% of the population. Such figures help make sense of the very high growth rates enjoyed by Indians and Chinese sitting at the bottom of the distribution. Whereas growth rates were substantial among the global bottom 50%, this group captured only 14% of total growth, just slightly more than the global top 0.1%—which captured 12% of total growth. Such a small share of total growth captured by the bottom half of the population is partly due to the fact that when individuals are very poor, their incomes can double or triple but still remain relatively small—so that the total increase in their incomes does not necessarily add up at the global level. But this is not the only explanation. Incomes at the very top must also be extraordinarily high to dwarf the growth captured by the bottom half of the world population.

The next step of the exercise consists of adding the populations and incomes of Russia (140 million), Brazil (210 million), and the Middle East (410 million) to the analysis. These additional groups bring the total population now considered to more than 4.3 billion individuals—that is, close to 60% of the world total population and two thirds of the world adult population. The global growth curve generated (not presented here) is similar to the previous one except that the "body of the elephant" is now shorter. This can be explained by the fact that Russia, the Middle East, and Brazil are three regions which recorded low growth rates over the period considered. Adding the population of the three regions also slightly shifts the "body of the elephant" to the left, since a large share of the population of the countries incorporated in the analysis is neither very poor nor very rich from a global point of view and thus falls in the middle of the distribution. In this synthetic global region, the top 1% earners captured 26% of total growth over the 1980–2016 period—that is, as much as the bottom 65% of the population. The bottom 50% captured 15% of total growth, more than the top 0.1%, which captured 12% of growth.

The final step consists of including all remaining global regions—namely, Africa (close to 1 billion individuals), the rest of Asia (another billion individuals), and the rest of Latin America (close to half a billion). In order to reconstruct income inequality dynamics in these regions, we take into account between-country inequality, for which information is available, and assume that within countries, growth is distributed in the same way as neighboring countries for which we have specific information. This allows us to distribute the totality of global income growth over the period considered to the global population.

When all countries are taken into account, the shape of the curve is again transformed (Figure 4). Now, average global income growth rates are further reduced because Africa and Latin America had relatively low growth over the period considered. This contributes to increasing global inequality as compared to the two cases presented above. The findings are the same as those presented in the right-hand column of Table 1.1.2: the top 1% income earners captured 27% of total growth over the 1980–2016 period, as much as the bottom 70% of the population. The top 0.1% captured 13% of total growth, about as much as the bottom 50%.

Figure 4 - Total income growth by percentile across all world regions, 1980-2016

iii. The geography of global income inequality was transformed over the past decades

What is the share of African, Asians, Americans, and Europeans in each global income groups and how has this evolved over time? Figures 2.1.5 and 2.1.6 answer these questions by showing the geographical composition of each income group in 1990 and in 2016. Between 1980 and 1990, the geographic repartition of global incomes evolved only slightly, and our data allow for more precise geographic repartition in 1990, so it is preferable to focus on this year. In a similar way to how Figures 2.1.2 through 2.1.4 decomposed the data, Figures 2.1.5 and 2.1.6 decompose the top 1% into 28 groups (see Box 2.1.1). To be clear, all groups above percentile 99 are the decomposition of the richest 1% of the global population.

In 1990, Asians were almost not represented within top global income groups. Indeed, the bulk of the population of India and China are found in the bottom half of the income distribution. At the other end of the global income ladder, US-Canada is the largest contributor to global top-income earners. Europe is largely represented in the upper half of the global distribution, but less so among the very top groups. The Middle East and Latin American elites are disproportionately represented among the very top global groups, as they both make up about 20% each of the population of the top 0.001% earners. It should be noted that this overrepresentation only holds within the top 1% global earners: in the next richest 1% group (percentile group p98p99), their share falls to 9% and 4%, respectively. This indeed reflects the extreme level of inequality of these regions, as discussed in chapters 2.10 and 2.11. Interestingly, Russia is concentrated between percentile 70 and percentile 90, and Russians did not make it into the very top groups. In 1990, the Soviet system compressed income distribution in Russia.

Figure 5 - Geographic breakdown of global income groups, 1990

Figure 6 - Geographic breakdown of global income groups, 2016

In 2016, the situation is notably different. The most striking evolution is perhaps the spread of Chinese income earners, which are now located throughout the entire global distribution. India remains largely represented at the bottom with only very few Indians among the top global earners.

The position of Russian earners was also stretched throughout from the poorest to the richest income groups. This illustrates the impact of the end of communism on the spread of Russian incomes. Africans, who were present throughout the first half of the distribution, are now even more concentrated in the bottom quarter, due to relatively low growth as compared to Asian countries. At the top of the distribution, while the shares of both North America and Europe decreased (leaving room for their Asian counterparts), the share of Europeans was reduced much more. This is because most large European countries followed a more equitable growth trajectory over the past decades than the United States and other countries, as will be discussed in chapter 2.3.

iv. The moderate decline of global inequality since 2000 vs. the rise of within-country inequality

How did global inequality evolve between 1980 and 2016? Figure 7 answers this question by presenting the share of world income held by the global top 1% and the global bottom 50%, measured at purchasing power parity. The global top 1% income share rose from about 16% of global income in 1980 to more than 22% in 2007 at the eve of the global financial crisis. It was then slightly reduced to 20.4% in 2016, but this slight decrease hardly brought back the level of global inequality to its 1980 level. The income share of bottom half of the world population oscillated around 9% with a very slight increase between 1985 and 2016.

The first insight of this graph is the extreme level of global inequality sustained throughout the entire period with a top 1% income group capturing two times the total income captured by the bottom 50% of the population—implying a factor 100 difference in average per-adult income levels. Second, it is apparent that high growth in emerging countries since 2000, in particular in China, or the global financial crisis of 2008 was not sufficient to stop the rise in global income inequality.

Figure 7 - Global top 1% and bottom 50% income shares, 1980–2016

When global inequality is decomposed into a between- and within-country inequality component, it is apparent that within-country inequality continued to rise since 2000 whereas between-country inequality rose up to 2000 and decreased afterwards. Figure 8 presents the evolution of the global 10% income share, which reached close to 50% of global income in 1980, rose to 55% in 2000–2007, and decreased to slightly more than 52% in 2016. Two alternative scenarios for the evolution of the global top 10% share are presented. The first one assumes that all countries had exactly the same average income (that is, that there was no between-country inequality), but that income was as unequal within these countries as was actually observed. In this case, the top 10% share would have risen from 35% in 1980 to nearly 50% today. In the second scenario, it is assumed that between-country inequality evolved as observed but it is also assumed that everybody within countries had exactly the same income level (no within-country inequality). In this case, the global top 10% income share would have risen from nearly 30% in 1980 to more than 35% in 2000 before decreasing back to 30%.

Figure 8 - Global top 10% income share, 1980–2016: between versus within-country inequality

v. Market exchange rate vs Purchasing Power Parity measures of global inequality

Prices can be converted from one currency to another using either market exchange rates or purchasing power parities (as we did above). Market exchanges rates are the prices at which people are willing to buy and sell currencies, so at first glance they should reflect people's relative purchasing power. This makes them a natural conversion factor between currencies. The problem is that market exchange rates reflect only the relative purchasing power of money in terms of tradable goods. But non-tradable goods (typically services) are in fact cheaper relative to tradable ones in emerging economies (given the so-called Balassa-Samuelson effect). Therefore, market exchange rates will underestimate the standard of living in the poorer countries. In addition, market exchange rates can vary for all sorts of other reasons—sometimes purely financial and/or political—in a fairly chaotic manner. Purchasing power parity is an alternative conversion factor that addresses these problems (based on observed prices in the various countries). The level of global income inequality is therefore substantially higher when measured using market exchange rates than it is with purchasing power parity. It increases the global top 1% share in 2016 from 20% to 24% and reduces the bottom 50% share from nearly 10% to 6% (Figure 9).

Figure 9 - Global top 1% and bottom 50% income shares, 1980–2016 : PPP versus market exchange rates

Purchasing power parity definitely gives a more accurate picture of global inequality from the point of view of individuals who do not travel across the world and who essentially spend their incomes in their own countries. Market exchange rates are perhaps better to inform about inequality in a world where individuals can easily spend their incomes where they want, which is the case for top global earners and tourists, and increasingly the case for anyone connected to the internet. It is also the case for migrant workers wishing to send remittances back to their home countries. Both purchasing power parity and market exchange rates are valid measures to track global income inequality, depending on the object of study or which countries are compared to one another.

5 Projecting the future of global income inequality

The past four decades have been marked by steeply rising income inequality within countries. At the global level, inequality has also risen sharply since 1980, but the situation more or less stabilized beginning in the early 2000s. What will happen in the future? Will growth in emerging countries lead to a sustained reduction in global income inequality? Or will unequal growth within countries drive global income inequality back to its 2000 levels? We now discuss different possible global income inequality scenarios between now and 2050.

Fortunately, more data are available to measure income inequality, and in this chapter we present more elaborate projections of global income inequality. Before discussing the results, it is necessary to stress what can and cannot be reliably projected. As the saying goes, "all models are wrong; some are useful." Our projections are attempts to represent possible states of global inequality in the future, so as to better understand the role played by key determinants. The purpose of our projections is not to predict the future. The number of forces (or variables) that we consider in our analysis is limited. This makes our projections straightforward and simple to understand, but also limits their ability to predict the future.

i. Under business as usual, global inequality will continue to rise, despite strong growth in low-income countries.

Figure 10 shows the evolution of the income shares of the global top 1% and the global bottom 50% for the three scenarios. Under the business-as-usual scenario (scenario 1), the income share held by the bottom 50% of the population slightly decreases from approximately 10% today to less than 9% in 2050. At the top of the global income distribution, the top 1% income share rises from less than 21% today to more than 24% of world income. Global inequality thus rises steeply in this scenario, despite strong growth in emerging countries. In Africa, for instance, we assume that average per-adult income grows at sustained 3% per year throughout the entire period (leading to a total growth of 173% between 2017 and 2050).

These projections show that the progressive catching-up of low-income countries is not sufficient to counter the continuation of worsening of within-country inequality. The results also suggest that the reduction (or stabilization) of global income inequality observed since the financial crisis of 2008, discussed in Chapter 2, could largely be a short-run phenomenon induced by the shocks on top incomes, and the growth slowdown in rich countries (particularly in Europe).

Figure 10 -Top 1% versus bottom 50% shares of global income, 1980–2050

In scenario two, future global income inequalities are amplified as compared to scenario one, as the gap between the global top 1% share and the global bottom 50% share in 2050 widens. In this scenario, the global top 1% would earn close to 28% of global income by 2050, while the bottom 50% would earn close to 6%, less than in 1980, before emerging countries started to catch up with the industrialized world. In this scenario, the increase in the top 1% income share (a positive change of eight percentage points over the 2016–2050 period) is largely, but not entirely, made at the expense of the bottom 50% (a negative change of four percentage points).

Scenario three presents a more equitable global future. It shows that global inequality can be reduced if all countries align on the EU inequality trajectory—or more equitable ones. In this scenario, the bottom 50% income share rises from 10% to approximately 13% in 2050, whereas the top 1% decreases from 21% to 19% of total income. The gap between the shares held by the two groups would, however, remain large (at about six percentage points). This suggests that, although following the European pathway in the future is a much better option than the business-as-usual or the US pathway, even more equitable growth trajectories will be needed for the global bottom 50% share to catch up with the top 1%. Achieving a world in which the top 1% and bottom 50% groups capture the same share of global income would mean getting to a point where the top 1% individuals earn on average fifty times more than those in the bottom half. Whatever the scenarios followed, global inequalities will remain substantial.

ii. Within country inequality trends are critical for global poverty eradication

What do these different scenarios mean in terms of actual income levels, and particularly for bottom groups? It is informative to focus on the dynamics of income shares held by different groups, and how they converge or diverge over time. But ultimately, it can be argued that what matters for individuals—and in particular those at the bottom of the social ladder—is their absolute income level. We stress again here that our projections do not pretend to predict how the future will be, but rather aim to inform on how it *could* be, under a set of simple assumptions.

Figure 12 depicts the evolution of average global income levels and the average income of the bottom half of the global population in the three scenarios described above. The evolution of global average income does not depend on the three scenarios. This is straightforward to understand: in each of the scenarios, countries (and hence the world as a whole) experience the same total income and demographic growth. It is only the matter of how this growth is distributed within countries that changes across scenarios. Let us reiterate that our assumptions are quite optimistic for low-income countries, so it is indeed possible that global average income would actually be slightly lower in the future than in the figures presented. In particular, the global bottom 50% average income would be even lower.

In 2016, the average per-adult annual income of the poorest half of the world population was €3 100, in contrast to the €16 000 global average—a ratio of 5.2 between the overall average and the bottom-half average. In 2050, global average income will be €35 500 according to our projections. In the business-as-usual scenario, the gap between average income and the bottom would widen (from a ratio of 5.2 to a ratio of 5.6) as the bottom half would have an income of €6 300. In the US scenario, the bottom half of the world population earn €4 500 per year and per adult—rising the global average income to bottom 50% income ratio of 7.9. Average income of the global bottom half will be €9 100 in the EU scenario, reducing the bottom 50% to average income ratio to 3.9.

The gap between global average income and the average income of the bottom half of the population is particularly high in all scenarios. However, the difference in average income of the bottom 50% between the EU scenario and the US scenario is important, as well. Average income of the global bottom 50% would be more than twice higher in the EU scenario than in the US scenario at €9 100 versus €4 500. This suggests that within-country inequality trajectories matter—and matter substantially—for poverty eradication. In other words, pursuing high-growth strategies in emerging countries is not merely sufficient to lift the global bottom half out of poverty. Reducing inequality within countries is also key.

Figure 12 - Global average income versus global 50% average, 1980–2050

Figure 1 - Global bottom 50% average income, 1980–2050

The scenarios point toward another crucial insight: global inequality is not bound to rise in the future. Our analysis of the different income inequality trajectories followed by countries showed that, if anything, more equitable growth does not mean dampened growth. This result is apparent when time periods are compared (the United States experienced higher growth in the 1950s–1960s when inequality was at its lowest) or when countries are compared with one another (over the past decades, China grew much faster than India, with a lower level of inequality, and the EU had a more equitable path than the United States but a relatively similar growth rate). This suggests that it is possible to pursue equitable development pathways in a way that does not also limit total growth in the future.

6 Conclusion

Despite the limited available data on global inequality, we have attempted to estimate the main features of global inequality dynamics in the last 40 years by making assumptions about inequality trajectories within broad geographical areas, and on the basis of Distributional National Accounts already covering a large share of global income. Interestingly, and partly because existing inequality data from WID.world already covers about three quarters of world income and two thirds of world population, our results are relatively robust to alternative specifications for missing countries.

We find that the global top 1% captured 27% of total income growth between 1980 and 2016, against 12% for the bottom 50%. We also show that global inequality is likely to further rise in the future, even under optimistic growth assumption in emerging countries, if countries follow their own inequality trend. These results suggest a necessary discussion over the types of policies implemented by governments to trigger and redistribute income growth.

We have proceeded in a transparent manner, providing detailed codes and sources on WID.world, so as to contribute to increase the level of transparency of existing global inequality statistics. As more reliable estimates will become available for a growing number of "missing" countries, especially in South-East Asia, Africa, Eastern Europe and Latin America, we will be able to get a more precise picture of global inequality. In the future, we also hope to gradually improve our projections of global inequality by testing more scenarios and formulating plausible assumptions about growth dynamics in the long run.

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Table 1 – The distribution of world national income and gross domestic product, 1980: Purchasing Power Parity

	Population *(million)*				GDP *(trillion 2016 € PPP)*	CFC *(% of GDP)*	NFI *(% of GDP)*	National Income *(trillion 2016 € PPP)*		Per adult National Income *(2016 € PPP)*	Equivalent per adult monthly income *(2016 € PPP)*
	Total		Adult								
World	7 372	**100%**	4 867	**100%**	92	14%	-0.5%	78	**100%**	16 100	1 340
Europe	747	**10%**	593	**12%**	19	15%	-0.6%	16	**20%**	27 100	2 260
incl. European Union	523	**7%**	417	**9%**	16	17%	-0.2%	13	**17%**	31 400	2 620
incl. Russia/ Ukraine	223	**3%**	176	**4%**	3	9%	-2.5%	3	**4%**	16 800	1 400
America	962	**13%**	661	**14%**	23	15%	-0.2%	19	**25%**	29 500	2 460
incl. United States/Canada	360	**5%**	263	**5%**	16	16%	0.9%	13	**17%**	50 700	4 230
incl. Latin America	602	**8%**	398	**8%**	7	12%	-2.5%	6	**8%**	15 400	1 280
Africa	1 214	**16%**	592	**12%**	4	10%	-2.1%	4	**5%**	6 600	550
incl. North Africa	240	**3%**	140	**3%**	2	9%	-1.7%	2	**2%**	11 400	950
incl. Sub-Saharan Africa	974	**13%**	452	**9%**	3	11%	-2.3%	2	**3%**	5 100	430
Asia	4 410	**60%**	2 994	**62%**	44	14%	-0.4%	38	**49%**	12 700	1 060
incl. China	1 382	**19%**	1 067	**22%**	18	14%	-0.7%	15	**19%**	14 000	1 170
incl. India	1 327	**18%**	826	**17%**	7	11%	-1.2%	6	**7%**	7 000	580
incl. Japan	126	**2%**	105	**2%**	4	21%	3.5%	3	**4%**	31 000	2 580
incl. Other	1 575	**21%**	995	**20%**	16	13%	-0.7%	14	**18%**	14 200	1 180
Oceania	39	**1%**	27	**1%**	1	16%	-1.5%	1	**1%**	31 700	2 640
incl. Australia and NZ	29	**0.4%**	21	**0.4%**	1	16%	-1.5%	1	**1%**	38 200	3 180
incl. Other	10	**0.1%**	5	**0.1%**	0.03	7%	-2.4%	0.03	**0%**	5 600	470

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, Europe represented 20% of world income measured using Purchasing Power Parity. Europe also represented 12% of the world's adult population and 10% of the world's total population. GDP: Gross Domestic Product. CFC: Consumption of Fixed Capital. NFI: Net Foreign Income. PPP: Purchasing Power Parity. All values have been converted into 2016 Purchasing Power Parity (PPP) euros at a rate of €1 = $1.3 = ¥4.4. PPP accounts for differences in the cost of living between countries. Values are net of inflation. Numbers may not add up due to rounding.

Table 2 – The distribution of world national income and gross domestic product, 2016: Market Exchange Rates

	Population *(million)*				GDP *(trillion 2016 € MER)*	CFC *(% of GDP)*	NFI *(% of GDP)*	National Income *(trillion 2016 € MER)*		Per adult National Income *(2016 € MER)*	Equivalent per adult monthly income *(2016 € MER)*
	Total		Adult								
World	7 372	**100%**	4 867	**100%**	68	15%	0%	58	**100%**	11 800	980
Europe	747	**10%**	593	**12%**	17	16%	-0.2%	14	**24%**	23 800	1 980
incl. European Union	523	**7%**	417	**9%**	16	17%	0.04%	13	**23%**	31 100	2 590
incl. Russia/ Ukraine	223	**3%**	176	**4%**	1	9%	-2.5%	1	**2%**	6 500	540
America	962	**13%**	661	**14%**	23	15%	0.2%	19	**34%**	29 400	2 450
incl. United States/Canada	360	**5%**	263	**5%**	18	16%	0.9%	16	**27%**	59 500	4 960
incl. Latin America	602	**8%**	398	**8%**	4	12%	-2.4%	4	**7%**	9 600	800
Africa	1 214	**16%**	592	**12%**	2	10%	-2.0%	2	**3%**	2 900	240
incl. North Africa	240	**3%**	140	**3%**	1	9%	-1.5%	1	**1%**	4 300	360
incl. Sub-Saharan Africa	974	**13%**	452	**9%**	1	11%	-2.2%	1	**2%**	2 500	210
Asia	4 410	**60%**	2 994	**62%**	25	15%	0.1%	21	**37%**	7 100	590
incl. China	1 382	**19%**	1 067	**22%**	10	14%	-0.7%	9	**15%**	8 300	690
incl. India	1 327	**18%**	826	**17%**	2	11%	-1.2%	2	**3%**	2 200	180
incl. Japan	126	**2%**	105	**2%**	4	23%	3.5%	4	**6%**	34 400	2 870
incl. Other	1 575	**21%**	995	**20%**	8	14%	-0.5%	7	**12%**	7 000	580
Oceania	39	**1%**	27	**1%**	1	18%	-1.9%	1	**2%**	38 800	3 230
incl. Australia and NZ	29	**0.4%**	21	**0.4%**	1	18%	-1.9%	1	**2%**	47 500	3 960
incl. Other	10	**0.1%**	5	**0.1%**	0.03	7%	-2.4%	0.02	**0%**	4 300	360

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, Europe represented 24% of world income measured using Market Exchange Rates. Europe also represented 12% of the world's adult population and 10% of the world's total population. GDP: Gross Domestic Product. CFC: Consumption of Fixed Capital. NFI: Net Foreign Income. MER: Market Exchange Rate. All values have been converted into 2016 Market Exchange Rate euros at a rate of €1 = $1.1 = ¥7.3. Figures take into account inflation. Numbers may not add up due to rounding.

Table 3 – The distribution of world national income and gross domestic product, 1980: Purchasing Power Parity

	Population *(million)*				**GDP** *(trillion € PPP 2016)*	**CFC** *(% of GDP)*	**NFI** *(% of GDP)*	**National Income** *(trillion 2016 € PPP)*		**Per adult National Income** *(2016 € PPP)*	**Equivalent per adult monthly income** *(2016 € PPP)*
	Total		**Adult**								
World	4389	**100%**	2400	**100%**	28	13%	-0.2%	25	**100%**	10500	880
Europe	673	**15%**	470	**20%**	11	14%	-0.1%	9	**37%**	20000	1670
incl. European Union	469	**11%**	328	**14%**	8	14%	-0.2%	7	**28%**	21600	1800
incl. Russia/ Ukraine	204	**5%**	142	**6%**	3	17%	0.0%	2	**9%**	16200	1350
America	598	**14%**	343	**14%**	9	14%	-0.4%	7	**30%**	21700	1810
incl. United States/Canada	252	**6%**	172	**7%**	6	15%	0.9%	5	**20%**	29600	2470
incl. Latin America	346	**8%**	172	**7%**	3	11%	-3.0%	2	**9%**	13800	1150
Africa	477	**11%**	215	**9%**	1.3	10%	-1.9%	1	**5%**	5500	460
incl. North Africa	111	**3%**	51	**2%**	0.5	10%	-2.1%	0.5	**2%**	9200	770
incl. Sub-Saharan Africa	365	**8%**	163	**7%**	0.8	10%	-1.8%	1	**3%**	4332	360
Asia	2619	**60%**	1359	**57%**	7.1	12%	0.2%	7	**27%**	5000	420
incl. China	987	**22%**	532	**22%**	0.9	11%	0.0%	1	**3%**	1500	130
incl. India	697	**16%**	351	**15%**	0.8	7%	0.6%	1	**3%**	2200	180
incl. Japan	117	**3%**	81	**3%**	1.9	17%	0.0%	2	**6%**	19900	1660
incl. Other	817	**19%**	394	**16%**	3.4	10%	0.4%	4	**15%**	9300	780
Oceania	22	**1%**	14	**1%**	0.4	15%	-1.6%	0.3	**1%**	21300	1780
incl. Australia and NZ	18	**0.4%**	12	**0.5%**	0.3	16%	-1.5%	0.3	**1%**	24200	2020
incl. Other	5	**0.1%**	2	**0.1%**	0.0	7%	-4.2%	0.0	**0%**	4400	370

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 1980, Europe represented 37% of world income measured using Purchasing Power Parity. Europe also represented 20% of the world's adult population and 15% of the world's total population. GDP: Gross Domestic Product. CFC: Consumption of Fixed Capital. NFI: Net Foreign Income. PPP: Purchasing Power Parity. All values have been converted into 2016 Purchasing Power Parity (PPP) euros at a rate of €1 = $1.3 = ¥4.4. PPP accounts for differences in the cost of living between countries. Values are net of inflation. Numbers may not add up due to rounding.

Table 4 – The distribution of world national income and gross domestic product, 1980: Market Exchange Rates

	National Income		National Income per capita		National Income per adult	
	1950–1980	1980–2016	1950–1980	1980–2016	1950–1980	1980–2016
World	282%	226%	116%	85%	122%	54%
Europe	256%	79%	181%	54%	165%	36%
incl. European Union	259%	94%	192%	66%	180%	45%
incl. Russia/ Ukraine	249%	31%	156%	18%	129%	4%
America	227%	163%	78%	62%	80%	36%
incl. United States/Canada	187%	164%	89%	84%	82%	71%
incl. Latin America	365%	161%	116%	49%	117%	12%
Africa	258%	233%	72%	30%	85%	20%
incl. North Africa	394%	235%	130%	58%	148%	24%
incl. Sub-Saharan Africa	203%	232%	46%	22%	58%	18%
Asia	446%	527%	188%	230%	198%	152%
incl. China	273%	1864%	106%	1237%	114%	831%
incl. India	199%	711%	61%	299%	67%	223%
incl. Japan	740%	103%	504%	86%	372%	56%
incl. Other	518%	376%	187%	99%	203%	52%
Oceania	208%	194%	38%	69%	50%	49%
incl. Australia and NZ	199%	193%	69%	81%	71%	58%

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

Between 1950 and 1980, Africa's income grew by 258%, whereas income per adult grew by only 85% during the same period. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

Table 5 - Global income growth and inequality, 1980–2016

	Total cumulative real growth per adult					
Income group	**China**	**Europe**	**India**	**Russia**	**US-Canada**	**World**
Full Population	831%	40%	223%	34%	63%	60%
Bottom 50%	417%	26%	107%	-26%	5%	94%
Middle 40%	785%	34%	112%	5%	44%	43%
Top 10%	1 316%	58%	469%	190%	123%	70%
Top 1%	1 920%	72%	857%	686%	206%	101%
Top 0.1%	2 421%	76%	1 295%	2 562%	320%	133%
Top 0.01%	3 112%	87%	2 078%	8 239%	452%	185%
Top 0.001%	3 752%	120%	3 083%	25 269%	629%	235%

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

From 1980 to 2016, the average income of the Bottom 50% in China grew 417%. Income estimates are calculated using 2016 Purchasing Power Parity (PPP) euros. PPP accounts for differences in the cost of living between countries. Values are net of inflation.

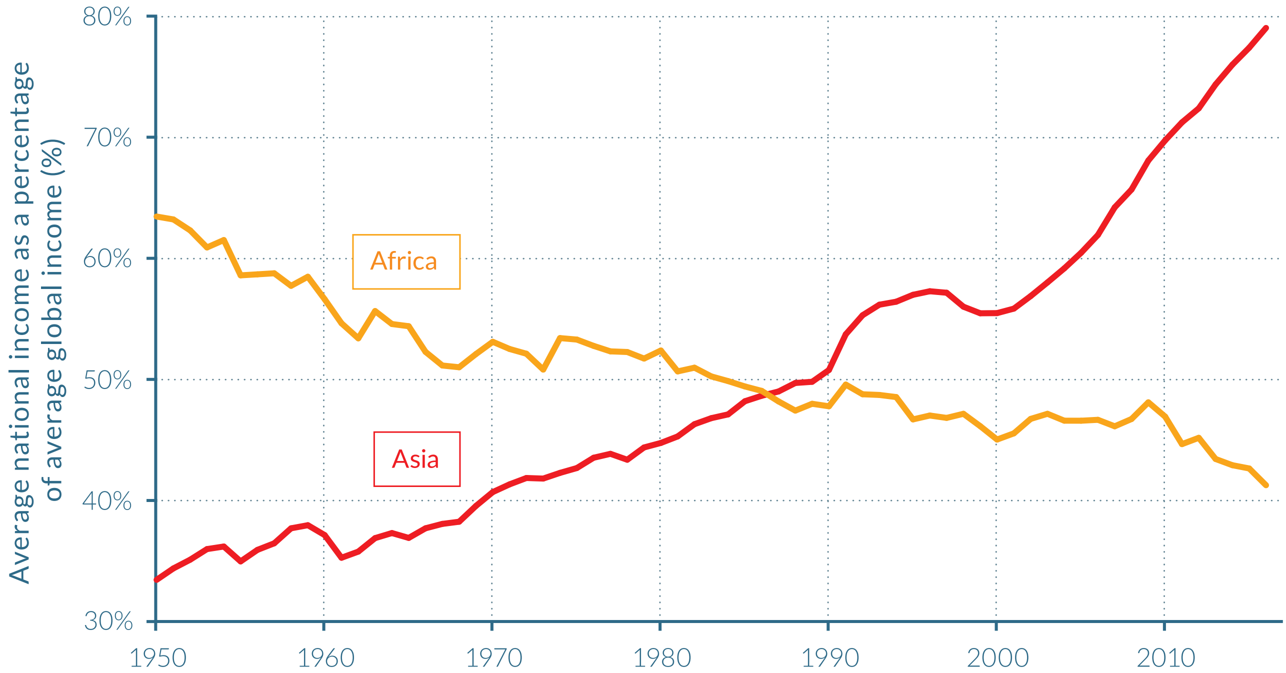
Table 6 - Share of growth captured by income groups, 1980–2016

Income group	China	Europe	India	Russia	US-Canada	World
Full Population	100%	100%	100%	100%	100%	100%
Bottom 50%	13%	14%	11%	-24%	2%	12%
Middle 40%	43%	38%	23%	7%	32%	31%
Top 10%	43%	48%	66%	117%	67%	57%
Top 1%	15%	18%	28%	69%	35%	27%
Top 0.1%	7%	7%	12%	41%	18%	13%
Top 0.01%	4%	3%	5%	20%	9%	7%
Top 0.001%	2%	1%	3%	10%	4%	4%

Source: WID.world (2017). See wir2018.wid.world for data series and notes.

From 1980 to 2016, the Middle 40% in Europe captured 38% of total income growth in the region. Income estimates are calculated using 2016 Purchasing Power Parity (PPP) euros. PPP accounts for differences in the cost of living between countries. Values are net of inflation.

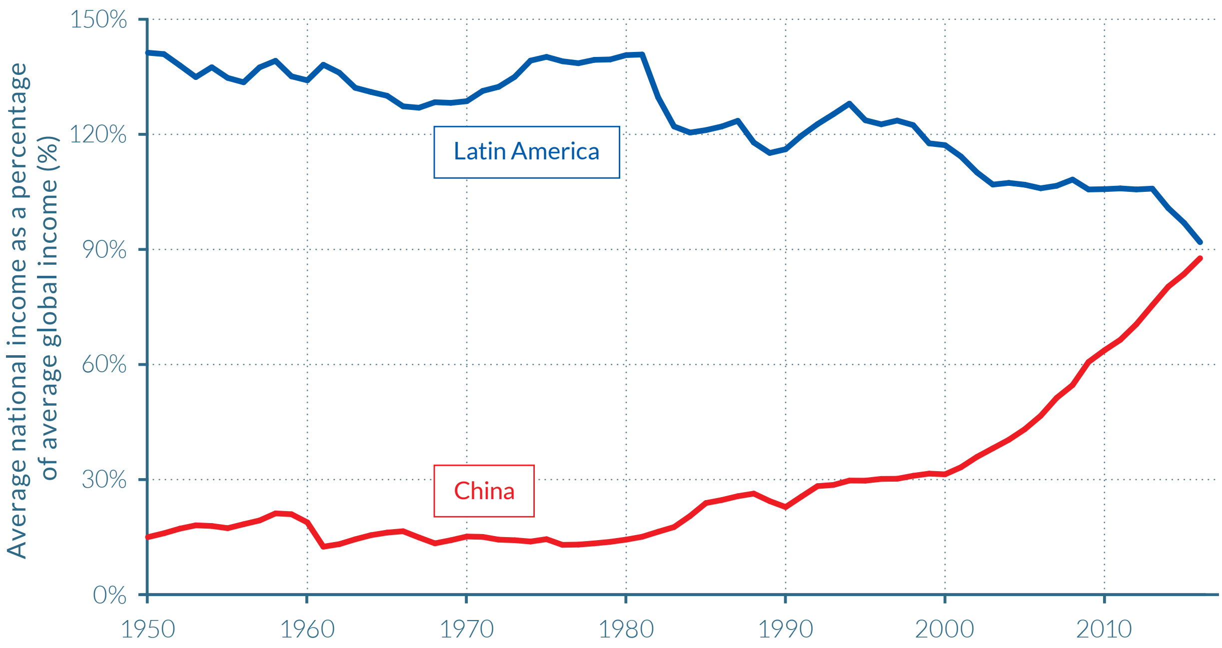
Figure 1a - Africa and Asia average incomes to global average, 1950–2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 1950, average real income per adult in Africa was 63% of the world average income. This figured decreased to 41% in 2016. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

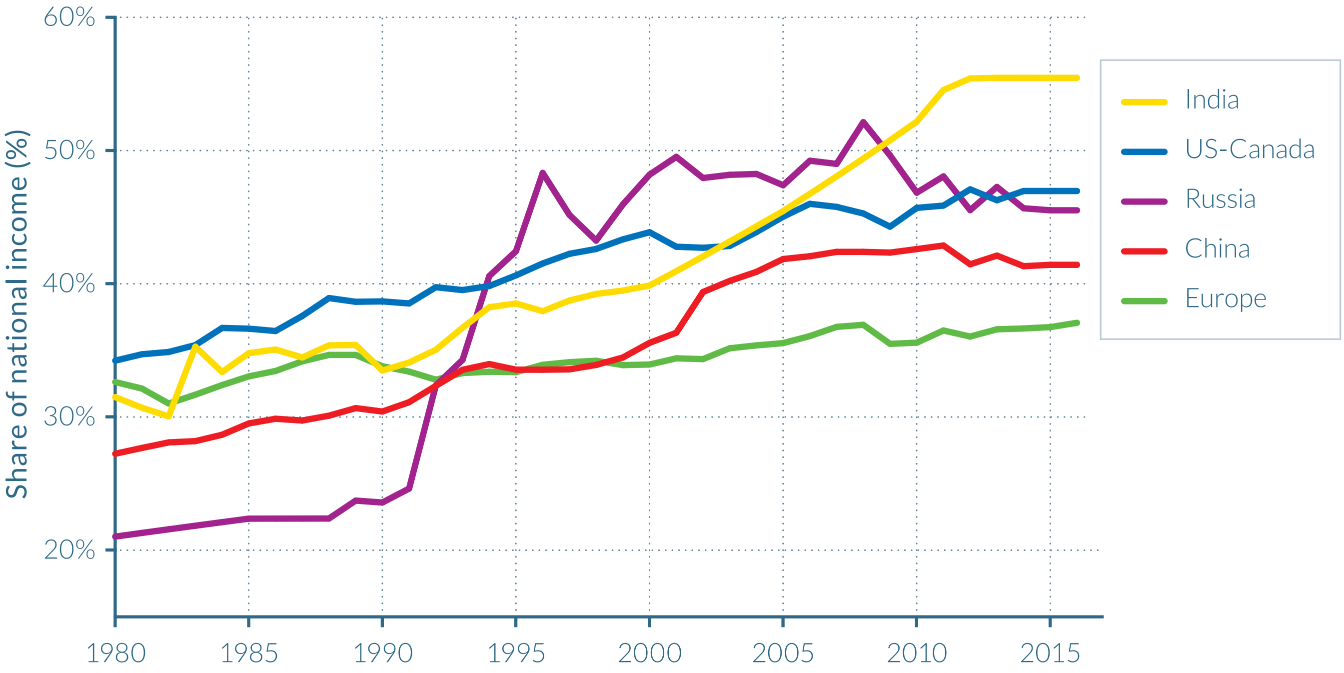
Figure 1b - China and Latin America average incomes to global average, 1950–2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 1950, average real income per adult in Latin America was 141% of the world average income. This figure decreased to 92% in 2016. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

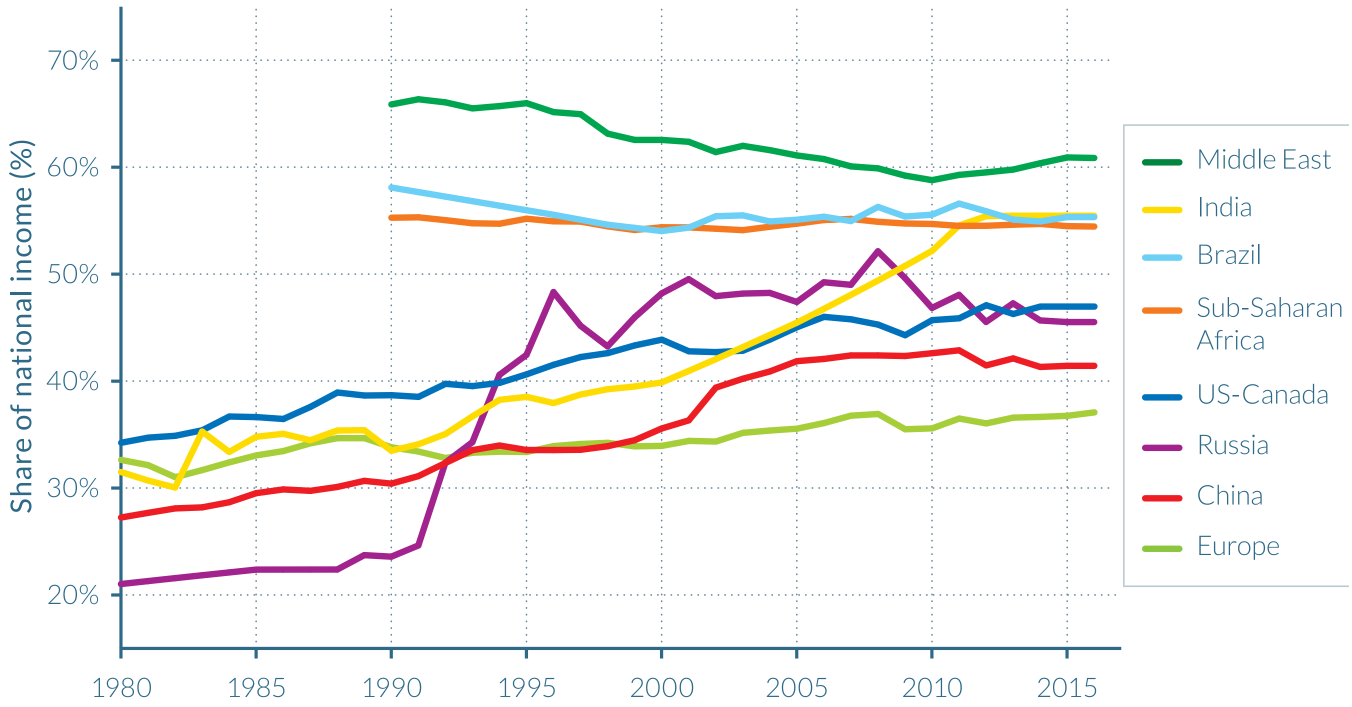
Figure 2a - Top 10% income shares across the world, 1980–2016: Rising inequality almost everywhere, but at different speed



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 47% of national income was received by the top 10% in US-Canada, compared to 34% in 1980.

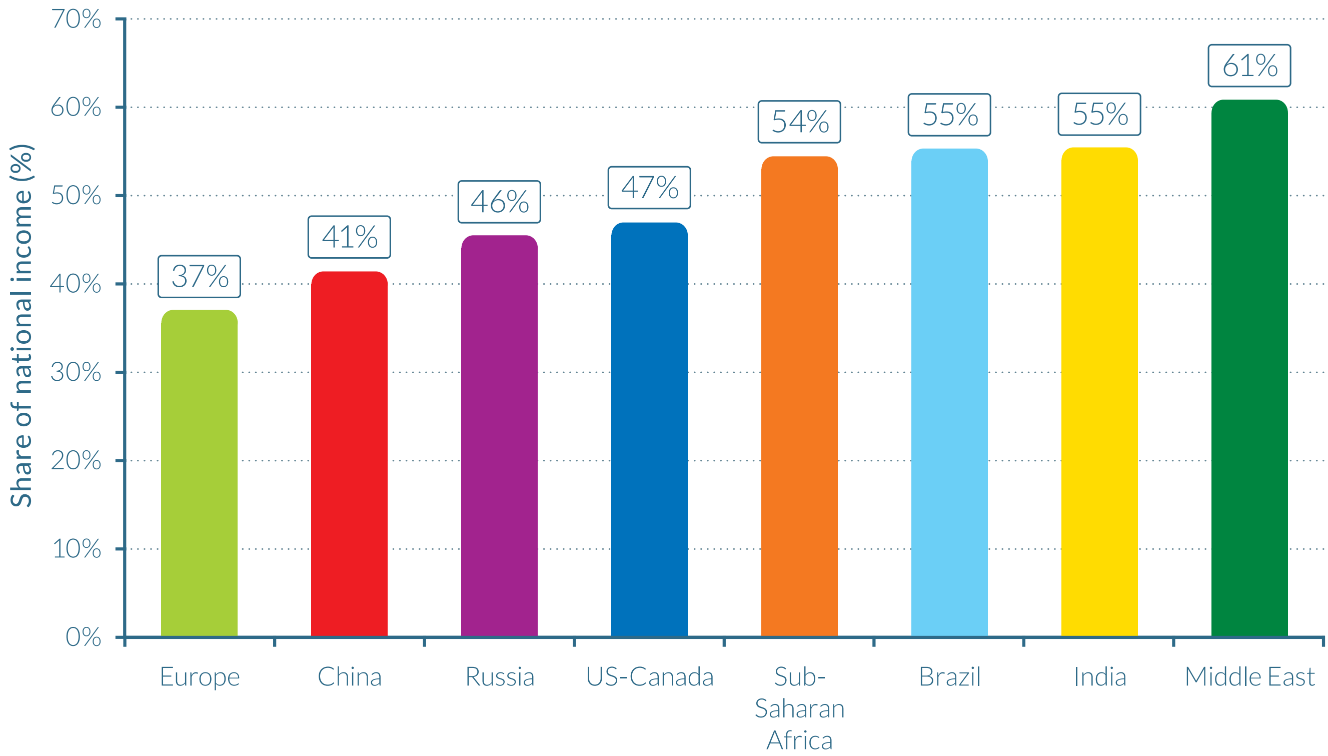
Figure 2b - Top 10% income shares across the world, 1980–2016: Is world inequality moving toward the high-inequality frontier?



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 55% of national income was received by the Top 10% in India, against 31% in 1980.

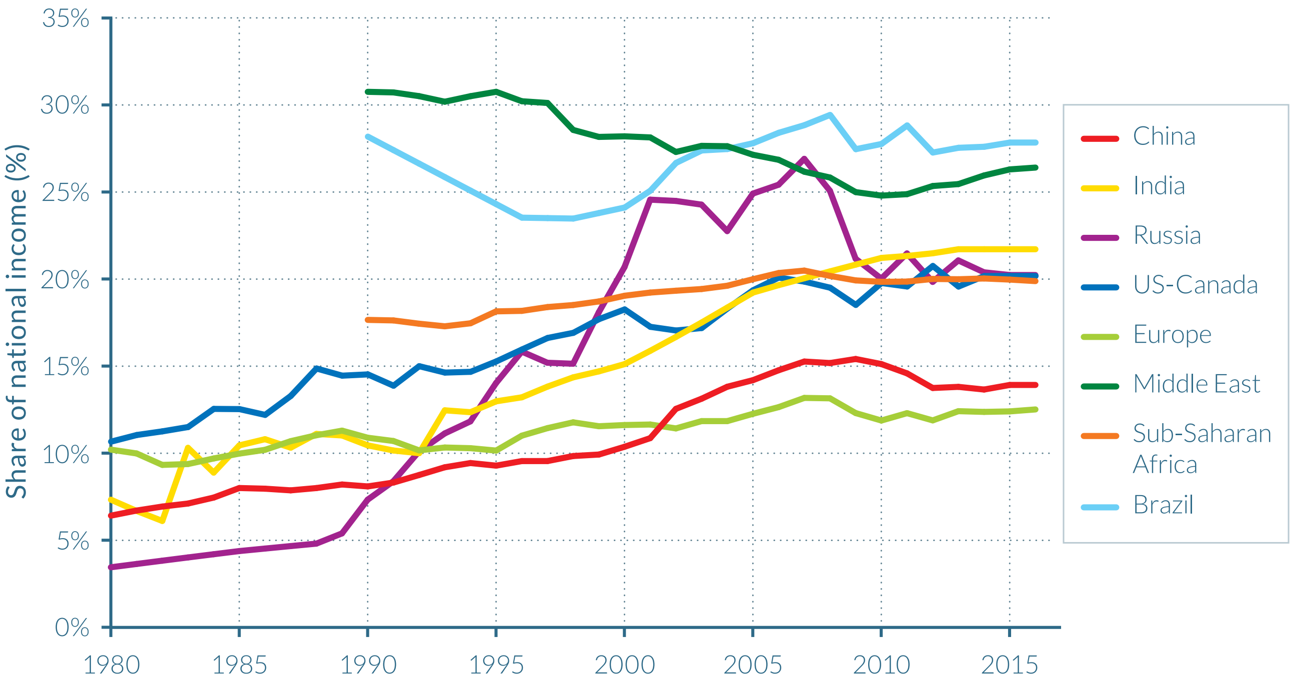
Figure 2c - Top 1% income shares across the world, 2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 37% of national income was received by the Top 10% in Europe against 61% in the Middle-East.

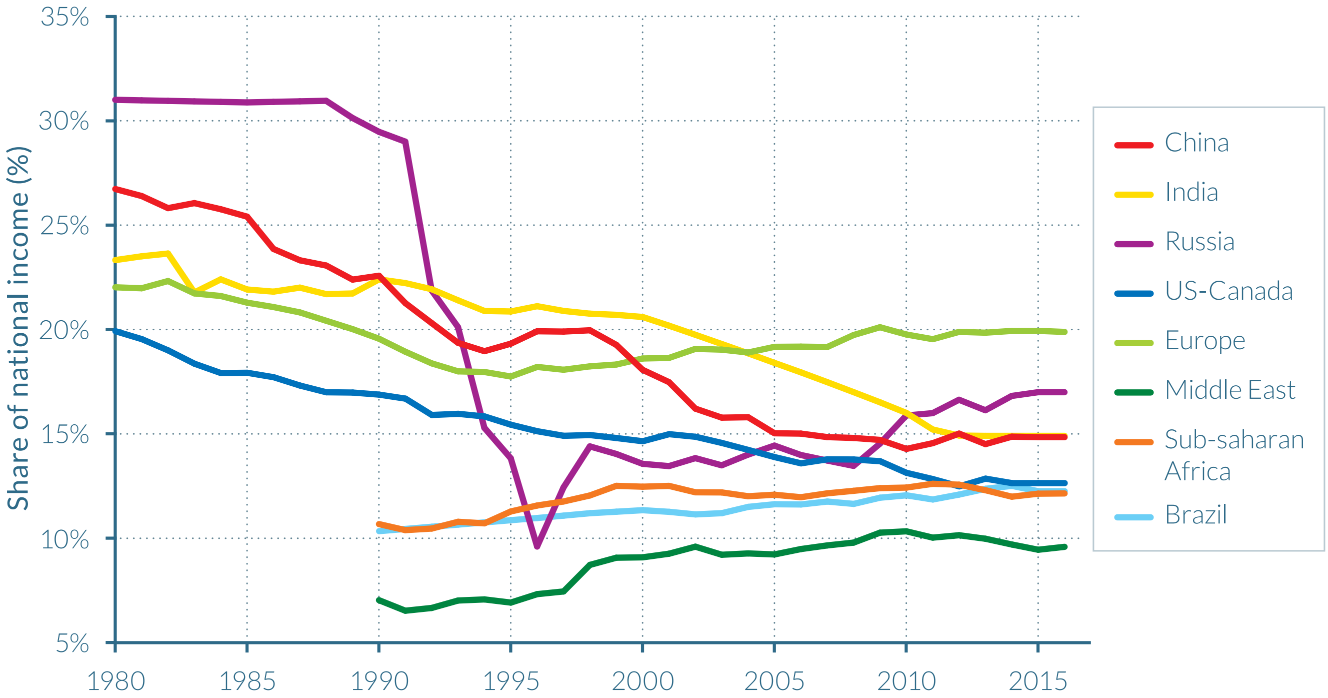
Figure 2d - Top 1% income shares across the world, 2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 14% of national income was received by the Top 1% in China.

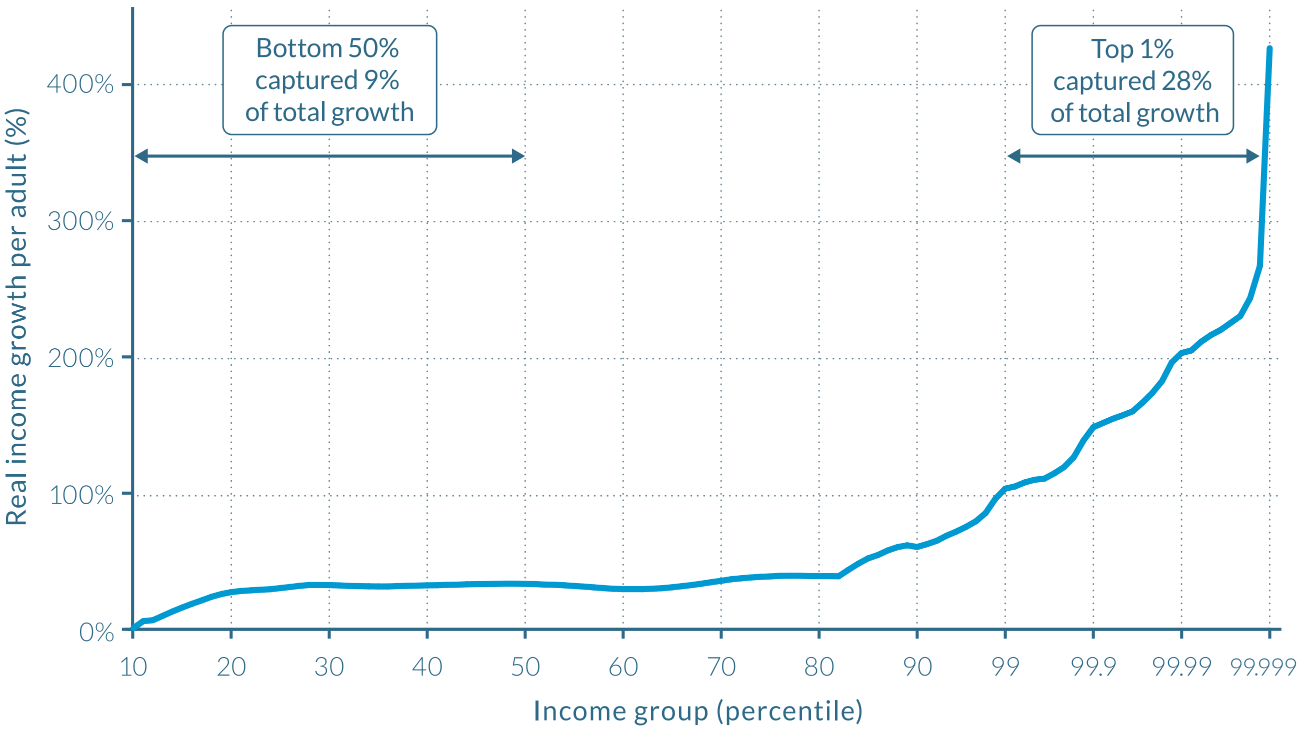
Figure 2e - Bottom 50% income shares across the world, 1980–2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 12% of national income was received by the Bottom 50% in Sub-Saharan Africa.

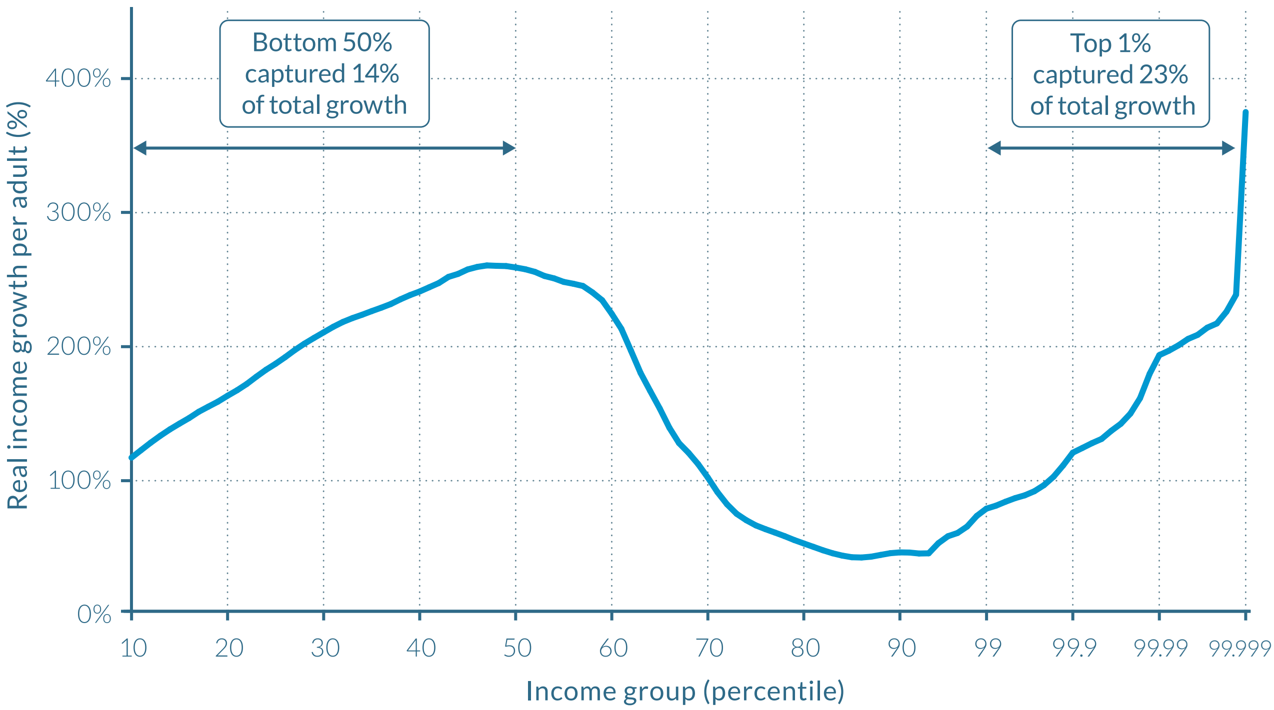
Figure 3a - Total income growth by percentile in US-Canada and Western Europe, 1980-2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

On the horizontal axis, the world population is divided into a hundred groups of equal population size and sorted in ascending order from left to right, according to each group's income level. The Top 1% group is divided into ten groups, the richest of these groups is also divided into ten groups, and the very top group is again divided into ten groups of equal population size. The vertical axis shows the total income growth of an average individual in each group between 1980 and 2016. For percentile group p99p99.1 (the poorest 10% among the world's richest 1%) growth was 104% between 1980 and 2016. The Top 1% captured 28% of total growth over this period. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

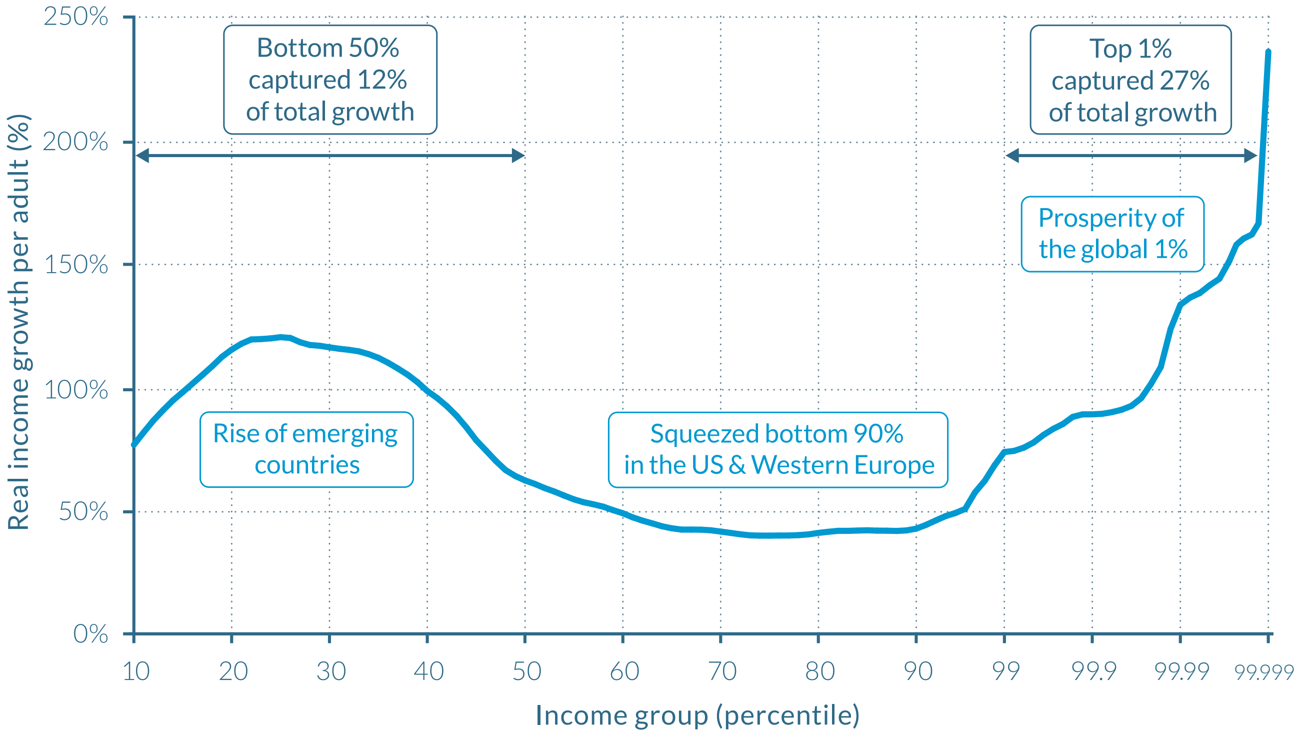
Figure 3b - Total income growth by percentile in China, India, US-Canada, and Western Europe, 1980-2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

On the horizontal axis, the world population is divided into a hundred groups of equal population size and sorted in ascending order from left to right, according to each group's income level. The Top 1% group is divided into ten groups, the richest of these groups is also divided into ten groups, and the very top group is again divided into ten groups of equal population size. The vertical axis shows the total income growth of an average individual in each group between 1980 and 2016. For percentile group p99p99.1 (the poorest 10% among the world's richest 1%), growth was 77% between 1980 and 2016. The Top 1% captured 23% of total growth over this period. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

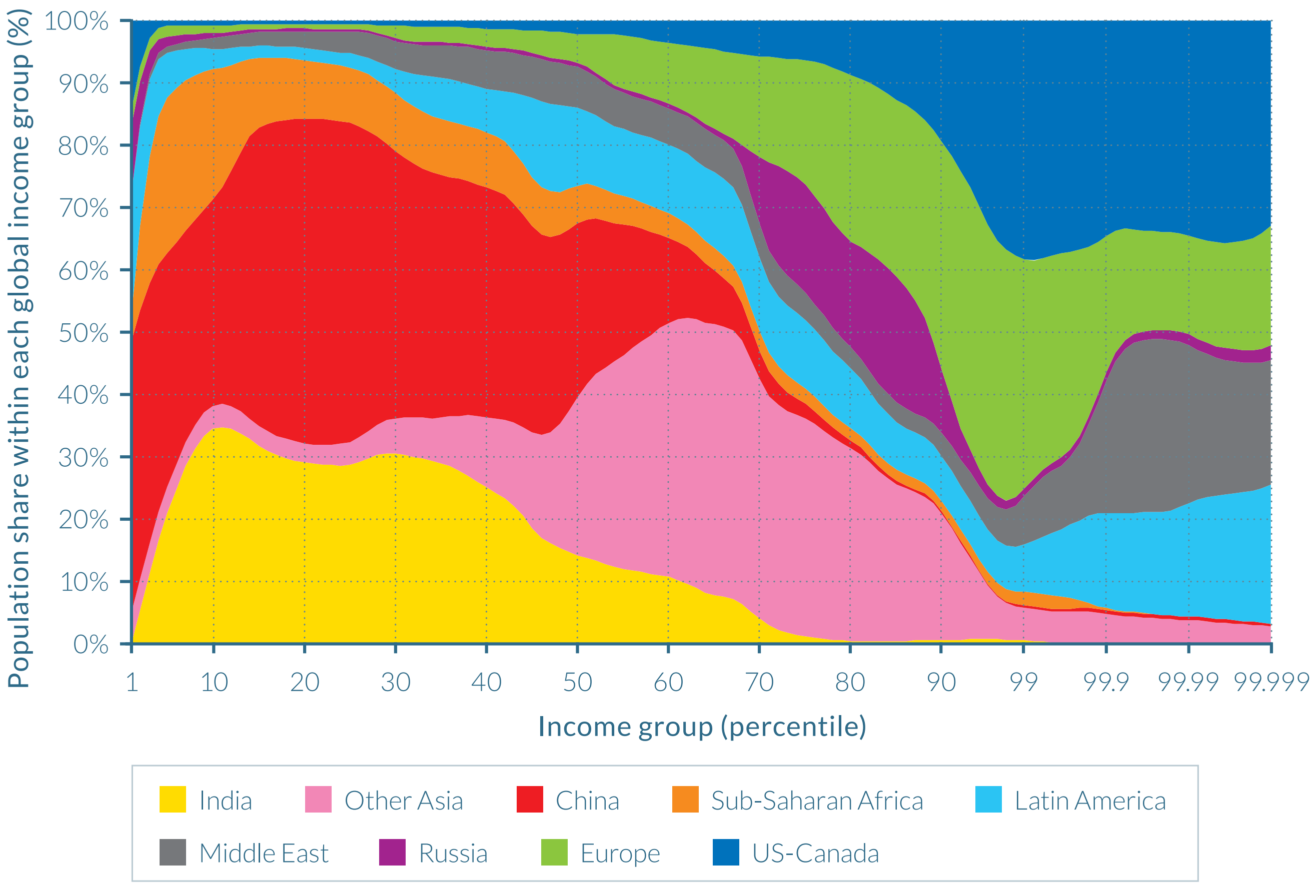
Figure 4 - Total income growth by percentile across all world regions, 1980-2016



Source: WID.world (2017). See wir2018.wid.world for more details.

On the horizontal axis, the world population is divided into a hundred groups of equal population size and sorted in ascending order from left to right, according to each group's income level. The Top 1% group is divided into ten groups, the richest of these groups is also divided into ten groups, and the very top group is again divided into ten groups of equal population size. The vertical axis shows the total income growth of an average individual in each group between 1980 and 2016. For percentile group p99p99.1 (the poorest 10% among the world's richest 1%), growth was 74% between 1980 and 2016. The Top 1% captured 27% of total growth over this period. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

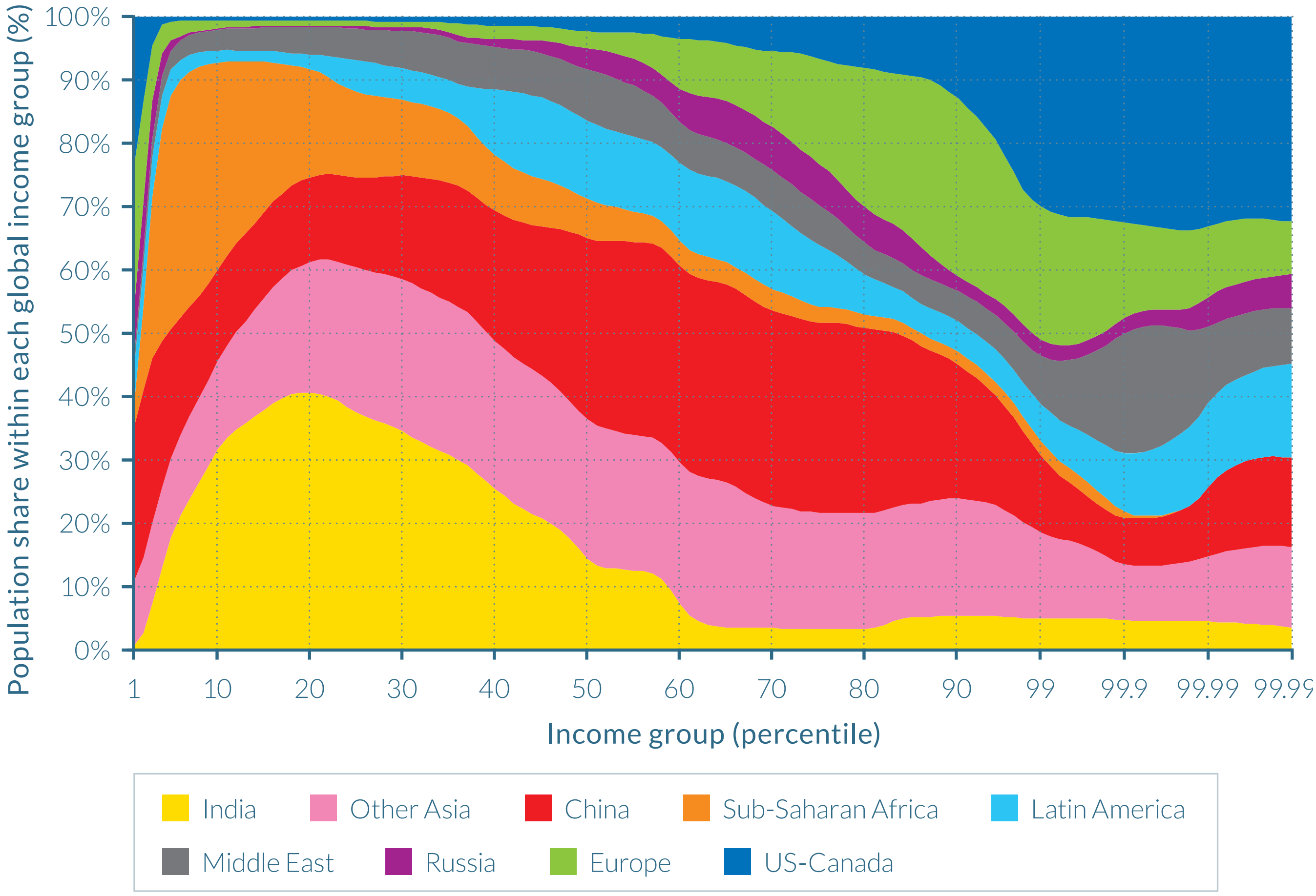
Figure 5 - Geographic breakdown of global income groups, 1990



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 1990, 33% of the population of the world's Top 0.001% income group were residents of the US and Canada.

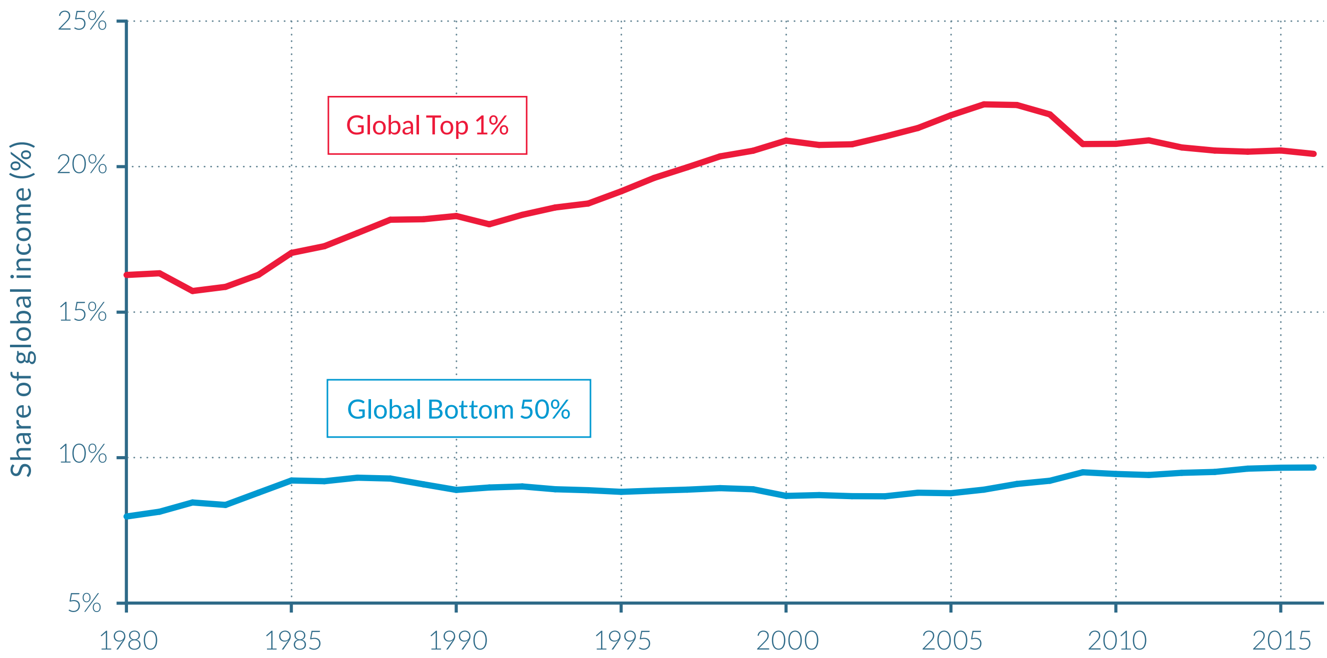
Figure 6 - Geographic breakdown of global income groups, 2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 5% of the population of the world's Top 0.001% income group were residents of Russia.

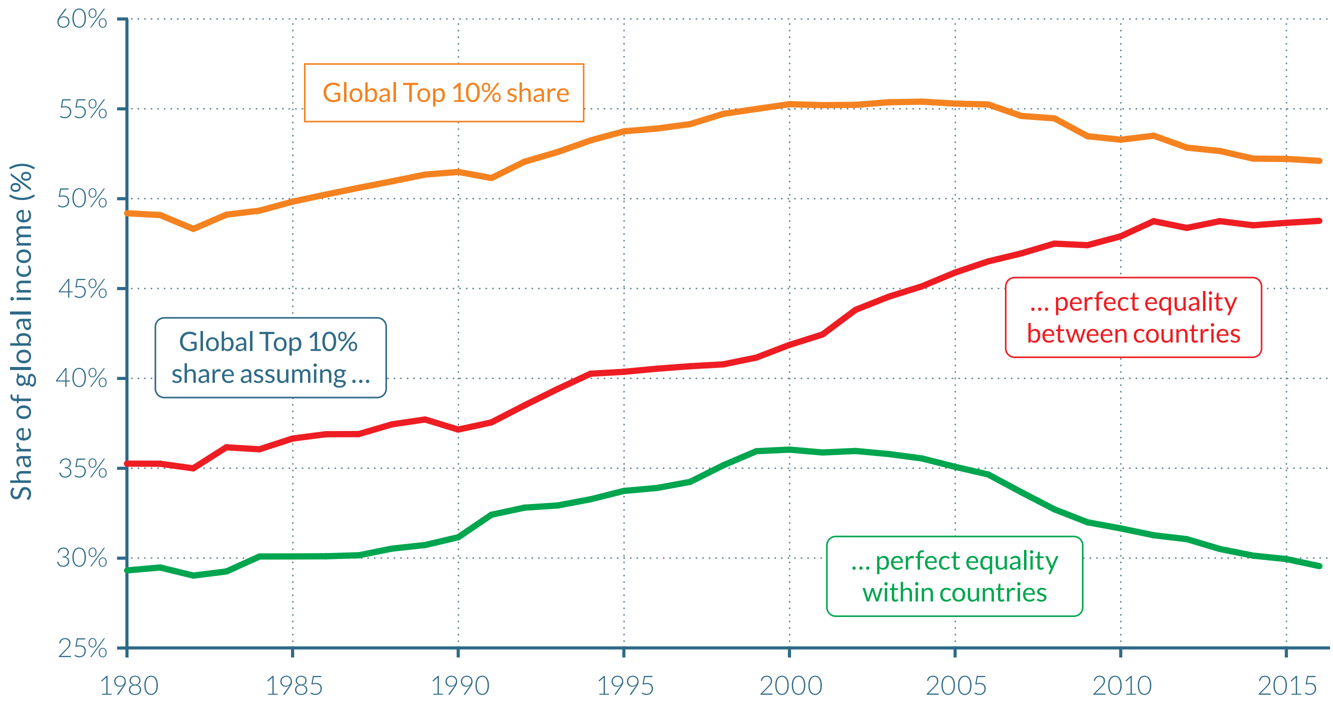
Figure 7 - Global top 1% and bottom 50% income shares, 1980–2016



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2016, 22% of global income was received by the Top 1% against 10% for the Bottom 50%. In 1980, 16% of global income was received by the Top 1% against 8% for the Bottom 50%.

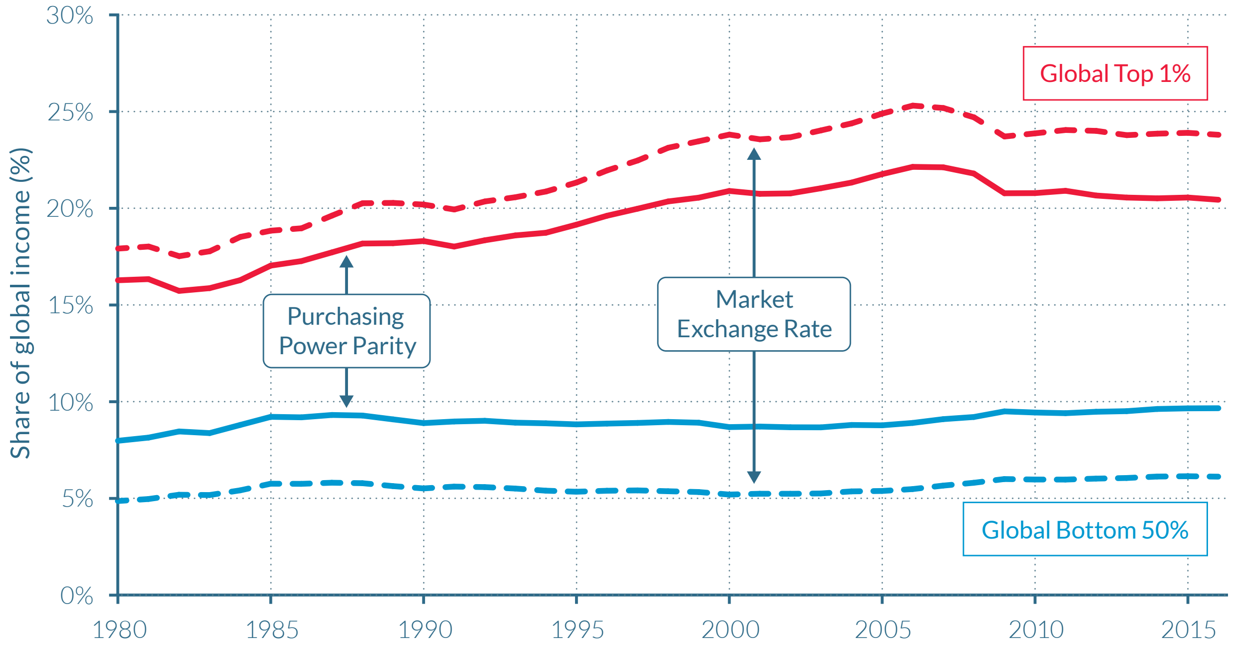
Figure 8 - Global top 10% income share, 1980–2016: between versus within-country inequality



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2010, 53% of the world's income was received by the Top 10%. Assuming perfect equality in average income between countries, the Top 10% would have received 48% of global income.

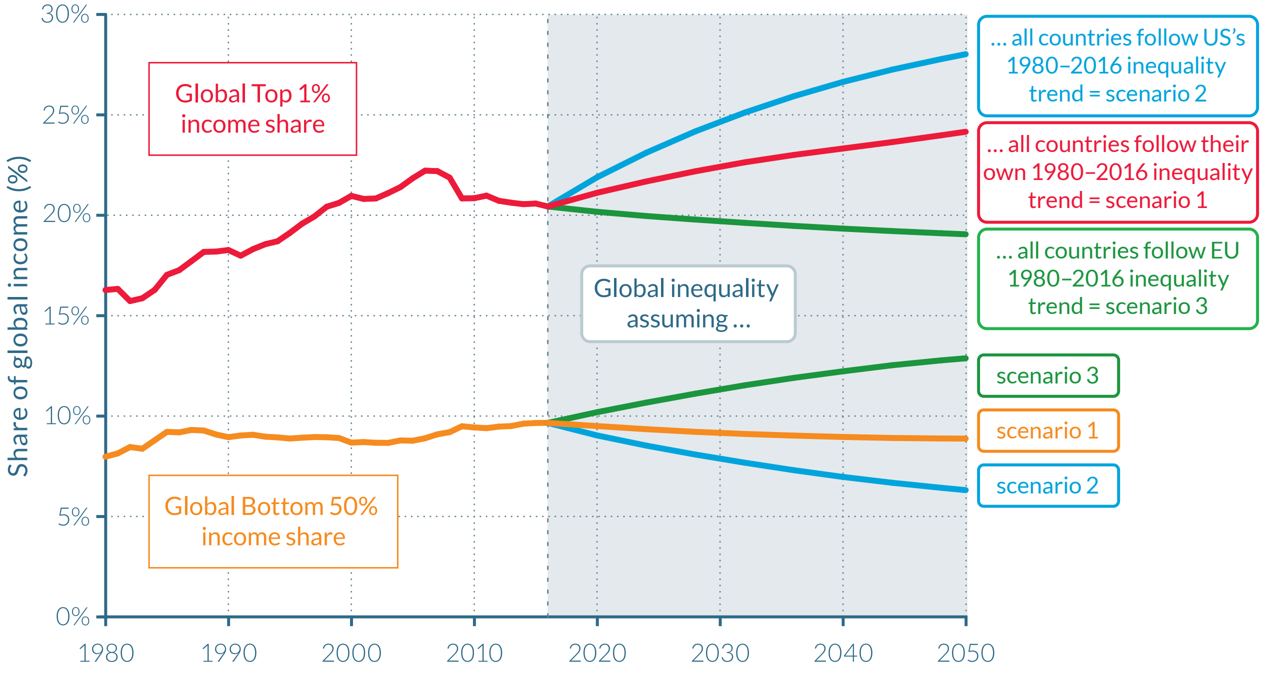
Figure 9 - Global top 1% and bottom 50% income shares, 1980–2016 : PPP versus market exchange rates



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

In 2010, the Top 1% received 24% of global income when measured using Market Exchange Rates (MER). When measured using Purchasing Power Parity (PPP), their share was 21%. Thick lines are measured at PPP values, dashed lines at MER values. Income estimates account for differences in the cost of living between countries. Values are net of inflation.

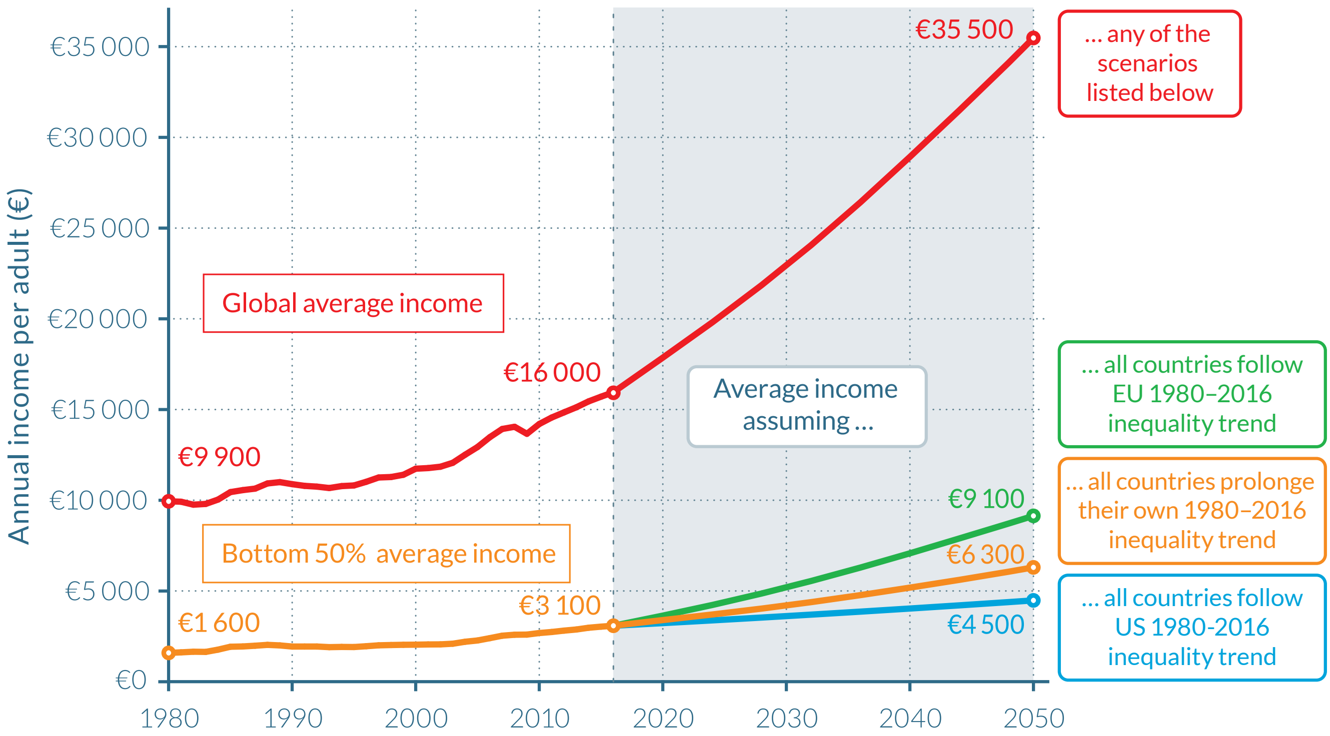
Figure 10 - Top 1% versus bottom 50% shares of global income, 1980–2050



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

If all countries follow the inequality trajectory of the US between 1980 and 2016 from 2017 to 2050, the income share of the global Top 1% will reach 28% by 2050. Income share estimates are calculated using Purchasing Power Parity (PPP) euros. PPP accounts for differences in the cost of living between countries. Values are net of inflation.

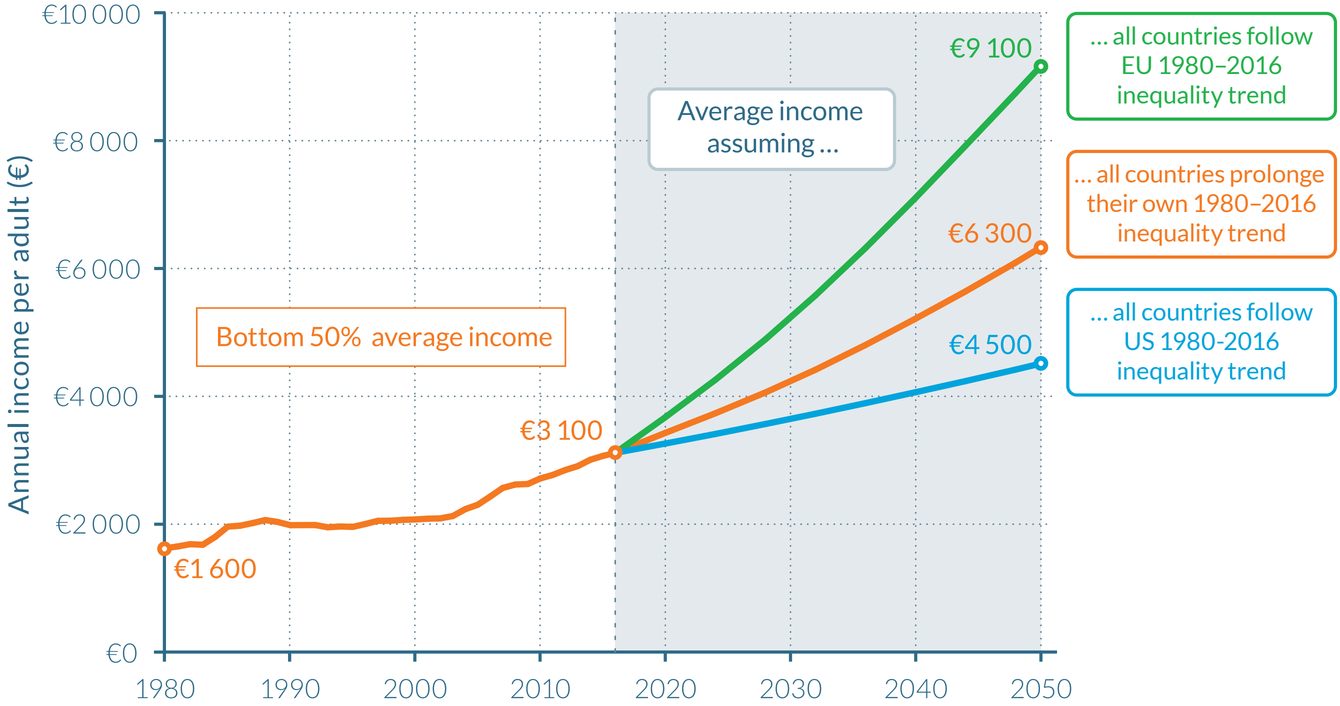
Figure 12 - Global average income versus global 50% average, 1980–2050



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

By 2050, the global average income will reach €35 500, compared to €16 000 in 2016. If all countries follow Europe's inequality trajectory between 1980 and 2016, the average income of the Bottom 50% of the world population will be €9 100 by 2050. Income estimates are calculated using Purchasing Power Parity (PPP) euros. For comparison, €1 = $1.3 = ¥4.4 at PPP. PPP accounts for differences in the cost of living between countries. Values account for inflation.

Figure 13 - Global bottom 50% average income, 1980–2050



Source: WID.world (2017). See wir2018.wid.world for data series and notes.

If all countries follow the inequality trajectory of Europe between 1980 and 2016, the average income of the Bottom 50% of the world population will be €9 100 by 2050. Income estimates are calculated using Purchasing Power Parity (PPP) euros. For comparison, €1 = $1.3 = ¥4.4 at PPP. PPP accounts for differences in the cost of living between countries. Values are net of inflation.

Part II

Environmental inequality

CHAPTER 3

Are younger generations higher carbon emitters than their elders?

Inequalities, generations and CO_2 emissions in France and in the USA

Abstract. Proper understanding of the determinants of household CO_2 emissions is essential for a shift to sustainable lifestyles. This chapter explores the impacts of date of birth and income on household CO_2 emissions in France and in the USA. Direct CO_2 emissions of French and American households are computed from consumer budget surveys, over the 1980-2000 time period. Age Period Cohort estimators are used to isolate the generational effect on CO_2 emissions – i.e. the specific effect of date of birth, independent of the age, the year and other control variables. The chapter shows that French 1935-55 cohorts have a stronger tendency to emit CO_2 than their predecessors and followers. The generational effect is explained by the fact that over their lifespan, French baby boomers are better off than other generations and live in energy and carbon inefficient dwellings. In the USA, the absence of a generational effect on CO_2 emissions can be explained by the fact that intergenerational inequalities are weaker than in France. Persistence of the generational effect once income and housing type is controlled for in France can be explained by the difficulty for French 1935-55 cohorts to adapt to sobre energy consumption patterns.

1 Introduction

The last three decades witnessed two parallel trends in most industrialized economies, which pose threats to social and environmental sustainability, namely the rise in income and wealth inequalities (Piketty, 2013) and the continued rise in national CO_2 emissions levels (IPCC, 2013). Attempts to better understand synergies between CO_2 emissions and household income are flourishing (see Druckman et al, 2008; Weber *et al.* 2008) but the literature often lacks historical empirical material to develop sound analyses on this topic.

I argue in this chapter that an important dimension of environmental and social change has been overlooked by researchers in this field: the generational dimension. Cohorts (i.e. groups of individual born at the same date) may have a strong role to play in determining consumption patterns in general and energy consumption in particular. By integrating early life conditioning and historical or economic trends which shape their life trajectories, cohorts may actually drive social and behavioral change (Ryder, 1965). This chapter is the first known attempt to explore interactions between generational and income-expenditure effects on household CO_2 emissions. Precisely, the objective of this study is to provide historical empirical material on the interactions between income inequalities and inequalities in resource use in France and in the USA.

Firstly, I show that direct CO_2 emissions of French and American households are relatively stable over the time period – while bottom decile emissions increase. Results also reveal that it is not possible to talk about any environmental Kuznet's curve[40] associated to direct CO_2 emissions: as households get richer, direct CO_2 emissions do not decrease. Secondly, the chapter reveals how certain generations emit more CO_2 than others once age and period are controlled for. The effect is very clear in France

[40] i.e. an inversed U curve associated to environmental pressure.

and is the translation of important inter-generational inequalities. Income and housing type differences between generations and, potentially, higher ability to monitor energy consumption by post 1960-cohorts explain the CO_2 generational gap.

The rest of this chapter consists of a brief literature review on the main determinants of energy consumption and CO_2 emissions (2), a description of the methodology followed (3), a presentation of the results (4), a discussion of their relevance (5) and a conclusion (6).

2 Inequalities, generations and household CO_2 emissions

i. Drivers of household direct CO_2 emissions

Grossman and Krueger (1995) posited an inverse-U shape relationship between income and environmental footprint - the so called Environmental Kuznets Curve[41] (EKC). According to the relationship, environmental pressure increases with income on the one hand and on the other, willingness to pay for environmental protection increases as income grows. Under a certain income threshold, pollution increases and once this threshold is reached, environmental impact is ultimately reduced. The EKC has been criticized as a *general* relationship between income growth and pollution .Several empirical tests tested this hypothesis and validated the EKC for certain types of pollutants (e.g. SO2, see Roca *et al.*, 2001) but not for others (e.g. GHG, see Stern *et al.*, 1996).

Studies focusing on CO_2 emissions and household income in developed countries, showed that there is a non-linear relationship, reflecting decreasing marginal CO_2 emissions with income (cf. Lenzen *et al.* 2006). But authors fail to notice any absolute

[41] After Kuznets (1955) who showed an inversed U shape relationship between income and inequalities in the first half of the XXth century in the US.

reduction in CO_2 emissions across the income spectrum. Interestingly, the literature shows the importance of non-economic drivers of CO_2 emissions: there is a large variability of energy consumption and CO_2 emissions levels within income groups (Combet *et al.* 2010, Jamasb *et al.* 2010). It is thus necessary to look at non-monetary drivers of CO_2 emissions differences between households.

Several factors other than income drive energy consumption and households CO_2 emissions. It is helpful to distinguish between "environmental" factors (urban density, local climate, type of dwelling, type of energy conversion devices) and "lifestyle" (size of the household, surface of the dwelling, temperature in the room, habits). Among "environmental" factors, urban density generally stands out as a good predictor of transport-related household direct CO_2 emissions. In dense urban centers, public transportation systems are better developed and people live closer to their work, shopping and leisure places and hence require less energy for transportation. Studies find that direct CO_2 emissions are 10-20% higher in rural households, all else being equal, in the UK (Fahmy *et al.*, 2011).

Local climate is indeed a good predictor of heating requirements of households, and hence CO_2 emissions. In France, 1°C difference in local climate explains 5% difference in heating related CO_2 emissions (Cavaillhès *et al.*, 2012). But heating related CO_2 emissions also very much depend the type of dwelling. Whether the dwelling is a flat or a house, modern or old, it will have different heating and cooling energy and CO_2 requirements. In France, pre-1980 buildings tend to emit 20% more heating related CO_2 emissions, once other factors are controlled for (*ibid*). Technological efficiency (e.g. heating systems or types of cars) can also explain large CO_2 emissions variations for households with similar geographical or economic characteristics. In fact, a household equipped in 2013 with the latest energy efficient appliances can have twice as low electricity related CO_2 emissions as a household who purchased its equipments in the late 1990s (Pourouchottamin *et al.*, 2013).

Looking at "lifestyle" factors, family size plays a significant role in explaining per capita CO_2 emission levels. Larger families emit more CO_2 as a whole, but *per capita* emissions tend to be reduced in larger families, as they have more opportunity to "share" heating-related emissions (Lenglart *et al.* 2010). Age also plays on CO_2 emissions, revealing complex dynamics: retired people tend to use their cars less as they do not commute to work, but may travel more for leisure. The elderly also tend to heat more, but generally live in smaller dwellings than active people (Maresca *et al.* 2009). Lenglart *et al.* (2010) show that CO_2 emissions vary with age but their analysis does not allow them to distinguish between age or proper generational effects: *"we compare consumption habits of different generations at the same date and we are not able to differentiate specific effects of date of birth and age. For instance, low levels of transport related-CO_2 emissions of the elders may be due to lesser demand and need for mobility after a certain age, as well as a low travel habits of generations born up to the 1930s."*

There has been a lot of debate over supposed *generational* drivers of environmental impacts. American sociologist Ronald Inglehart (1977) supports that younger households tend to have stronger environmental *concerns* than the elderly. Such discussions often lack empirical support and when they do, they focus on reported *values* or "willingness to pay" for environmental protection (see Pampel *et al.*, 2012) and do not take into account actual environmental pressure levels.

ii. Measuring generational impacts on CO_2 emissions

There are convincing theoretical and empirical arguments to focus on energy consumption and generational dynamics. The epidemics, economics, geography or sociology literature showed that generational factors can be important determinants of observed differences between individuals and households (see Chauvel (2014) for France or Krugman (1977), Yang and Land (2006) for the USA). By shaping life chances (level of income, access to education, employment, housing), date of birth can also impact consumer behavior and ultimately environmental footprint.

According to Ryder (1965), early life exposure to a certain socio-economic context can shape behaviour throughout ones' life trajectory. Date of birth can also affect values and consumption norms. This calls for the study of *scarring effects* associated to energy consumption. For instance, cohorts which lacked resources in general and energy in particular in their young age may have kept low consumption habits over time (e.g. generations raised during war times). Cohorts raised during economic booms may prolong their energy consumption habits over time, and have more difficulties to adapt to reduced energy consumption habits.

For Inglehart (1977), new values are not disseminated homogeneously among the population; instead, generations are the vectors through which values emerge and these are formulated in the context of family and public education. The author states that post-1950 cohorts are characterized by strong "post-materialistic" values, supposedly higher concern for environmental protection, more community interactions and altruism. "Post-materialism" has been criticized for its lack of empirical basis or weak conceptualization (Flanagan, 1980; Van Deth, 1983). But the idea that younger generations may have stronger environmental concerns and hence different consumption behavior clearly deserves attention.

The difficulty with research on generational trends is methodological. Conceptually, the Lexis diagram (1880) maps the interactions between three dimensions (Figure 1): age (on the y-axis), periods (on the x-axis) and cohorts. Diagonals correspond to the lifelines of cohorts: the "68 generation" was born in 1948 and was twenty in 1968.

Figure 1 - The Lexis diagram

In mathematical terms, an Age Period Cohort model with an explained variable y_i^{apc} (say the logged-CO_2 emissions of household *i,* of age *a,* cohort *c* and at period *p*) can be written as follows:

$$y_i^{apc} = \mu + \alpha_a + \pi_p + \gamma_c + \varepsilon_i \qquad (1)$$

Where α_a, π_p and γ_c are the coefficients on age, period and cohort respectively; μ the model constant and ε_i an error term.

The problem with Age Period Cohort (APC) analysis is the perfect colinearity between age, period and cohort variables, that is, cohort = period – age. Colinearity between regressors of a statistical model implies that the model produces an infinite number of possible solutions for the least squares or maximum likelihood estimators (Yang *et al.* 2004). In other words, the model does not have a unique solution and cannot be identified.

One way to bypass the *identification problem* is then to impose restrictions on the model (Mason *et al.* 1973). Restrictions consist in constraining coefficients of some variables (such as assuming that all time periods have the same effect). By setting such an additional constraint, the model becomes *just-identified*, and the estimators exist. This is the approach followed by Constrained Generalized Linear Models (CGLIM). The theoretical foundation of CGLIMs is to use extra information so as to constrain coefficients based on theory or external information for instance.

But CGLIM have been criticized precisely for their reliance on external, extra information when such information often does not exist or is hard to verify. Glenn (1976) shows that model effects are sensitive to the choice of the equality coefficient constraints. Trying to overcome these problems, Yang *et al.* (2004) derived an APC estimator called the *intrinsic estimator (IE).* The IE is a special case of a classical ridge estimator for a linear regression model that is used when regressors are highly collinear (see Fu, 2000 for more details). The IE consists in using a principal component analysis in order to reduce the three collinear age, period and cohort dimensions to a bidimensional plane. This provides a linear combination of the number of age, period and cohorts, which is then used as a constraint on the model – thus solving the identification problem. According to the others, this constraint would be intrinsic to the problem analyzed, i.e. depend only on the number of age, period and cohorts and not on arbitrary constraints set by the researcher (Yang *et al.*, 2008).

This solution was however criticized by O'Brien (2011) and more fundamentally by Luo (2013). For these authors, the intrinsic constraint is as arbitrary as in any other CGLIM. The model thus produces estimates, but these are not necessarily meaningful. Another solution proposed by Chauvel (2013) deserves attention as it offers an original answer to the model identification problem.

Chauvel suggests to focus solely on non-linear cohort effects, i.e. on a variations from the temporal linear trend. The linear trend, as reminded by O'Brien and Luo, cannot be adequately modeled with an APC model because of the indetermination problem. An APC-Detrended model (APCD) focusing on variations from the temporal trend can on the contrary yield meaningful results. In fact, the restrictions placed on an APCD would ensure that the model is identified. Rather than being arbitrary, the restrictions are here meaningful: they ensure that the model captures non-linear trends only. Precisely, Chauvel's APCD model incorporates two time parameters which absorb linearity. In the model, the sum of age, cohort and period coefficients to zero is set to zero, as well as the slopes – or regression coefficients - of these coefficients which are also set to zero. These last two constraints imply that the "detrended estimator" informs about fluctuations of APC variables around their respective means and along a zero slope line.

This set of constraints ultimately ensures that the model yields a unique solution and hence offers a solution to the model identification problem. In brief, contrary to the APC-IE which attempts at isolating a linear trend specific to cohorts, the APCD focuses on cohortal fluctuations, i.e. non linearities which cannot be purely represented by the combination of age and period variables. Mathematically, derivation of the detrended estimator can be written as follows:

$$\begin{cases} y^{apc} = \alpha_a + \pi_p + \gamma_c + \alpha_0 + \gamma_0 + \mu + \sum_j \beta_j X_j + \varepsilon_i, p = c + a \\ \begin{cases} \sum_a \alpha_a = \sum_p \pi_p = \sum_c \gamma_c = 0 \\ Slope_a(\alpha_a) = Slope_p(\pi_p) = Slope_c(\gamma_c) = 0 \\ \min(c) < c < \max(c) \end{cases} \end{cases} \tag{2}$$

With $\sum_j \beta_j X_j$ the control variables included in the model (which can be continuous or discrete variables). α_0 is the slope of the age variable and γ_0 is the linear trend. Given the linear dependency between age, period and cohort, and because α_0 and γ_0 are by definition temporal alignment coefficients, one should not interpret their values as the causal linear effects associated to cohorts. $\sum_a \alpha_a, \sum_p \pi_p, \sum_c \gamma_c$ are the sums of age, period and cohort coefficients and $Slope_a(\alpha_a)$, $Slope_p(\pi_p)$ and $Slope_c(\gamma_c)$ the respective slopes or regression coefficients of age, period and cohort coefficients. The estimator of true interest is γ_c , the specific effect of date of birth on the output variable. If any of the γ_c coefficients is statistically significantly different from 0, the model reveals cohort specificities. If none is statistically significantly different from zero, a simple Age Period model would suffice to explain the trends observed in the data.

3 Methodology

i. Constructing direct household CO_2 footprints from French and American budget surveys

In order to derive APC estimators, one must construct historical household CO_2 emission databases. The database constructed for the study uses US Consumer Expenditure (CE) and the French Budget de Famille (BDF) surveys. The CE survey is performed by the Census Bureau for the Bureau of Labor Statistics in the US on an annual basis and distinguishes between 109 income, expenditure and wealth categories. The sample is obtained from a uniform randomization from Census surveys and consists of about 1,700 dwelling units[42]. The datasets chosen for this study correspond to the first quarter waves of survey of 1980, 1985, 1990, 1995 and 2000.

The BDF survey is performed every five years by the National Institute for Statistics (INSEE). The survey sample is obtained from uniform randomization and consists of about 10,000 dwelling units[43]. The datasets chosen for this study correspond to years 1979, 1985, 1989, 1995 and 2000. Since 1995, expenses are ventilated using the Classification of Individual Consumption according to Purpose (COICOP). Evolution of the nomenclature over the time period studied required significant amount of harmonization. A description of categorical variables used for the study can be found in the Appendix.

In both countries, expenditure per consumer unit is used as a proxy for living standard. Expenditure can be considered as a better marker for standard of living as it is smoothed over time while income can vary in the short run. Expenditure is weighted by consumer unit[44] in order to account for family size and to bring perceived and measured changes in welfare better in line (see Ruiz, 2009).

This study focuses solely on direct energy carbon footprints which can be computed directly from household budget surveys, under a set of assumption regarding fuel mix, fuel price and the carbon content of fuels. I compute per capita CO_2 emissions equivalents[45] associated with energy bills reported for electricity, gas, liquid home fuel, gasoline, coal, personal transportation and air transport.

[42] Given a certain amount of attrition in the data, Congressional Budget Office recommends the use a weighting factor provided in the dataset (see Haris & Sabelhaus, 2000).

[43] I also use of a weigthing factor, provided in the dataset, as recommended by Insee.

[44] For simplification purposes, consumer unit is defined as the square root of the number of inhabitants. Using more frequent methodologies, like the OECD modified scale, requires precise information on the number of adults and children in the household. This information was not available for all households and all periods. But when I compare both scales on subsample which have this information, the two scales yield very similar results (the pairwise correlation coefficient is 0.98).

[45] Per capita emissions is preferred to per consumer unit emissions, since the latter is not used in the policy debate.

Emissions are computed from expenditure on fuels, applying mean year fuel prices obtained from (MEDDAT, 2010 for France and DoE, 2010 for the USA) to all households. I use IPCC emission factors and historical carbon content of electricity provided by national energy agencies (DoE and ADEME). Emission factors include CO_2, CH_4 and N_2O [46]. A strong assumption is the use of a single price per fuel for all households of the country at a given date - this is standard in other household carbon footprint studies using consumer budget surveys, but may overestimate higher income groups consumption as they generally pay less per unit energy. Air travel emissions are computed from household expenses on air travel and the carbon content of flights is computed from the average distance travelled per unit expenditure, derived from air transport databases (BTS, 2011). Databases were not available for France so the US carbon per unit expenditure values were used, correcting for exchange rate and average flight price differences in 2010. Indeed, this methodology may artificially increase air related CO2 emissions of the rich (who may pay more per kilometre –in first class- than the worse off) and lower air related CO2 emission of the poor. However, results showed that air transport emissions account for less than 10% of top decile emissions – if there is a bias introduced by the price effect, it remains fairly contained.

The direct carbon footprint can be written as follows:

$$CO_{2it} = \sum_{k=1}^{N} \frac{exp_{ikt}}{price_{kt}} \times content_{kt} \qquad (3)$$

With CO_{2it}, the total household direct emissions for household i at time t, exp_{kt} the expenditure on fuel k at time t, $price_{kt}$ price of fuel k at time t and $content_{kt}$ the carbon content of fuel k at time t.

[46] I thus use "CO_2" or "CO_2-e" without distinction.

ii. Age Period Cohort estimations

In order to test whether there is a cohort effect on CO_2 emissions, and to understand what drives this effect, I use three different APC estimators: the *detrended* estimator, the *intrinsic* estimator and an arbitrary constrained estimator for which I set all period equals (i.e. an "Age-Cohort" model). The *detrended* estimator stands out as the most pertinent method to capture cohort effect and its results will be presented in the main sections of this article. Results obtained with the intrinsic and the CGLIM estimator is presented in the appendix (6a and 6b). The *intrinsic* estimator includes some bias and its results should be interpreted with precaution. The CGLIM estimates also have some bias: they correspond to cohort effects in a world in which there would be no time variation. The comparison of the three estimators will give insights as to the robustness of the trends observed.

As a first step, I estimate a model of log-CO_2 emissions household i of age a, cohort c and at period p, without further controls:

$$\log{(CO_2)_i}^{apc} = \mu_0 + \alpha_a + \pi_p + \gamma_c + \varepsilon_i \qquad (4)$$

Where μ_0 is the intercept or adjusted mean logged-CO_2 emissions, α_a the coefficient on age , π_p the period coefficient and γ_c the cohort coefficient, with c=p-a. ε_i is a random error with $E(\varepsilon_i) = 0$. In other words, the log of CO2 emissions of each household is predicted by the age the household, the date of birth of the head of the household and the year of survey plus a random error.

In a second step, I introduce socio-economic, geographical and technical controls in the model:

$$\log{(CO_2)_i}^{apc} = \mu_0 + \alpha_a + \pi_p + \gamma_c + \textstyle\sum_j \beta_j X_j + \varepsilon_i \qquad (5)$$

With β_j coefficient for control variable X_j. Control variables include total expenditure per consumer unit, number of inhabitants, number of rooms in the household, region (a proxy for climate), urban density, date of construction of the dwelling, education level and type of dwelling (see appendix 5).

The identification strategy is then simple: if the cohort coefficients γ_c of model 4 are statistically significantly different from zero, then there is a cohort effect on CO_2 emissions. If the γ_c coefficients of model (5) are significantly different from zero, there is a cohort effect on CO_2 emissions, which does not depend on the control variables included in model (5). The DE estimator, just like the IE and CGLIM, can be computed via statistical software STATA programs written by Chauvel (2012) and Schulhofer-Wohl *et al.* (2006).

4 Results and analysis

i. Descriptive statistics

This section gives a very brief overview of the descriptive statistics derived from the two datasets.

Table 1 - Descriptive statistics for the USA

Table 1 shows that there is a sharp rise in per capita direct CO_2 emissions over the time period, mainly due to a rise in electrical appliances and personal transportation related emissions. Over the time period, the average US household gets richer, older and smaller. The expenditure-gini significantly increases, showing strong variations behind mean variations. In fact, the income of bottom deciles stagnates while it increases for top fractiles(Piketty and Saez, 2003).

Table 2 - Descriptive statistics for France

The direct CO_2 emissions trend is somehow different in France (Table 2),emissions tend to stabilize or even slightly decrease from 1985 to 2000 (in line with

Poissonier et al, 2013). Over the time period average total expenditure increases, the expenditure-gini is relatively stable and households get smaller and older.

ii. Evolution of direct CO_2 emissions of top and bottom decile households

Figure 2 presents the evolution of direct CO_2 emissions of American top and bottom deciles. Breakdown of these emissions and emissions levels for other expenditure categories are presented in Appendix 3. Figure 2 shows a factor-three gap between top and bottom decile per capita direct CO_2 emissions. The difference in CO_2 emissions between rich and poor is due to three main factors: first to an intense use of the personal transport by top decile households (and possibly less efficient vehicles). Second, to the use of air travel by top decile households[47] and third, to a much more important u se of electricity by top decile households, largely due to the possession of a large set of electrical appliances. In 2000 in the USA, 83% of top quintile households had a dishwasher against 19% of bottom quintile households; 92% of top quintile households had a washing machine and a clothes dryer against only 45% of the bottom quintile (RECS, 2000). The rich have more energy intensive durables than the poor and use them more. In a context of high carbon content of electricity, this translates into high electricity related CO_2 emissions for the top decile. Figure 3 uses data from another survey, the Residential Energy Consumption Survey (RECS, 2000), to break down household electrical energy consumption in further detail.

Figure 2 - Evolution of CO_2 emissions of the richest and poorest 10% in the USA.

[47] Caution: air travel emissions may be over estimated (see Methodology section).

Figure 3 - Detailed sources of CO_2 emissions for top and bottom deciles of US household in 2000

The gap between top and bottom deciles is reduced over time due to an increase in poor households' direct energy consumption. This increase is characterized by higher use of private transport of poor households[48] and higher use of electric devices. In 1980, only 35% of US homes had a dishwasher against 60% in 2000 and the share of households with Air Conditioning increased from less than a quarter in 1980 to more than half in 2000 (RECS, 2000).

Figure 4 shows the evolution of CO_2 emissions of French households. There is a factor 3.2 gap between mean US and French household CO_2 emissions. The top US decile household emits three times more per capita than the top French decile household, while the bottom US decile household emit as much as the top French one – in line with the studies surveyed above. Two factors explain this result: first, the average top French decile household emits very low levels of electricity related emissions compared to American standards. This is due to the specific nature of the French electricity mix: 690gCO2e/kWh in the USA against 150gCO2e/kWh in France in 1990[49] and to a higher equipment rate in electric devices in the USA. For instance, in 2000, 92% of top quartile American families had an electric clothes dryer against only 36% of French top quartile households (RECS, 2000 and BDF, 2000).

Second, Americans of the poorest decile emit one ton CO_2 per year per capita due to private transportation, much more than their French counterparts, emitting 0.3 ton. Urban planning and sprawl (see Karlenzig, 2009) are important drivers of the Franco-American divergence. The gap between rich and poor direct CO_2 emissions is also

[48] From 1970 to 2000, distance driven per month by average households increased 50% (Ramey and Vine, 2010). The increase can also be due return to normarlcy after the second oil shock

[49] This value is due to a high share of nuclear electricity, relatively low carbon technology yet with its own types of pollutants which are not the subject of this study.

reduced in France over the time period and is characterized by an increase in gas and homefuel energy by bottom decile households.

Figure 4 - Evolution of CO_2 emissions of the richest and poorest 10% in France

iii. Comparison with other studies

Results are compared with other studies: Lenglart *et al.* (2010) for France, RECS (2000) and Weber *et al.* (2008) for the US. RECS estimates for bottom decile households match with the results (Tables 3 and 4). However, top decile households estimates are lower in the RECS than the CE survey (potentially due to inclusion of secondary household expenses in CE estimates and not in the RECS). In France, Lenglart and others find higher values for top and bottom decile direct CO_2 emission, but the top-bottom quintile gap is very close to this study: 2.3 for Lenglart vs. 2.6[50]. Comparisons with these studies show that estimates are meaningful enough to be used for further analysis. However, the aim of this chapter is not the presentation of precise CO_2 per capita estimates (data sets from surveys precisely targeting energy consumption would be more pertinent for this) but rather to inform on the long term dynamics of direct CO_2 emissions.

Table 3 - Comparison of estimates in RECS and this study

Table 4 - Comparison of estimates in Lenglart (2010) and this study

[50] Note: Lenglart and others do not present results for income deciles.

iv. Capturing the specific effect of date of birth

I then use equation (4) to compute γ_c, the coefficients specific to date of birth, i.e. the impact of date of birth on direct CO_2 emissions once age and year fixed effects are controlled for.

Cohort effect in France

In France, the results show a strong and statistically significant cohort effect, i.e. effect of date of birth once age and period effects are controlled for. Over the time period, cohorts born from 1920 to 1960 emit 20% more CO_2 emissions per capita than average (Figure 5). In particular, cohorts born from 1930 to 1955 stand at the top of the CO_2 emissions curve. Independently of their age and the year of the measure, baby boomers emit 20% more CO_2 than the average household.

Interestingly, the effect remains strong and statistically significant after the introduction of socio-economic, geographic and housing-type control (Figure 6). At the same age, same economic situation, location and same type of dwelling, babyboomers emitted 10% more CO_2 emissions than their followers and predecessors. I will come back on the significance of these results in the following section.

Figure 5 - Cohort effects on direct CO_2 emissions in France – without controls

Figure 6- Cohort effects on direct CO_2 emissions in France – with controls

The results are then compared with the two estimators discussed above. I first use the *intrinsic estimator*, which tends to validate the results: it shows an “inverted” U curve on CO_2 emissions in France (Appendix 5). The *intrinsic estimator* yields higher coefficient estimates than the *detrended* estimator presented above[51]. As discussed in section 2, the constraint on the IE induces some bias in the results which explains the difference with the results presented above.

I then use the *CGLIM* estimator for which I set coefficients on time periods to be zero. The CGLIM results for France again show a pattern similar to the one presented above (Appendix 5). The generational impact on CO_2 emissions thus stands out as a robust result. Independently of their age, and the year of the survey, 1930-1955 cohorts emit more than the others, over the 1980-2000 period. This result holds when controlling for households' expenditure level, the type of housing they have, the number of people in the household, their region, the urbanization pattern of their locality and their education level.

Looking into further details at cohort effects on the five CO_2 emissions sources in France (without controls), the followings trends can be observed (Figure 7):

Electricity: 1935-1955 cohorts emit relatively low level of electricity related CO_2 emissions over the time period, relative to their predecessors and followers. This may be due to a the absence of electric heating systems among these generations. Electric heating systems were installed in France from the 1970s onwards.

Gas: Cohorts born between 1930 and 1960 also emit less gas than average over the entire time period. This can also be due to specific heating devices used by these generations.

Private transport: There is a sharp increase in the emissions from private transport for cohorts born after 1930 and before 1950. Economic trends may explain this, like differential rates in unemployment or differences in income levels among generations.

Homefuel: Cohorts born between 1930 and 1950 emit 10 to 30% higher homefuel related emissions than other generations. They may emit more than their elders because

[51] Babyboomers emit 20% more CO_2 than average when all controls are included.

of more energy intensive consumption patterns, and their followers might have beneficiated from a progressive technology shift, from homefuel to gas and/or electricity.

Air transport: Not statistically significant emission differentials among cohorts stem out of the analysis. They are not presented here.

Figure 7 - Cohort effect on different emissions sources in France

Cohort effect in the USA

Figure 8 show a picture very different to France. In the USA, cohort effects are much smaller and not statistically significant – apart for year 1955. This result holds with the introduction of further controls – there no cohort effect at all on CO_2 emissions. Using the IE estimator or a CGLIM leads to the same conclusion (see Appendix 5).

Figure 8 - Cohort effects on direct CO_2 emissions in the USA

In fact, using the Bayesian Information Criterion[52] to assess the relevance of a model compared to another, I find that a model with solely Age and Period predictors performs better than a model with Age, Period and Cohort predictors. In other words, date of birth does not play a role in explaining differences in direct per capita household CO_2 emissions in the USA.

[52] The Bayesian Information Criterion (BIC) is a way to compare the validity or performance of a model compared to another. BIC has several limitations and should be used with precaution (see Gelmann *et al.* 1999). In our case, a lower BIC for the Age Period model in the USA shows that it is meaningless to interpret cohort coefficients, which have no statistical sense in the USA.

5 Discussion

In this section, I discuss the limitations of the work and its relevance according to sociological and economic literature.

i. Methodological issues

This study focuses on direct per capita CO_2 emissions computed from household expenditure surveys. Using expenditure data to measure CO_2 emissions gives an imperfect image of households' carbon footprints since all households are supposed to pay the same price for energy at a given date. As a result, households paying a higher price per unit energy are attributed higher energy consumption levels. Several OECD countries national statistical agencies are building *physical* national accounts which will help solve the problem for future research (OECD, 2005).

Another limit of the present work is that energy expenditures do not reflect all the energy –and the associated CO_2 emissions- required by households to meet their daily needs. Direct CO_2 emissions measured in this study relate to emissions required to meet households' heating, lighting, electricity and private transportation needs[53]. Total CO_2 emissions are composed of direct and indirect emissions. *Indirect* CO_2 emissions are emissions related to the *production* of goods and services purchased by households (like the CO_2 emission content of food - see Lenglart *et al.* 2010). According to recent studies using International Input-Ouput data, *indirect* emissions account for 40% of *total* household emissions in France in 2005 (Lenglart *et al.*) and to 50% of emissions in the USA in 2005 (Weber et al, 2008). This study thus focuses on 50% to 60% of total emissions. Focusing on indirect emissions on a retrospective basis is a

[53] Air travel emissions are also measured, as a way to verify if they distort individual transport estimates. I show that this is not the case.

methodological challenge calling for further research. Papathanasopoulou and Jackson (2009) have set the basis for such a work: the authors compute total energy consumption of UK households since the late 1970s and show that total energy consumption of the top income group increases more than the emissions of any other group over the time period.

Third, in terms of statistical analysis, there has been a lot of discussion within the epidemiology, sociology and statistics literature on the relevance of Age Period Cohort estimators used to capture the effect of date of birth – as discussed in chapter 2. Even if the *detrended* estimator used in this study seems more pertinent than the other estimators for the analysis carried out in this chapter, its results should be interpreted with precaution and the focus should be placed on the trends observed rather than on the precise value of estimates. In fact, the comparison of the three estimators reinforce the idea that the trends observed (or their absence) in the two countries are robust. But these trends are of little interest without solid sociological or economic explanation. The next section of this chapter discusses the drivers of trends.

ii. Understanding the generational effect on CO_2 emissions

This study reveals the presence of a generational effect on CO_2 emissions in France and not in the USA. Three main reasons can be given to explain this result: the income factor, the infrastructure factor and the behavioral factor.

The income factor

As discussed in the introductory section, income stands out in the literature as a strong driver of CO_2 emissions. As a result it can be assumed that in a society in which certain generations would be economically better off than others they would also emit higher CO_2 emission levels. This hypothesis is validated by the introduction of income as an explanatory variable in model (5). When included in the model, the income control significantly reduces the generational CO_2 emissions effect – by about 25% (Figure 9). In France, baby boomers emit more CO_2 because they are relatively richer than other cohorts - i.e. on average, at a given age, their standard of living is higher than other generations when they had the same age.

A large body of the literature has focused on intergenerational inequalities in France and in the USA. The fact 1935-55 cohorts in France enjoyed throughout their lives better life chances (i.e. access to employment, fast career progression, relatively cheap housing, etc.) than any other generations has been the subject of several empirical analyses confirming one another (see Baudelot and Establet, 2000; Chauvel, 2006). During the Trente Glorieuses (1940s-1970s), the young started their career with the same pay as their parents at the end of their career: they did better than their elders thanks to economic acceleration. With the post-1970 economic slowdown, new generations became more economically and socially fragile. The unemployment rate of those who left school within 24 months was 5% in 1974 and rose to 35% in 2000. Marginalized access to labor markets contributed to an increased earning gap between generations. In 1977, earnings gap between age group 30-35 and 50-55 was 15% and rose to about 40% in 2009 (Chauvel, 2010). Post 1960 generations are thus, on average, economically worse-off than their elders[54].

In the USA, younger generations are on average less economically marginalized than in France. As Krugman (1997) notes, there is an economic slowdown in the 1970s in the USA and Vietnam War veterans come back to an economy that is expanding as rapidly as it was twenty years before, when World War II veterans came back from battlefields. But inequality and age dynamics in the USA tend to be more complex and more equivocal than in France, with a stronger class and ethnic dimension in the USA, reducing the impact of date of birth vs. that of social background in the USA (Chauvel, 2014). There may be cohort differences among differences at some points (i.e. Vietnam War veterans born in the early 1950s), but these differences tend to be reduced over time – while they persist in France throughout life trajectories. Lesser economic

[54] Indeed, there are strong variations beyond the mean and higher intergenerational inequalities by no means imply leveling of intra-generational inequalities.

disparities between cohorts in the USA than in France mean lesser CO_2 emissions differentials between individuals born at different dates.

Figure 9 – Impact of income and housing effects on the CO_2 emission gap

The housing factor

Another factor explaining the generational CO_2 emission gap in France is the type of house and the heating system used by households. A large amount of pre-1980 buildings were equipped with homefuel heating devices, which progressively replaced coal over the second part of the twentieth century in France. In addition, more flats are built from the 1970s onwards in France, with the densification of the territory. Homefuel heating systems emit more CO_2 than gas and electric systems and detached houses require more energy and hence more CO_2 to be heated.

Cohorts born in the 1960s enter the housing market in the 1980s, when flats take over detached housing and new dwellings are equipped with electricity rather than fuel heating devices. In fact, the share of newly constructed homes equipped with electric heating system went up from 5% in the early 1970s to more than 40% in the early 1980s (Grosmenil, 2002). The share of newly constructed homes equipped with homefuel systems was divided by factor 12 over the same period in France. French baby boomers thus face a "technological lock-in": they are caught up in inefficient and high CO_2 emitting dwellings. This can be seen in the data. When included in model (5), housing controls (date of construction[55], housing type) further reduce the generational effect by 25% (Figure 9).

In the USA, the young live in households which are as energy and carbon intensive as their elders. The share of electric heating systems may have increased over time in the USA and younger generations also tend to live more in electricity-heated

[55] As it was showed, date of construction stands out as a good proxy for the heating system of the household.

households, but the electricity mix is much more carbon intensive in the USA than in France[56].

The behavioral factor

Introducing income, housing type and heating device controls in model (5), reduces the generational effect by half. Introducing other drivers of CO_2 emissions mentioned in section 2 does not further reduce the effect[57]. In other words, beyond income and housing, none of the variables presented in section 2 stand out as good drivers of the generational CO_2 emissions gap. One potential explanation could be that French younger generations have adopted more environmentally friendly lifestyles (less heating requirements, less inefficient lighting, etc.), when their parents didn't.

This could explain the fact beyond income differences and housing-type change, households born after the 1960s in France are lower carbon emitters. Post-1960 generations enter adult life after the second oil shock, when the need to reduce energy consumption is becoming a strong public concern. It may thus be relatively easy for these young adults to adopt energy-efficient habits from the very start of their adult lives. On the contrary, it may be hard for babyboomers to alter high energy consumption patterns adopted in their early adult life.

In the USA, it should be noted that younger generations declare higher willingness to pay for environmental protection (Pampel, 2012), but they do not display lower CO_2 emissions levels than the rest of society. In France, the babyboom generation which is often portrayed as the initiator of the environmental movement also stands at the top of the generational CO_2 emission curve. Beyond the "post-materialism"

[56] In France, households equipped with electric heating systems emit relatively low levels of CO_2 emissions due to nature of the electricity mix, i.e. a high proportion of nuclear energy. There are several concerns related to nuclear energy in terms of risk and pollution but this discussion goes beyond the scope of this chapter.

[57] The solid line of Figure 7 can be superposed to the lower line of Figure 10.

discourse, the data suggests more complex dynamics and individual or generational claims can be contradicted by actual behavior.

iii. Implications for environmental public policy and for sustainability research

The results presented in this study may provide useful insights for environmental public policy. In terms of inter-generational issues, the chapter revealed that French younger generations emit less CO_2, in part because they are economically worse off than their parents. This sheds light on a rather undesirable picture of social and environmental change. While some authors (Victor, 2008) call for intentional consumption "degrowth" to solve the climate problem, lower relative overall consumption of younger generations in France is clearly not intentional.

On a more positive note, French younger generations also emit less direct CO_2 because they are not trapped in carbon intensive infrastructures, like their parents were. But the chapter shows the time horizon of such a change. Once cohorts are "trapped" in inefficient housing stocks, they will remain trapped for decades. Strong policy support for low carbon infrastructure renewal (efficient heating systems, low or zero net energy consumption dwellings) is indeed key to speed up individual and economy-wide level carbon transitions.

Finally, the chapter shows that there can be gaps between claims for environmental support and actual practice. In the USA, there is no difference between CO_2 emissions levels of the young and of the elderly whereas the young are often pictured as more conscious of the global environment (Inglehart, 1977). In a country like France though, generational change may actually combine values change and intentional behavioral change. French post-babyboom generations may have intentionally adopted low carbon footprints habits. In that respect, education in early adult life can also be key for a transition to sustainable lifestyles. This would support the idea that neither technology, nor price mechanisms alone can solve the climate change problem.

As for sustainable consumption research, the cohort effect highlighted in the study shows that there is clear interest in applying Age Period Cohort models to (unsustainable) resource consumption. A fresh look at the postmaterialism literature is required. It is necessary to confront "willingness to pay" for environmental services with actual environmental footprints. It will also be particularly interesting to look at direct and indirect CO_2 emissions in the future, using Input-Output methodology (see Druckman *et al.* 2008). Beyond CO_2 emissions, other types of resources should also be looked at, such as water and land use. As the emissions gap has different characteristics in France and the USA, further cross country comparisons are required. In particular, APC analysis on resource use in emerging countries should provide interesting insights.

6 Conclusion

This chapter uses consumer household budget data to compute direct carbon footprints of different categories of households over time in France and in the USA.

The analysis first looks at income and CO_2 emissions gap between households. It shows that i) the richest 10% of the population emits around three times more direct CO_2 than the poorest 10% in both countries ii) there is a small but statistically significant reduction in the gap between rich and poor emissions over time iii) there is a substantial difference in terms of mean CO_2 emissions in both countries, which translates into the richest French emitting as much direct CO_2 as the poorest Americans.

Secondly, the analysis explores the role of date of birth in driving CO_2 emissions. An Age Period Cohort model is estimated with different types of Age Period Cohort estimators. The analysis shows that: i) there is no cohort effect on CO_2 emissions in the USA ii) there are clear cohort effect on CO_2 emissions in France: the 1930-1955 cohorts stand out as the highest emitters iii) Introducing further controls in the model shows that the generational effect is the reflection of a progressive economic marginalization of later cohorts and of carbon intensive infrastructures used by older generations. More environmentally friendly behavior of French younger generations could also explain part of the CO_2 emissions gap.

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Table 1 - Descriptive statistics for the USA

	1980	1985	1990	1995	2000
N	1,747	1,739	1,678	1,652	2,478
Age	46.6	46.4	47.5	47.9	48.5
	(.91)	(.77)	(.76)	(.77)	(.68)
Person/hh	2.9	2.7	2.6	2.6	2.5
	(.07)	(.06)	(.06)	(.06)	(.05)
tCO2cap	7.3	8.1	8..3	8..4	8.5
	(.22)	(.18)	(.20)	(.20)	(.18)
Total Exp /cu	7,359	10,919	11,454	12,225	12,560
	(249)	(258)	(304)	(342)	(296)
Gini	0.42	0.44	0.43	0.44	0.46

Source: Author Notes: Standard errors in parentheses. Total expenditure per consumer unit in 1980 US dollars.

Table 2 - Descriptive statistics for France

	1980	1985	1990	1995	2000
N	10,080	11,074	9,022	9,634	10,211
Age	47.7	48.6	49.5	49.3	50.9
	(.21)	(.18)	(.20)	(.19)	(.22)
Person/hh	2.84	2.73	2.7	2.5	2.5
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
tCO2cap	2.5	2.7	2.7	2.6	2.5
	(.02)	(.02)	(.03)	(.04)	(.06)
Total Exp /cu	46,182	46,234	49,159	52,408	54,409
	(302)	(325)	(384)	(491)	(588)
Gini	0.32	0.31	0.32	0.32	0.33

Source: Author's estimates. Notes: Standard errors in parentheses. Total expenditure per consumer unit in1980 FRF

Table 3 - Comparison of estimates in RECS and this study

		RECS	This study
10% Poorest	1990	6.3	**6.2**
		(.16)	**(.45)**
	2000	5.7	**6.1**
		(.13)	**(.46)**
10% Richest	1990	10.8	**14.2**
		(.29)	**(.79)**
	2000	9.4	**15.7**
		(.25)	**(.73)**

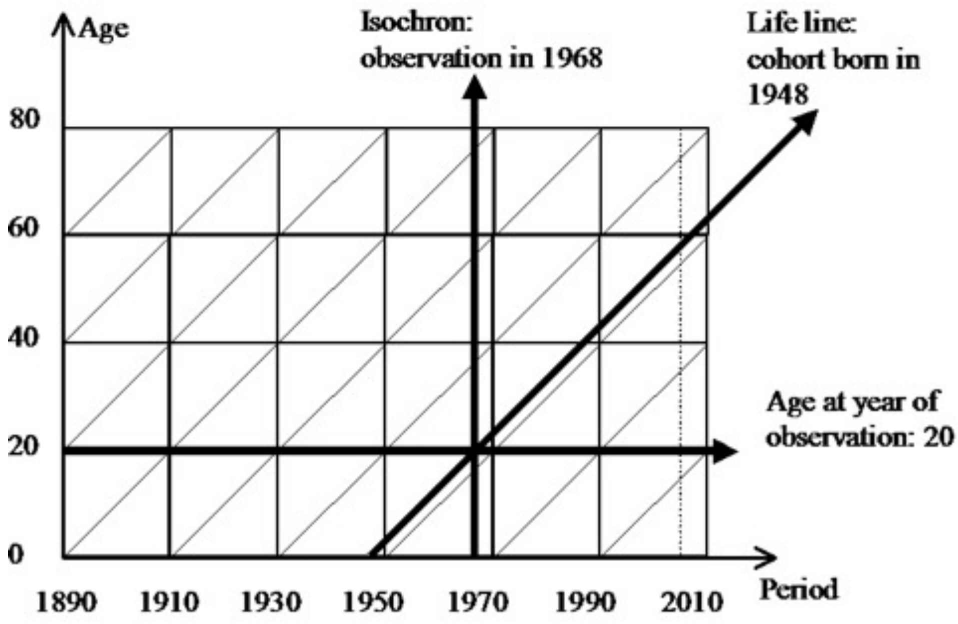
Source: Author's estimates. Key: in 1990, the RECS survey estimates direct CO_2 emissions (without transport) of the first American decile at 6.3tCO2 per year. Standard errors in parentheses

Table 4 - Comparison of estimates in Lenglart (2010) and this study

	Lenglart	This study
20% Poorest	4.9	3.3 (0.09)
20% Richest	11.1	8.9 (0.28)

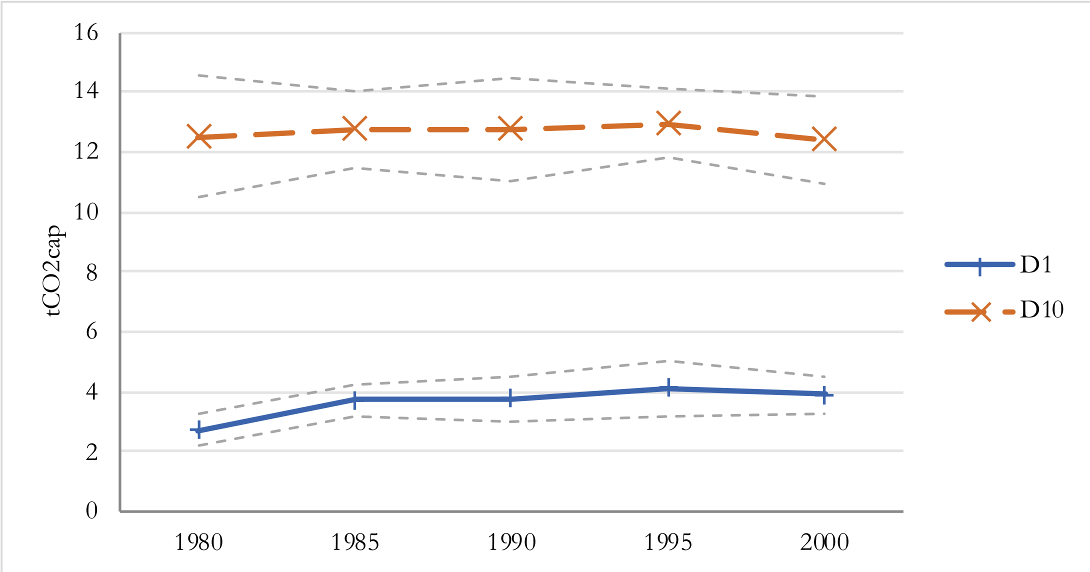
Source: Author's estimates. Standard errors in parentheses

Figure 1 - The Lexis diagram



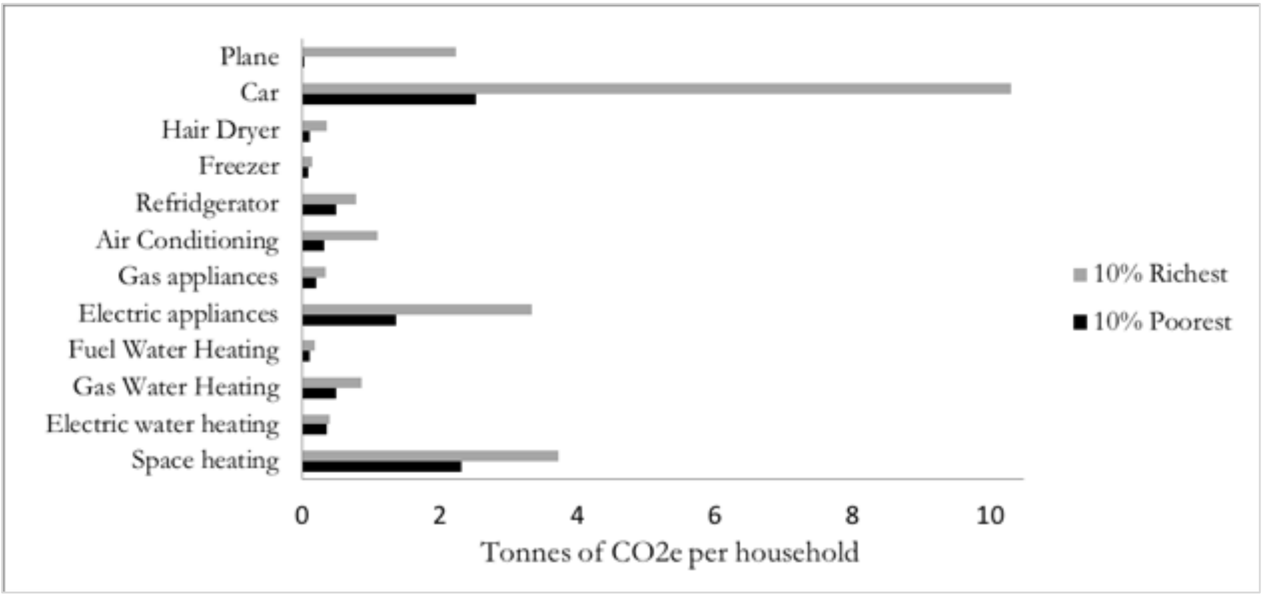
Source: Chauvel (2010)

Figure 2 - Evolution of CO_2 emissions of the richest and poorest 10% in the USA.



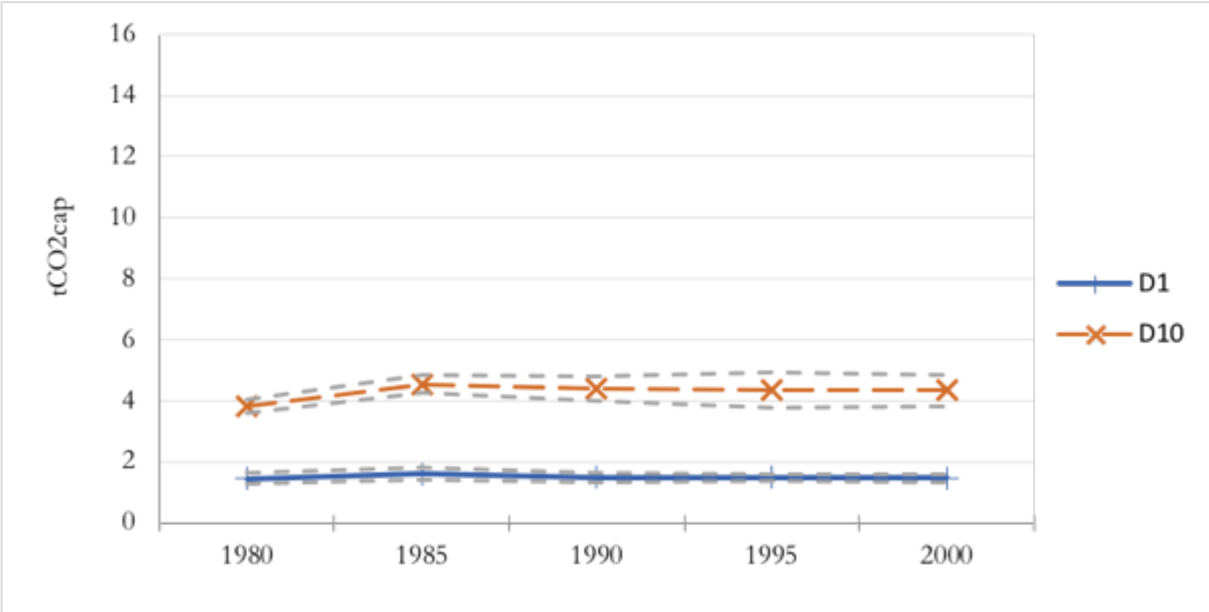
Source: Author. Notes:Per capita direct CO_2 emissions in top and bottom decile households. The dotted lines represent 95% confidence intervals. The 10% richest US citizens emitted about 12.5tCO2e per person in 1980.

Figure 3 - Detailed sources of CO_2 emissions for top and bottom deciles of US household in 2000



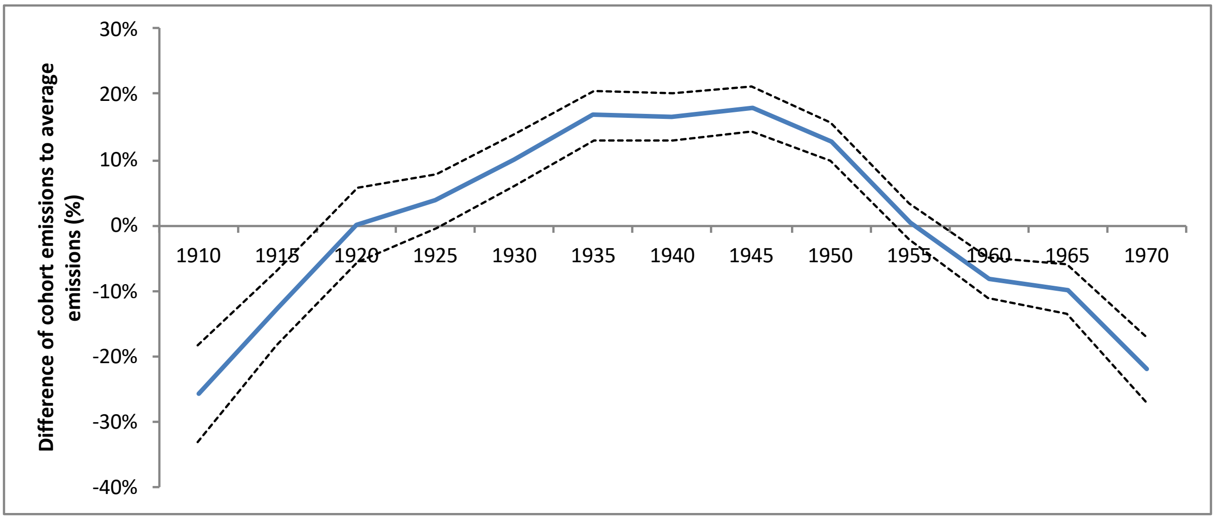
Source: Author. Notes: data from the US RECS 2000 (except for: car and plane computed from US CE survey).

Figure 4 - Evolution of CO_2 emissions of the richest and poorest 10% in France



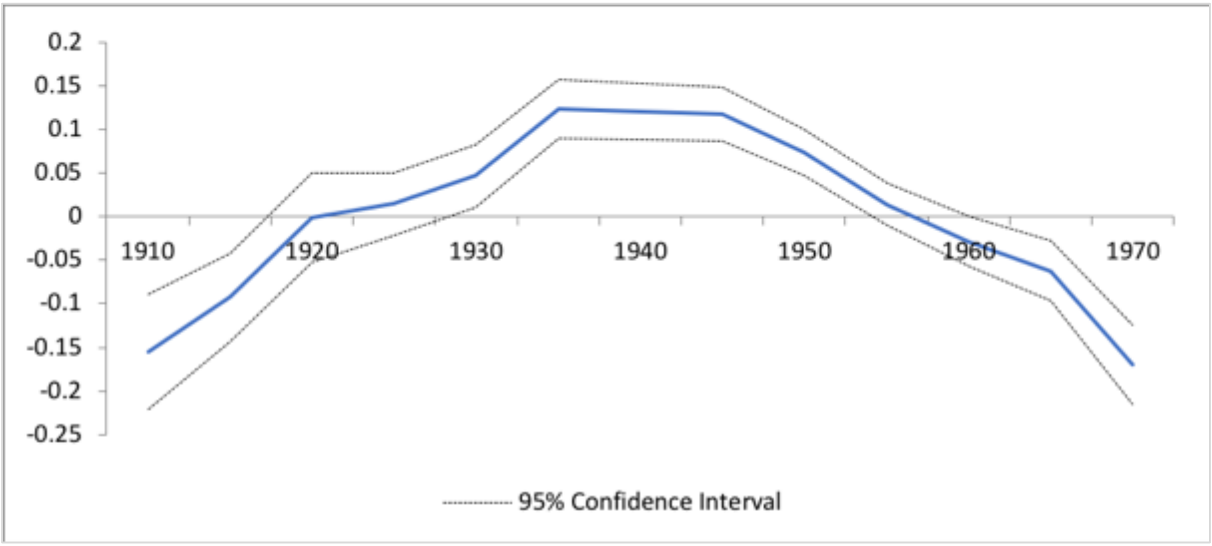
Source: Author. Notes: The dotted lines represent 95% confidence intervals. The 10% richest French emitted about 4tCO2e per person in 1980. The Y-scale is the same as for Figure 2 to facilitate comparison with the USA.

Figure 5 - Cohort effects on direct CO_2 emissions in France – without controls



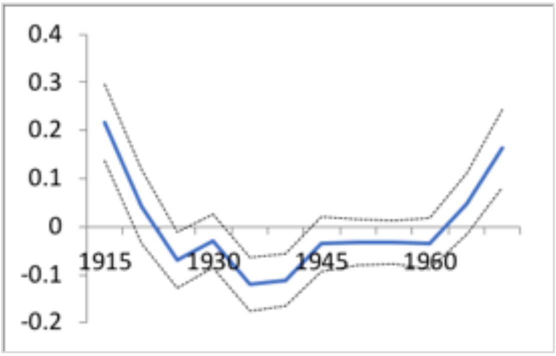
Source: Author. The thick line plots γ_c coefficient of model (4), the thin lines plot 95% confidence intervals. Key: Households whose head is born in 1945 emit 20% more CO_2 emissions than average, over the 1980-2000 time period. To compute the exact effect, take exp(γ). When α is small, exp(γ)≈ γ +1.

Figure 6 - Cohort effects on direct CO_2 emissions in France – with controls

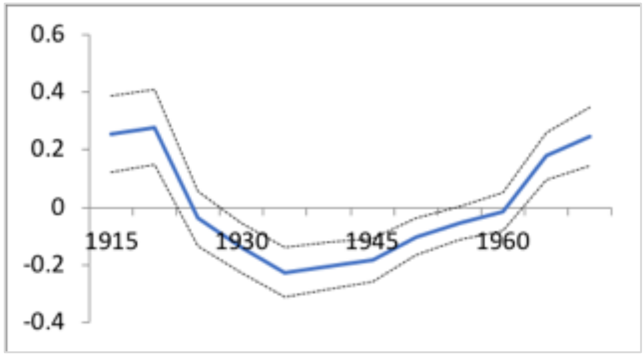


Source: Author. The thick line plots γ_c coefficient of model (5), the thin lines plot 95% confidence intervals. Key: Households whose head is born in 1945 emit 10 % more CO_2 emissions per capita than average, over the 1980-2000 time period. To compute the exact effect, take $\exp(\gamma)$. When γ is small, $\exp(\gamma)-1 \approx \gamma$.

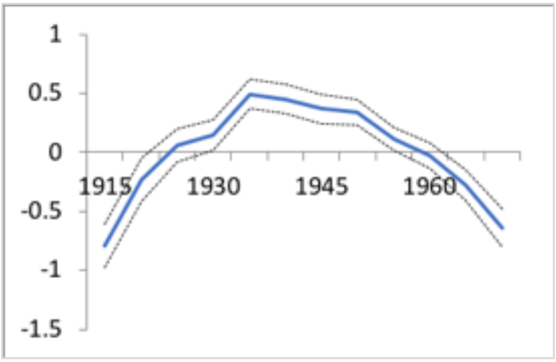
Figure 7 - Cohort effect on different emissions sources in France



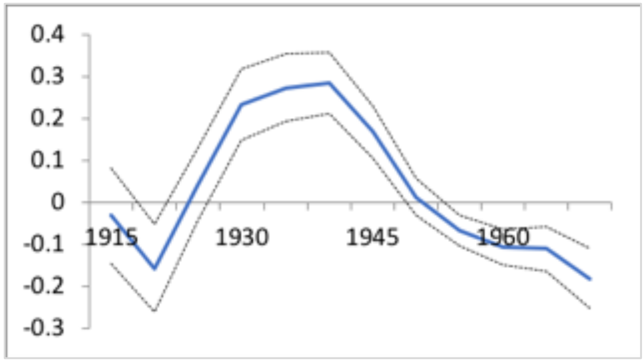
Electricity



Gas



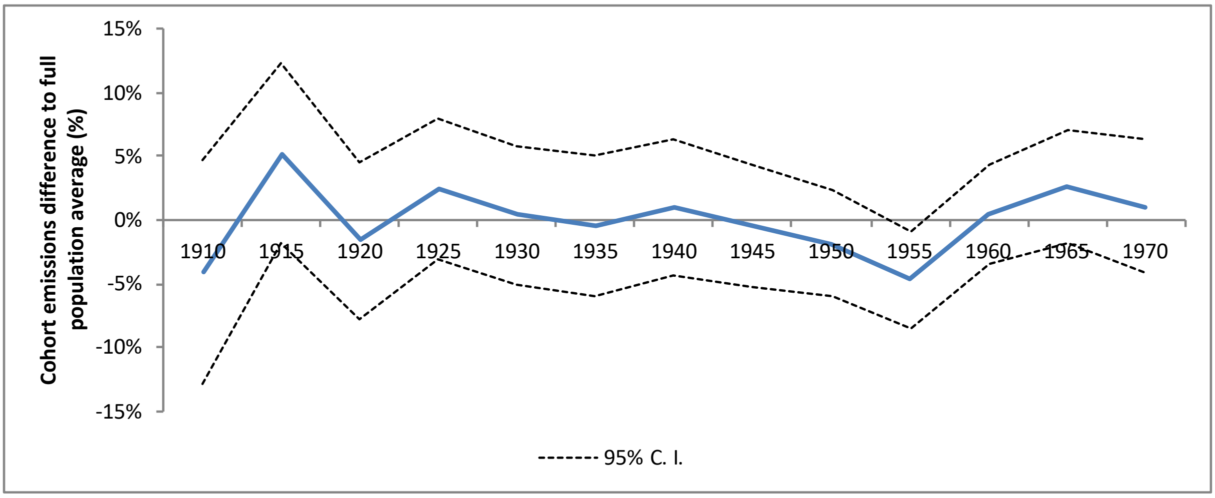
Private transport



Homefuel

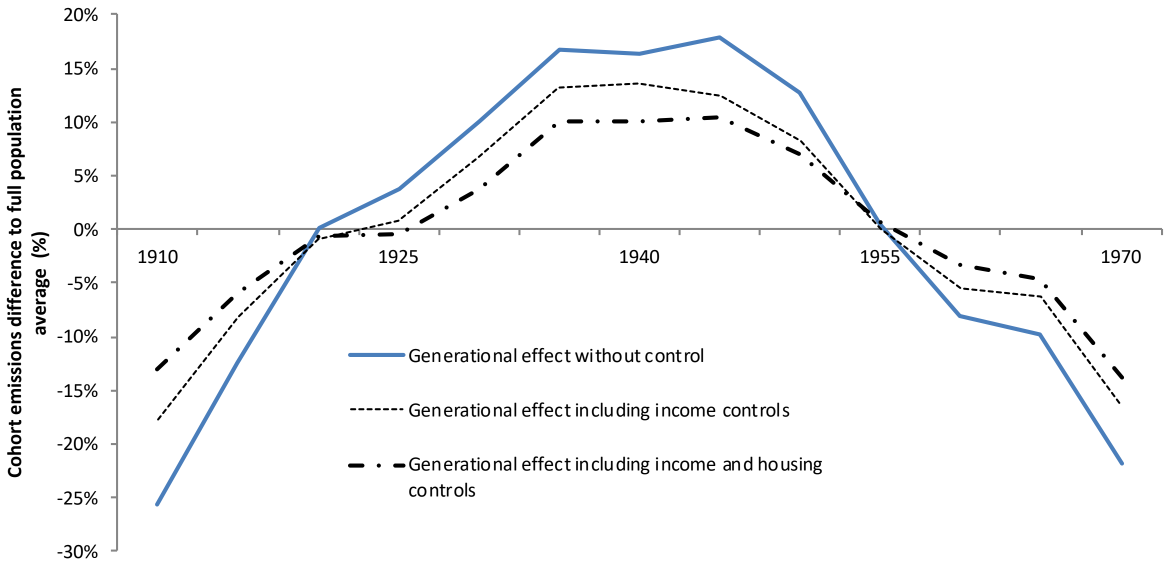
Source: Author. The thick line plots γ_c coefficient of model (4), the thin lines plot 95% confidence intervals. Key: (homefuel) Households whose head is born in 1940 emit 30% more homefuel-related CO_2 emissions than average, over the 1980-2000 time period. To compute the exact effect, take $\exp(\gamma)$. When γ is small, $\exp(\gamma)-1 \approx \gamma$.

Figure 8 - Cohort effects on direct CO_2 emissions in the USA



Source: Author. The thick line plots γ_c coefficient of model (4), the thin lines plot 95% confidence intervals. Key: Households whose head is born in 1955 emit 5% less per capita direct CO_2 emissions than average, over the 1980-2000 time period. To compute the exact effect, compute exp(γ). When γ is small, exp(γ)≈ γ +1.

Figure 9 – Impact of income and housing effects on the CO_2 emission gap



Source: Author. Key: Cohorts born in 1945 emit 18% more CO_2 emissions than average (solid line). When controlling for income (thin dotted line), they emit 12% more emissions than average. When controlling for income and housing (thick dotted line), they emit 10% more than average. Income and housing controls explain about 40% of the generational CO_2 gap.

CHAPTER 4

Carbon and inequality: from Kyoto to Paris

Trends in the global inequality of carbon emissions (1998-2013) & prospects for an equitable adaptation fund

This chapter presents evolutions in the global distribution of CO2e emissions (CO2 and other Green House Gases) between world individuals from 1998 and 2013 and examines different strategies to finance a global climate adaptation fund based on efforts shared among high world emitters rather than high-income countries. To this end, we combine data on historical trends in per capita country-level CO2e emissions, consumption-based CO2e emissions data, within-country income inequality and a simple income-CO2e elasticity model. We show that global CO2e emissions inequalities between individuals decreased from Kyoto to Paris, due to the rise of top and mid income groups in developing countries and the relative stagnation of incomes and emissions of the majority of the population in industrialized economies. Income and CO2e emissions inequalities however increased within countries over the period. Global CO2e emissions remain highly concentrated today: top 10% emitters contribute to about 45% of global emissions, while bottom 50% contribute to 13% of global emissions. Top 10% emitters live on all continents, with one third of them from emerging countries.

The new geography of global emitters calls for climate action in all countries. While developed and developing countries already engaged in mitigation efforts, contributions to climate adaptation funds remain almost entirely financed by developed nations, and for the most part by Europe. In order to increase climate adaptation finance and better align contributions to the new distribution of high emitters, we examine the implications of a global progressive carbon tax to raise €150 billion required annually for climate adaptation. In strategy 1, all emitters above world average emissions (i.e. all individuals emitting more than 6.2t per year) contribute to the scheme in proportion to their emissions in excess of this threshold. North Americans would contribute to 36% of the fund, vs. 21% for Europeans, 15% for China, and 20 % for other countries. In strategy 2, the effort is shared by all top 10% emitters in the world (i.e. all individuals emitting more than 2.2 times world average emissions), again in proportion to their emissions in excess of this threshold. North Americans would then contribute to 46% of the fund, vs. 16% for Europeans, 12% for China. In strategy 3, the effort is shared by all top 1% emitters in the world (i.e. all individuals emitting more than 9.1 times world average emissions). North Americans would then contribute to 57% of the fund, vs. 15% for Europeans, 6% for China. In these strategies, European contributions to adaptation finance would decrease in proportion compared to today, but substantially increase in absolute terms. We also discuss possible implementations via country-level carbon and income taxes or via a generalized progressive tax on air tickets to finance the adaptation fund. This latter solution might be easier to implement but less well targeted at top emitters.

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1 Introduction

Environmental degradation, in particular climate change (IPCC, 2014a), and rising economic inequalities (Piketty, 2014; OECD, 2011) are two key challenges for policymakers in the decades to come. Both challenges endanger democratic institutions and social contracts. In order to address these two challenges, it is essential to better understand interactions between economic inequalities and environmental degradation.

Different types of "environmental inequalities" can be distinguished: inequalities in terms of *exposure* to environmental degradation, and inequalities in contribution to pollution. Exposure inequalities occur between countries (tropical countries are more exposed to climate change than more temperate zones, for instance- see IPCC, 2014), but also within countries and among social or ethnic groups. Aizer et al. (2015), for instance, showed how African-Americans are more likely to suffer from exposure to lead pollution in Northeastern USA, which in return affects their life chances and capabilities. The second type of environmental inequality, upon which we focus in the present study, relates to *contribution to pollution* inequalities, or to the differentiated impacts of social groups or individuals on environmental degradation (Chakravarty and Ramana, 2011). Environmental inequalities can also take a third form, namely *policy effect* inequalities. These are inequalities generated by environmental policies that alter income distributions. Energy policies which increase the price of energy can have regressive impacts (or at least are often perceived to be unfair, see Sterner, 2011). A fourth form of environmental inequalities relates to *policy making* inequalities, i.e. different social groups do not access environmental policy making in the same way (Martinez-Alier, 2003).

This study focuses upon the second type of environmental inequalities (unequal contributions to pollution). We present novel and up-to-date estimates of the global distribution of individual CO2e emissions (and other green house gases, or GHG[58]) between world individuals from 1998 and 2013. We then examine different strategies to contribute to a global climate adaptation fund based on efforts shared among high emitters rather than high-income countries or historical emissions. In effect, we simulate different variants of a global progressive carbon tax. We also discuss possible implementations via country-level carbon and income taxes or via a generalized progressive tax on air tickets. Our basic premise is that in order to increase funding and acceptability for a world adaption fund, it is necessary to deepen our understanding of what an equitable distribution of effort between countries should look like. Rather than clearing developed countries from their responsibilities, this approach calls for an increase in current contributions from high emitters wherever they are on the planet.

The rest of this chapter is organized as follows: in section 2, we review the current debate on climate adaptation funds and the need to find new financing schemes. Section 3 provides data on historical regional CO2e emissions trends. Existing literature on global distributions of CO2e emissions is discussed in section 4 and section 5 presents the methodology followed. Section 6 presents our results on the current distribution of individual CO2e emissions and its evolution over the past 15 years (1998-2013). Finally, section 7 applies our results to different progressive carbon tax options on the world top carbon emitters in order to finance adaptation funds.

[58] Unless specified, CO2e, CO2e equivalent (CO2e) and GHG are used interchangeably.

2 The climate adaptation funding gap

The effects of climate change are already palpable: warmer temperatures, ocean and sea level rise as well increased frequency of high precipitations events (IPCC, 2013). Further warming will inevitably occur in the decades to come - the question is whether it can be limited to a two degree rise - and will place higher pressure on ecosystems and human populations, particularly those living in tropical areas and close to seashores of the developing world[59] (IPCC, 2014a). Estimates of costs to adapt to such changes in developing countries range from €60 billion per year according to the IPCC (2014b) up to €300 billion per year[60], according to the United Nations Environmental Program (UNEP, 2014). Recall however that many types of climate change impacts cannot easily (or not at all) be valued in economic terms (for e.g. human losses or the extinction of living species).

Current flows for climate adaptation in developing countries fall short of these figures. According to the OECD (2015), they reached only about €10bn in 2014, with less of €2bn in donations. In comparison, funds allocated to climate mitigation in developing countries (i.e. actions to reduce carbon emissions rather than adapt to a warmer climate) are four times higher. The OECD and the UNEP anticipate a climate adaptation finance gap, despite the diversity of global funds existing to finance adaptation in developing countries: the newly established Green Climate Fund should in theory dedicate half of its resources to adaptation, but only 20% of the €4.3bn pledged currently support adaptation programs. Other climate international funds are specifically directed at adaptation, such as the World Bank's Pilot Program for Climate

[59] Even though other zones, including temperate regions in developed countries are also at risk.

[60] According to the latest Adaptation Gap publications (UNEP, 2014), adaptation costs could climb as high as $150 billion (€125bn) by 2025/2030 and $250-500 billion per year (€208bn - €416bn) by 2050.

Resilience and the UNFCCC Least Developed Countries Fund but their volume remains low compared to the requirements[61].

As crucial as the question of the volume of finance required for adaptation is the repartition of the financial effort and the equity logic followed to share the contributions. In order to increase the total volume of finance that countries are ready to allocate to the fund, it seems critical to better understand how an equitable distribution of contributions should look like. Figure 1A presents the regional breakdown of global climate adaptation funds contributors. Such data is indeed imperfect given the difficulty to measure such financial flows, but remains a useful benchmark. According our estimates, the European Union provides more than 60% of funds, the USA a quarter, other rich countries making up 13% of the effort.

Figure 1a - Contributors to global adaptation funds (2014)

While this breakdown could a priori be justified by countries' historical responsibilities for climate change - in line with "retributive justice" principles and the UNFCCC "Common But Differentiated Responsibilities" (CBDR) principle, such arguments need to be made more explicit. We show below that European countries are responsible for less than 20% of current emissions, and 20% of cumulated emissions since the industrial revolution - and emerging countries already account for more than a third of cumulated historical CO2e emissions (see figures 1B-1C). Another logic which could justify such a breakdown of the contributions to adaptation could be ability to pay of contributors (for e.g. their GDP per capita and income levels - see figure 1D)

[61] These two schemes respectively operated €800m and €750m in 2014. Other schemes include the Special Climate Change Fund with €280m, both established by the UNFCCC and operated by the Global Environmental Facility, the Adaptation for Smallholder Agriculture Program with €250m, administered by the UN International Fund for Agricultural Development as well as the Adaptation Fund established by the UNFCCC, with €180m. The Global Climate Change Alliance of the European Union also acts in the field of Adaptation with about €120m in 2014. In addition, not listed here, are all the funds directly disbursed by developing countries.

following a "distributive justice" principle or the "Respective Capabilities" principle of the UNFCCC. This logic may however also be challenged, given the importance of within-country inequalities. Once again, our objective is not to clear Europe (or the USA) from their responsibilities - their contributions to adaptation should substantially increase, but rather examine novel effort sharing strategies in which within-country inequalities would also be taken into account.

It is interesting to note the presence of contributors from emerging and developing countries in Fig. 1A. South Korea, Mexico, Peru and Columbia contribute to global climate adaptation finance via their recent pledges to the Green Climate Fund. Their contributions only represent 1% of all adaptation finance, but it is noteworthy because it is de facto calling into question standard understanding of climate equity principle in climate debates. There is thus an opportunity to reassess the current repartition of climate adaptation funding efforts -with the objective to increase the volume of efforts- in the light of new equity principles[62]. In this paper, we examine a logic in which individuals, rather than countries would contribute to adaptation efforts, on the basis of their current contributions to climate change. This calls for the construction of an up-to-date global distribution of individual CO2e emissions, as it does not exist so far.

Figure 1b - Distribution of current production-based CO2e emissions

Figure 1c - Distribution of cumulated production-based historical CO2e emissions

Figure 1d - Current distribution of global GDP

[62] For a review of different proposal for climate adaptation finance and different equity approaches to it, see Brown and Vigneri (2008) and Baer (2006).

3 Historical GHG emissions: facts and figures

i. Global GHG budget and annual emissions

Before turning to a global distribution of individual CO2e emissions, and its implications for climate adaptation finance, we review a few key facts and figures of the global climate change debate, which will be referred to later in this chapter. In order to secure reasonable chances to limit global warming to a 2°C average temperature rise the Intergovernmental Panel on Climate Change (IPCC) estimates that we are left with the equivalent of about 1000 gigatonnes (Gt) of CO2e (emissions of carbon dioxide and other green house gases, such as methane) to emit before 2100. In 2014, global CO2e emissions reached approximately 45 GtCO2e[63]. At this rate of emissions, the world will reach the 2°C limit in about twenty years and a prolongation of current emissions trends throughout the century will increase global temperatures by more than 4°C by 2100 (IPCC, 2014a). From the 1000 Gt budget, it is possible to calculate the sustainable level of emissions per capita, i.e. the amount of CO2e emissions each individual is entitled to emit, between now and 2100. The sustainable level of CO2e to emit per person per year, from now to 2100 is approximately 1.26tCO2e[64] - about 6 times lower than the current average annual per capital emission level of 6.2tCO2e.

Since the first industrial use of coal in the early 18th century Britain, the geographical repartition of CO2e emissions changed constantly and radically (Fig. 2A). At the end of the first industrial Revolution, in the 1820s, emissions from Western Europe accounted for more than 95% of the global total. A hundred years later, in

[63] It is about 43GtCO2e excluding for all GHGs excluding land-use change and 46GtCO2e including land-use change (such as deforestation for agriculture for instance).

[64] The IPCC RCP 2.6 scenario (IPCC, 2013) estimates that the leftover budget, accounting for non-CO2 GHG, is 275 PgC, i.e. about 1000GtCO2e. We divide the 1000GtCO2e by estimated cumulated annual population from now to 2100 estimated by the UN, i.e. 795 billion year-individuals.

1920, North America was the highest emitting region in the world, with 50% of global emissions. Another hundred years down the line (that is today), both Western Europe and North America's shares in global emissions had shrunk, though not at the same pace: Western Europe represents 9% of global emissions today (about 3.6 Giga tonnes of CO2e per year), while North America maintains itself at a relatively high level: it represents 16% of emissions (7 Gt). The new high global emitting region is indeed Asia, and in particular China, which emits close to 25% of world CO2e emissions (11 Gt). Fig. 2B shows the change in cumulated historical emissions per region. It comes out that emissions stemming from Western Europe, North America, Japan and Australia account for less than 50% of global historical emissions since the industrial revolution[65]. China accounts for 12% of all anthropic emissions ever produced.

Figure 2a - Share in global CO2e emissions since 1820

Figure 2b - Share in cumulated global CO2e emissions since 1820

Figure 3 - Global CO2e emissions per region, from 1820 to today

ii. Per capita emissions over time

China is the world's highest emitter today, but its emissions per head are still below those of most of western European countries and the USA. It is essential to go beyond national totals in order to get a sense of how CO2e is distributed among humans. In 1820, per capita CO2e emissions were zero for most of the world and 0.5t

[65] Looking at consumption-based emissions (as we do below) rather than production base emissions would increase the share and responsibility for developed countries.

per person in Western Europe. In 1920, world CO2e emissions' average was close to 3.4 tonnes per capita: the second industrial revolution had occurred and spread to the North American continent. North American emissions had skyrocketed to 19 tonnes per person, while Western Europeans emitted about 6 tonnes of CO2e.

This early gap between American and European per capita emissions deserves attention: as early as the 1920s, Americans were consuming three times more energy per capita than Europeans and emitting three times more CO2e emissions as a result. If Europeans slightly caught up with their American counterparts after the second World War (thanks to the so-called "Golden age of growth", the development of mass private transportation and mass consumption) a 10 tonnes difference persisted between Americans and Western Europeans throughout the 20th century, despite harmonization in per capita income between the two regions[66].

Figure 4 - Per capita GHG emissions per world region.

Today, each American emits about 20 tonnes of CO2e per year, while a typical Western European emit more than two times less: 9 tonnes, in a close range to the average Russian. An average person from the Middle East emits around 8 tonnes per capita, a figure similar to Chinese per capita emissions, above the world average, i.e. 6.2 tonnes per capita, while south Asians and Africans emit respectively close to 2.4tCO2e per capita[67]. Table 1 presents the ratio between regional per capita emissions and world average. Regional averages are all above the sustainable level of CO2e emissions of 1.2tCO2e per head.

[66] The Europe/US gap is further discussed in section 4.1 below.

[67] Note that when emissions from land use change are included, world average is 6.5CO2etCO2e, African average emissions are 3.4CO2etCO2e and Latino American average emissions come about 7.4CO2etCO2e, a large difference explained by deforestation in tropical regions. However, the proper way to measure emissions associated with land use is still debated and it is very hazardous to reconstruct historical series accounting for land -use change - we thus only include all GHG without land use change values in our figures.

Table 1 - Current per capita GHG emissions - production base

Such values however suffer from two key limitations. The first one is that they reflect production-base (or territorial) emissions. Production-base emissions relate to all CO2e emitted on a given territory: emissions attributed to China take into account all emissions which were produced in China, even if these emissions were used to produce goods or services consumed elsewhere in the world. It is then misleading to only focus on production base emissions and one should also look at "consumption-based emission": emissions attributed to countries or individuals on the basis of what they really consume. There is a growing amount of work on consumption-based emissions (see for instance Peters and Hertwich, 2008; Wood et al., 2014), but constructing these estimates is a complicated task and they are available for a few years only, certainly not in relatively homogenous series dating back to 1820 as we present here - that is why only production base emissions are presented in this historical section.

The second key limitation of these graphs is that they inform on national per capita averages and not on any disparity within countries. Indeed, within countries, individuals do not have the same energy consumption and resulting CO2e emission levels as lifestyles and income levels are not homogenous: in Western Europe for instance, urban dwellers, using public transportation will not have the same level of energy consumption and CO2e emissions as peri-urban neighbours, who take the car every day - even if a few holiday air trips (or inefficient heating systems) can counterbalance differences in CO2e emissions from daily transportation. In India, individual emissions between a peasant of rural Maharashtra (Bombay State) and a motorized urban upper middle class individual living in Bombay are even more likely to differ.

4 Combining income inequality statistics with CO2e emissions: a literature review

i. CO2e emissions, living standards and income levels

National statistical institutes were not historically well equipped to provide detailed information of environmental resource consumption, and even less on individual level consumption of environmental goods and services. There have been important evolutions over the past decade to better account for the evolution of the environmental resources and services, as well as of the evolution of within country income distributions (UN, 2014). However, detailed statistics on the distribution of pollution or consumption of environmental within countries is still among individuals is generally missing.

Existing research however lays the ground to develop such statistics. There is an important amount of work on the determinants of energy consumption and CO2e emissions for instance, and a growing interest in the specific question of CO2e emissions and income distributions (Jackson and Papathanasopoulou, 2008; Lenzen et al., 2006; Weber and Matthews, 2008). Such literature puts forward income or expenditure level as the most important driver of CO2e emissions, even though other important variables have a role to play.

ii. Income, expenditure, energy consumption CO2e emissions.

Income or expenditure levels are generally put forward as the main drivers explaining energy consumption or total CO2e emissions differences among individuals and households (see for instance Wier et al., 2001; Lenzen et al., 2006). It is important here to define what we call *total* individual CO2e emissions: these refer to the sum of *direct* emissions (emitted directly by individuals, such as emissions from individual car transportation, or from personal gas heating devices) and *indirect* emissions (emissions embedded in the consumption of goods and services consumed by individuals).

Income or overall consumption level is particularly closely correlated with *indirect* individual emissions, while direct individual CO2e emissions rise less proportionally than income or consumption (Herendeen and Tanaka, 1976). One way to explain this is that there is a limit to the amount of heat most individuals use every day, or to the amount of fuel they put in their cars (when they have several cars, people cannot drive them all at the same time). On the opposite, there is little limit to the amount of "stuff" (and services) purchased by wealthy individuals. While cars parked in garages all day to not add to direct CO2e emissions of individuals, the CO2e used for their construction is taken into account in indirect CO2e estimates[68]. This explains why the share of indirect CO2e emitted by individuals within a given country rises with their income level: two thirds of total emissions are indirect for bottom decile in China, versus about four fifths for the top decile (Golley and Meng, 2012). The top 3% urban earners emit more than 83% of their total emissions as indirect CO2e, and it is generally less than 75% for other groups (Parikh et al., 2009). Top 20% Americans and top 20% French income earners emit more than 75% of their total emissions as indirect emissions against two thirds for bottom quintiles (Lenglart et al., 2010; Weber and Matthews, 2008).

Even if there are a few (and a growing) number of studies measuring inequalities in individual or household CO2e emissions, precise estimation of indirect CO2e of individuals remains a complex task, with no harmonized methodologies to do so (see the methodology section[69]). Nevertheless, several studies provide estimates for CO2e (or energy) to consumption expenditure *elasticity*, that is the ratio informing on the percentage change in CO2e associated to a percentage change consumption expenditure, within a given country. When the CO2e-income elasticity is 0.9, this

[68] Pourouchottamin et al. (2013) show that indirect required for transportation (i.e. for the production of transportation material, sales, and repair) falls in a similar range to direct energy required to fuel cars.

[69] Physical data for CO2e emissions at the household level have to be reconstructed from household consumption surveys and national physical energy and CO2e accounts. To do so, one must attribute CO2e emissions of various production sectors (such as "shoe production sector" or "electronic appliances production sector") to various consumption categories used in household surveys (in our cases, shoes, TVs or HIFI systems). Data for the indirect CO2e requirements of production sectors are obtained from Input-Output studies (see Peters et al., 2011), following the work of W. Leontief (1970).

means that a household earning (or spending) 10% more than its neighbour emits 9% more CO2e. Elasticity values for consumption expenditures to energy and CO2e collected by Chakravarty et al. (2009) from 17 countries and time periods, range from 0.4 to 1 for energy and from 0.6 to 1 for CO2e, with most results in the 0.8-1 range. Nevertheless, as reminded by Lenzen et al. (2006) there is no "one fits all" value for elasticity, which varies from country to country and over time. In addition, such multi-study aggregations suffer from systematicity as different studies do not necessarily use the same definitions of consumption, or the same formulas, to derive elasticity values.

One specific issue relates to the measurement of emissions associated to savings and investments of individuals. Complicated methodological and normative issues are raised here: in the case of the construction of a factory, who should be attributed emissions from the initial construction of the building? The ultimate consumers of the goods produced by the factory? Or the owners of that factory? Such questions have been rarely discussed in the literature and have no simple answer. Choices made to reallocate emissions from capital spending to individuals can clearly alter the elasticity values presented above. While data from CICERO (Peters and Andrew, 2015) tends to support that overall investments are less carbon intensive than overall consumption[70], this is clearly not the case if we compare certain sectors (indeed, the construction is highly CO2e intensive per euro spent) to the environmental footprint of overall consumption. The question thus remains open and calls for the use of multiple elasticity values as well as a cautious interpretation of results based such elasticities.

iii. Beyond income

If income stands out as the main driver of total CO2e emission levels among individuals, it is not the only one. There are many other factors which play a role in

[70] The CO2e per euro spent ratio is 2.4 and 3.8 times lower in France and the USA respectively for investments than for household consumption.

determining energy consumption and CO2e requirements. The first way to illustrate this is to compare Americans and Europeans average incomes (which are fairly similar) to their CO2e emissions levels (which are twice bigger in the American case - as we have seen in section 3, Figure 4). The US-Europe gap can be explained by differences in the efficiency of energy production process, a different relationship to space (massively available in the USA and lacking in Europe), which determines the organization of cities and the distances travelled by individuals and goods, and the energy and CO2e associated to it; as well as by different forms taken by the consumer culture (see for instance Flacher, 2003 or Kenworthy, 2003). This shows that national level drivers (energy mixes, urban forms and national consumption patterns) have a very important role to play on individual or household CO2e emissions[71].

At the individual level as well, several drivers play on CO2e emissions levels beyond income levels. They can be distinguished in three categories: *socio-demographic, geographic* and *technical* factors. Among socio-demographic drivers, size of household is often presented as a key determinant of total individual CO2e emissions, as several energy consumption devices can be shared among individuals of the same house (heating and cooling systems), thus reducing the individual footprints of people living in large families. Education or social status have also been discussed as a significant driver of CO2e emissions - but with varying effects according to countries and studies. Education can act negatively on energy consumption - once income is controlled for- in developing countries (Pachauri, 2004) but can also play a significant role in shaping individual preferences towards more energy-intensive lifestyles. In France, Nicolas and Verry (2015) show that *educational degree*, rather than income, determines a high propensity to emit transport - related CO2e emissions among top income groups. It is important here to stress that their study does not focus on CO2e emissions other than from transport (if it were focusing on total CO2e emissions, consumption level would most likely be more important than education level). *Age* has also been discussed on

[71] See also Lamb et al. (2014; Wiedenhofer et al. (2013). Note that we show in Section 6, Figure 8 that national level drivers are becoming less and less important to explain the global disparity in individual CO2e emissions.

several occasions (Wilson et al., 2013; Lenglart et al., 2010), with an inverse U-shape relationship between age and CO2e emissions. These interactions are however complex: retired persons may use their car less on a daily basis than professionals, but may travel more to leisure places, using air transport; in addition, retired people are also more likely to live alone, requiring more energy to heat. The impact of *date of birth* on CO2e emissions was also looked at in the USA and in France (see the chapter of this Thesis entitled "*Are younger generations higher carbon emitters than their elders*") and it was shown that beyond differences attributed to income differentials between generations, date of birth may also influence CO2e emissions via differences in habits.

Turning to *geographic drivers*, it is possible to cite *local climate*, with 1° temperature change across regions associated with an additional 5% energy consumption in a country like France, controlling for other factors (Cavailhes and Hilal, 2012)[72]. Proximity to public transport or to urban centres also plays a role in determining transport related emissions. Ummel (2014) shows that there is a strong, negative correlation between urban density and CO2e footprint in the USA above a certain density threshold[73]. Kenworthy (2003) shows a general negative pattern between urban density and energy use required for transport in 84 global cities.

Technical factors also have a role to play, as households and individuals make different choices with respect to their energy appliances, and can also be trapped in certain infrastructure contexts which they could alter but which are difficult to change for economic, legal or psychological reasons (like energy inefficient homes for instance). Pourouchottamin et al. (2013) compare two households, one equipped with energy appliances from the 1990s and another one with 2010s top efficiency energy appliances (as well as highly efficient insulation system) and show that emissions can differ in their energy and CO2e emission levels by factor 3, for the same level of energy service.

All in all, it clearly stands out that income alone cannot predict an individual CO2e emissions level within a country with a high degree of precision. However, income

[72] See Wiedenhofer et al. (2013) for a review on these factors in the case of Australia.

[73] i.e. densities over 6000 persons per square mile.

or consumption level remains the main driver explaining variations in *total* CO2e emissions among households and individuals and it is the best available proxy if we want to construct a global distribution of CO2e with individual level emissions, rather than national per capita averages, as the building block.

iv. Previous estimates of the global distribution of CO2e consumption

At the national level, several studies, already mentioned above, focus on within country distribution of CO2e footprints (Pachauri, 2004; Jackson and Papathanasopoulou, 2008; Weber and Matthews, 2008; Lenglart et al., 2010; Ummel, 2014). Such studies even date back several decades: Herendeen and Tanaka, as soon as the 1976, derived the direct and indirect energy footprint of American households[74].

There are to our knowledge only a few attempts to build a world distributions of CO2e emissions on the basis of individual emissions. The previous attempt (and first, to our knowledge) to achieve such a task is Chakravarty et al. (2009). In their study, Chakravarty et al. use a straightforward method: CO2e emissions of individuals are assumed to be a simple power law of income:

(1) $$CO2e_{ic}=k_c y_i^{e}$$

Where $CO2e_{ic}$ is the CO2e emission level of individual *i* from country *c*, with income y. k_c is a country-specific term and *e* is the income elasticity of CO2e emissions.

Authors derive Gamma probability density functions from seven income or consumption quantile shares obtained from World Development Indicators and then modify these density functions into Generalized gamma CO2e density functions, using

[74] The authors concluded that affluent households used about 35% of its total energy requirement in the form of direct energy, while the figure would be inversed for poor household, using 65% their requirement as direct energy and 35% as indirect energy. Nevertheless, there is a renewed interest in the distribution of CO2e within countries.

income elasticity *e* and national emissions average as parameters. They then measure the number of individuals in each region of the world, over and under a global cap and floor of CO2e emissions. The authors' main interest lies in *"the reality that emissions from OECD countries and from countries outside the OECD are now roughly equal, and therefore tough global atmospheric stabilization targets require the participation of the developing countries".* According to the authors, regardless of where people lived, individuals emitting similar amounts of CO2e should contribute to CO2e emissions reductions in the same way.

This study attracted considerable attention before the Copenhagen Summit of 2009 in part because it called into question the Annex I / non-Annex I differentiation principle, one of the pillars of the IPCC. According to this principle, Annex I countries (mostly rich countries) had a higher responsibility burden than non-Annex I countries (developing and emerging nations). By measuring and revealing the number of high emitters in non-Annex I countries, the study may well have contributed to shift climate policy debates within certain countries (Chakravarty and Ramana, 2011).

However, as we noted in section 1, if both developing and developed countries contribute to mitigation efforts today, this is still not the case for adaptation efforts - in other words, Chakravarty et al.'s main message didn't completely make its way through climate changes debates. In addition, Chakravarty et al.'s estimates had several limitations, some of them criticized by Grubler and Pachauri (2009) for instance, who rejected the unitary elasticity assumption. In our opinion, one strong limitation is that the income or consumption distribution statistics they used were based on 2003 estimates and dependent on data shortcomings of the time. Since then, there are more up to date and more precise world inequality datasets. On the environmental side, authors' interest lied only in CO2e emissions and neglected about a quarter of all green house gases. And finally, the authors did not take into account consumption-based emissions. For a country like China, the gap between production and consumption-based emissions is as high as 25% (CICERO, 2015). It is thus important to correct national emissions for trade exchanges in order to better represent carbon footprints associated to one's lifestyle rather than with the production structure of one's national economy.

v. Previous estimates of global distribution of CO2e production

Taking a standpoint opposite to the one presented above, some authors have also looked at the concentration of emissions from the point of view of CO2e "producers"[75]. Such studies are interesting as they call into question the very notion of what being "responsible" of emissions means. Heede (2014), for instance, attributes all CO2e emissions since 1854 to oil and gas majors which extracted these emissions. It comes out that close to 70% of all CO2e emissions ever emitted by humans can be traced back to only 86 oil or gas majors or other industries such as cement producers. Such a distribution reminds us that, at the beginning of the pipe, there are only a few actors extracting fossil fuels. However, the concept of CO2e production and of responsibilities in CO2e emissions used in Heede's study are criticisable. First, oil producers extract oil from the ground, but do not emit most of the CO2e emissions associated to oil consumption: other industries, or households -using their cars for instance- do so. Second, policy options based on such a concept of responsibility may in fact fail to reach their objective (i.e. make the industries pay). Richards and Boom (2014), on the basis of this study, suggest a tax on oil and gas majors to raise climate adaptation and mitigation funds. While taxing producers may *a priori* seem to be a fair idea, such an option is in fact blind to the distributional effects of taxes on energy producers. Fossil energy being constitutive of the way of life of billions of individuals, it cannot easily be replaced[76]. As a result, a tax on producers ultimately passes on to consumers - and generally has regressive - i.e. unequal - effects on income distributions.

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[75] The standpoint is in fact that of oil producers - and some industrial CO2e producers, such as cement. Extracting oil and releasing CO2e is however not the same.

[76] For other types of pollutants (CFCs for instance, responsible for Ozone layer destruction and used in fridges up to the Montreal protocol which banned them), specifically targeting producers may lead to rapid shifts in production patterns. In the case of oil,

vi. Recent research on the world distribution of income

Moving on to income inequalities, recent years triggered renewed interest in inequality debates, in particular following the publication of new long run historical series on top income shares (see e.g. Piketty and Saez, 2003; Atkinson et al., 2011; Alvaredo et al., 2013; Piketty, 2014). The World Top Income Database (WTID) now covers over thirty countries, with about forty additional countries under study, and on-going extensions to wealth distributions. The debate reached the global policy arena, as publications from international organizations reflect (OECD, 2009, 2011; UNDP, 2011; Dabla-Norris et al., 2015). While the availability and quality of national level inequality statistics is growing, there is still a limited amount of work on the combination of such data into a coherent, systematic, global distribution of income and wealth. In sum: we know a bit more than we used to, but we still know far too little.

In parallel to these attempts to improve country-level inequality estimates, there has been some attempts to aggregate within-country data into estimates of the world distribution of income. In particular, Lakner and Milanovic (2015) produced a harmonized dataset representing the evolution of income distribution, for approximately 90% of world population, using a combination of income and consumption expenditure surveys throughout the world, from 1988 to 2008. Survey data is well-known to suffer from several limitations, including underreporting at the top of the distribution. In order to better represent top incomes, Lakner and Milanovic apply Pareto interpolation techniques for the top 1% and top 5% of the population. [77] In one of their variant, they also attribute the difference between survey total income and national accounts statistics to the top 1%, thus assuming that the totality of the

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which cannot easily be replaced (even though there are plenty alternatives to it, their implementation takes time), the tax passes on to consumers.

[77] Computed from the top 20% and top 10% shares, such that $\alpha = \frac{1}{1 - ln\left(\frac{share_n}{share_{n+1} \times ln(2)}\right)}$ assuming the coefficient is constant, the share of top 1% income is then derived from the formula: $s_1 = s_{10} \times (0.1)^{\frac{\alpha - 1}{\alpha}}$, where s_1 and s_{10} are the respective income shares of top 1 and 10%.

difference between survey and national accounts is income accruing to the richest segments of society.

One problem with this method is that the attribution of the difference between survey income and national accounts very likely leads to an overestimation of top incomes. Not all the difference between surveys and national accounts accrues to the richest. The Pareto interpolation technique is potentially a better way to proceed. However WTID series indicates that Pareto coefficients are not completely stable within top deciles. In the future, it would be desirable to develop flexible, non-parametric techniques to interpolate Pareto curves (see e.g. Fournier, 2015).

In order to further refine Lakner and Milanovic's global distribution estimates, Anand and Segal (2014) attempt to use WTID data in a more direct way in order to correct with top 1% and top 5 % income shares obtained from tax statistics. Contrarily to survey data, tax statistics provide a much more detailed representation of top incomes - either under-represented or missing in household surveys. Combining the two datasets is however not straightforward and would require the development of more sophisticated estimation techniques. Anand and Segal (2014) adopt a more direct and simpler method and regress existing top 1% shares from WTID data on top ten percent share and GDP per capita data in Lakner-Milanovic in order to predict top 1 shares for countries and periods with missing WTID data. Anand and Segal then assume that survey data in the Lakner-Milanovic dataset represent only 99% of the population, and append the top percentile with its income share from the tax data (the share of control income is assumed to be equal to the share of survey income). As a result, authors have to re-estimate (i.e. increase) mean income for each country. This method is not perfectly satisfactory, but it provides a reasonable compromise. Below we explain how we have followed the general methodology pioneered by Lakner-Milanovic (2015) and Anand-Segal (2014) - although our method slightly differs from theirs[78].

[78] We are most grateful to Lakner-Milanovic and Anand-Segal for sharing their data sets and computer codes with us.

5 Methodology

In this section we describe the main steps of the methodology that we use in order to estimate trends in the world distribution of carbon emissions over the 1998-2013 period. For further details, we refer interested readers to our computer codes and data files, which are all available on-line[79], so that robustness checks can easily be carried out and alternative estimation strategies can be implemented.

i. Distribution of income

We start from the Lakner-Milanovic data set and proportionally rescale each income group's income so that all country income totals matches Household Final Consumption Expenditures (HFCE) values provided by the World Bank. This scaling choice is motivated by the fact that HFCE definition and data is more homogenous across countries than income and consumption surveys. In order to estimate top 1% income shares, we follow the Anand-Segal methodology and regress existing top 1% income shares (from WTID) on top 10%, bottom 10% share present in Milanovic dataset and a time indicator.[80] That is, each country is simulated with a distribution comprising 11 synthetic individual observations (one for each of the bottom nine deciles, one for fractile P90-99, and one for the top 1%), all of which are weighted by the relevant population weight and merged in order to estimate the world income distribution.[81] We stress that the estimates used in this study should not be seen as definitive values for the world income distribution, but as a first attempt to combine global income distributions with top incomes data, following Lakner-Milanovic (2015) and Anand-Segal (2014). This will clearly need to be improved in the future: this

[79] http://piketty.pse.ens.fr/files/ChancelPiketty2015.zip

[80] Note that our regression is slightly different to Anand and Segal, who regress top shares on top 10% shares and GDP per capita.

[81] For China, India and Indonesia, we use separate distribution estimates for the rural and urban sectors, so in effect we have 21 synthetic observations for each of these three countries. See on-line computer codes and data files for details.

includes the need to develop more flexible Pareto interpolation techniques (see the above discussion) and to simulate higher numbers of country-level synthetic observations. We have made a large number of robustness checks (in particular regarding the regression specification), and the main conclusions that we stress in the present chapter appear to be robust to alternative specifications.

We also update GDP, HFCE and population data in order to expand the Lakner-Milanovic dataset to 2013 (initial data stops in 2008). The strong assumption that we make here is that income distribution within countries does not change between these years (note however that we correct top 1% estimates for countries with available WTID data for year 2013). The Lakner-Milanovic dataset is in 2005 USD PPP. It is converted back into Local Currency Unit of 2005 transformed into its 2014 equivalent and then converted back into 2014 € PPP, using World Bank PPP estimates[82].

Finally, we reconstruct income distributions for certain countries not present in the Lakner-Milanovic dataset (Gulf countries and Iran). For Arab Gulf countries, we follow Alvaredo and Piketty (2014) and assume that Saudi Arabia and the United Arab Emirates (for which raw data sources are inadequate) have very high inequality levels (similar to Columbia). For Iran, inequality estimates for one year is missing and we assume no change occurred in the distribution of income between this year and the closest year available.

ii. CO2e budgets : Life Cycle vs. Input Output methods

In order to measure the pollution or energy consumption associated to individuals' lifestyles, two approaches can be followed. One way - call it the *micro* method - consists in measuring the pollution associated to each and every good or serviced consumed by the household using Life Cycle Analyses (LCA). These are accounting techniques to trace the amount of pollutants, reconstructing the production chain of a good. Such a method delivers precise data on specific goods or services. However, it can suffer from

[82] WB estimates for 2014 are derived from a statistical model based on the 2011 ICP.

multiple counting (one unit of energy used in production processes is counted more than once), which would result in national totals higher than their real values. As such, the LCA method is pertinent when we focus on individual level or sectoral studies, but the construction of national and global level estimates on the basis of LCA is hazardous. In practice, very few studies use LCA to derive macro-economic estimates because of this[83].

The second method - the *macro* method - is based on the work of V. Leontief (1941), known as the Input-Output (I-O) framework, extended to the environment (Leontief, 1970). It does not provide detailed information on the energy or CO2e content of precise types of good or services (it is impossible to discern whether an "Iphone" is more carbon intensive than a "Galaxy phone" for instance), however, it provides macro-economic consistency, i.e. one unit of energy or one unit of CO2e cannot be counted twice. In addition, the I-O approach makes it easy to trace back the origins of CO2e or energy imports embedded in a certain sector. A technical description of the Input-Output method applied to environmental accounting is presented in **"Carbon and Inequality: From Kyoto to Paris - Appendix A"**.

In this study, we use an existing environmental IO database. There are a few good candidates for the provision of environmental Input Output estimates. To name but a few, we can cite GTAP (Andrew and Peters, 2013), Exiobase (Wood et al., 2014), WIOD (Genty et al., 2012) or EORA (Lenzen et al., 2012). Our main interest was two-fold: we wanted to go as far as possible back in time and have an important number of countries to cover as much as possible the Lakner-Milanovic income distribution dataset. This left aside Exiobase and WIOD which are relatively well disaggregated at the within country level (it is possible to know the CO2e emissions associated to the consumption of several sectors of the economy - up to 163 in Exiobase), but which display a limited number of countries (about 40 countries or regions only). EORA and GTAP were candidates with a large number of countries represented (more than a 100 in 2007 for GTAP, and about 70 in 1997).

[83] One method using elements of LCA analysis to derive macro estimates is the Environmental Footprint.

For certain countries, EORA values were surprising: Sudan and Central African Republic ranked highest in world CO2e per capita consumption levels. This indeed cannot reflect true CO2e consumption statistics: living standards of a few elite Sudanese or Central Africans cannot be so high that the country average would rank first in the world. GTAP itself is not deprived from limitations. For instance, its global CO2e emissions level is smaller than in other databases (22.8GtCO2e in GTAP compared to 28.2 in EORA and 25.3 in WIOD for year 1997), we thus have relatively low world per capita GHG averages compared to other databases. Nevertheless, GTAP data standed as the best available source of consumption data for our purposes. Other I-O databases will be made available in the near future (Exiobase for instance, will soon provide historical estimates, rather than only two years currently available), and can also be used to refine our methodology.

GTAP consumption-based data provided by G. Peters and R. Andrew[84] was itself harmonized. In particular, the few countries (representing 13% of total emissions in the database in 1997-8 and 5% in 2007-8) which are aggregated into regions were assigned national totals. In order to do so, we assume that emissions are proportional to the population of the country within the region. In other words, we assumed that all individuals in the region have the same CO2e emissions per capita level. This assumption can be justified by the fact that we are talking about neighbour countries, with relatively homogenous average standard of living and production structures. In order to construct 2003 and 2013 consumption-based emissions levels, not available in the database, we assume that the ratio between production-based emissions and consumption-based emissions for 2003 is the same than for 1997 and that the 2013 ratio equals that of 2007. Given that we have production-based emissions in 2003 and 2013 for all countries, it is possible to approximate consumption-based emissions.

[84] We are most grateful to them and the CICERO team for sharing with us their CO2e consumption-based data and exchanging on the methodology.

iii. From national averages to individual emissions

In order to move from country average emissions to emissions of different individual (income) groups within countries, we use the following formula:

$$CO_2e_i = \frac{CO_2e_{tot}}{\sum_{j=1}^{N} pop_j \times y_j^e} \times Y_i^e \qquad (2)$$

Where pop_j is the population within income group j, y_i is mean income in group i $CO2e_{tot}$ represent total emissions in the country, N the number of income groups, e is the income-CO2e elasticity. We then divide $CO2e_i$ by the total population of group i to obtain per capita estimates. Note that our income/consumption dataset doesn't provide information on the age of individuals: it is assumed that all individuals living in a household share household income and CO2e emissions equally. We also chose to redirect all consumption-based emissions of a given country to individuals of this country, i.e. this includes emissions associated to government expenditures and investments. This choice is motivated by the fact that these emissions ultimately serve households' actual final consumption.

We use several elasticity values from 0.6 to 1.5 in order to account for different forms of the CO2e-income relationship. Our core results are based on an elasticity value of 0.9, which comes out as a median value of existing estimates (see section 4.1), the same for all countries even though as mentioned above, these are likely to differ. However, in the absence of systematic income-elasticity studies over the world, it seemed to us more straightforward to present standard results based on a single elasticity for all nations rather than modify them for a few countries. We nevertheless tested scenarios with elasticity modified for a few countries with specific elasticity data and our main results seem robust to such changes.

iv. Current and historical responsibility shares

The following formula is used to measure each individual's contribution to our solidarity schemes.

$$T_{i\theta} = \frac{T_{tot} \times mCO_2e_{i\theta}}{\sum_{j=1}^{N} mCO_2e_{j\theta}} \qquad (3)$$

Where T_{ik} is the contribution of individual i to scheme S with an emissions threshold k. T_{tot} is the total amount of money to be raised by the scheme and $mCO2e_{ik}$ are the marginal emissions of individual i, above emissions threshold k. Our emissions thresholds k_1, k_2 and k_3, respectively correspond to world average annual per capita emissions (6.2 tCO2e), top 10% emitters threshold, (13.4tCO_2e) and the top 1% global emitters threshold (56.3tCO_2e).

Historical emissions shares are calculated on the basis of data obtained from the World Resource Institute CAIT [45]. Emissions include GHG gases (excluding land use change) from 1990 to 2012. Emissions from 1850 to 1990 only include CO_2. In order to correct current individual emissions for historical national responsibilities, we first compute a corrected national emissions total for each country as in (4) and distribute it across income groups following (2).

$$totCO_2e_{cn\gamma} = totCO_2e_{wn} \times S_{c\gamma} \qquad (4)$$

Where $CO_2e_{cn\gamma}$ is equal to the emissions of country c *for year n corrected for historical* emissions since year γ, *CO_2e_{wy}, world CO_2e emissions for year n, $S_{c\gamma}$ the share of country* c *in historical emissions since year γ.*

v. Data coverage

Our dataset covers approximately 95% of GDP from 1993 onwards, about 90% of world population and slightly under 90% of world GHG emissions from 1998 to 2013.

The share of world GDP, population and GHG emissions not covered is explained by the lack of GHG emissions or income distribution data for specific years (see Lakner and Milanovic (2015) for income and Andrew and Peters (2013) as well as (WRI, 2015) for more details).

Table 2 - Global GDP, Population and GHG coverage (%)

6 A global distribution of carbon emissions: from Kyoto to Paris

We now present the results of our estimates of the world distribution of carbon emissions over the 1998-2013 period.

i. From production to consumption-based emissions

In order to better represent individual responsibilities to climate change, we believe it is essential to move from production-based emissions (see Table 1) to consumption-based emissions. Below, we present consumption-based per capita averages for the different regions of the world (Table 3) and variations between production-based emissions and consumption-based estimates. Unsurprisingly, emissions of North Americans and Europeans are higher than when measured from a production or territorial perspective (13% higher for North Americans, 41% higher for Western Europeans[85]) and lower for emerging or developing countries (25% lower for China, 21% lower for Africans). Moving from production-based emissions to consumption-based emissions reallocates emissions from a large number of relatively poor individuals (Chinese, South Asians) to a fewer number of relatively rich

[85] The percentage change between consumption and production-base emissions is much larger in Europe than in the USA, largely because production base emissions are already extremely high in the USA (see Figure 4) compared to Europe.

individuals (North Americans and Western Europeans): focusing on consumption-based emissions thus tends to increase the level of global individual CO2e emissions inequalities[86].

Table 3 - Current per capita GHG emissions - consumption-based

ii. Where do high and low emitters live?

Figure 5 presents the regional breakdown of CO2e emissions according to different world regions, over five quintiles of the global CO2e distribution. Sub Saharian Africa, India and South East Asia make up most of emissions at the bottom of the distribution, while North America and Europe, absent among bottom quintiles, are over represented at the top. China, Latin America or Middle East/North Africa embrace the entire spectrum of the global emissions distribution, with significant emissions among the bottom 2 quintiles as well as emission among top quintiles.

Figure 5 - Regional composition of emissions per global CO2e quintile.

In Appendix B Figure 1, we show the absolute number of emitters for different categories of emissions across all world regions. In particular, it shows that half of the world population emits below 3tCO2e per person and per year, while 90% of the world population emit below 15tCO2e per year.

[86] This holds true for several environmental indicators except for biomass, see for instance (Teixidó-Figueras and Duro, 2015).

iii. Who is hiding behind the numbers? Focus on top, bottom and middle emitters.

If we zoom into the very bottom of the distribution of GHG emitters, we find the bottom decile of African and Latino-american least developed countries: Honduras, Mozambique, Rwanda, Malawi and Zambia (Table 4). Emission levels among these population are extremely low - ten to twenty times below the continental average - and about 50 times below world average.

Table 4 - Bottom global CO2e emitters, 2013

Such values match with existing studies on CO2e emissions of very low income groups in the developing world. For instance, Parikh et al. (2009) find a similar value of 0.15tCO2e for the poorest 7% of the population in India. In rural areas of developing countries (as well in several urban places), households still largely rely on traditional energy sources[87] such as charcoal or firewood to cook and heat (IEA, 2014). As long as such fuels are sustainably harvested[88], the net cooking and heating CO2e emissions of individuals using these traditional fuels can be close to zero[89]. Kerosene or candle lighting is sometimes used and can add 0.05 tCO2e per year to individual CO2e budget. Another 0.1tCO2e is associated to the few goods purchased by individuals.

Let us now turn to the other end of the distribution of emitters and focus on the 5 highest emitting groups in the world. At the top of the world CO2e distribution lie, unsurprisingly, top 1% Americans, Luxembourgers, Saudis and Canadians.

Table 5 - Top global CO2e emitters in 2013

[87] 2.7 billion individuals currently use traditional biomass for cooking purposes (IEA, 2014).

[88] This is indeed not always the case, but it surely is in many places.

[89] It is of 0.008CO2etCO2e for poorest Indians according to Parikh et al. (2009)

These groups are comprised of individuals emitting more than 200tCO2e per year and per person. Our figures go as high as 320tCO2e per year per individual for top1% Americans, i.e. about 50 times world average and 2500 times the lowest CO2e emitters groups presented above. Our results are higher than those of the few studies existing on CO2e emissions of very top income earners. Ummel (2014), for instance, using a different method to ours, estimates CO2e emissions of top 2% Americans to be close to 55tCO2e. However, the data he uses does not allow him to precisely capture top incomes[90].

The 300tCO2e figure for the top 1% Americans can then be seen as a plausible value for the top1% richest individuals of this planet. In order to better represent what 300tCO2e per year and per person mean in practice, we present a possible breakdown of such a carbon budget: a rich American travelling 5 times a year from New York to Los Angeles (round trips, first class) and twice a year to Europe can emit up to 35tCO2e per year, solely for her air transport emissions - indeed, for some Americans among the top 1%, air emissions will be less than that, but they can also be much higher for very frequent travellers or for those who have private jets for instance[91].

Car emissions can add another 10tCO2e per year (that's twice the average figure for top10% Americans - see Chancel, 2014). CO2e emissions associated to household energy requirements (cooling, heating, electrifying) can reasonably add another 10tCO2e, assuming, here again, the individual is twice more "energy opulent" than the average top 10% American - note that top 1% Americans earn four times more than the average top 10% American, so our assumption can be seen as conservative. Transport and household energy thus represent about 55tCO2e per year for our top 1% income earner. In order to come up to the 300tCO2e, another 250tCO2e of carbon must then be associated to the production of all the services and goods purchased by

[90] Since he uses consumer spending data - see the methodology section for a discussion on consumer budget vs. tax data to capture top incomes.

[91] There are 11 000 jets in the USA.

the household that given year: i.e. for the production, transport, trade and sale of food, cars, apparel, water, hotel services, etc. purchased by the individual as well as the CO2e associated his or her investments.

Referring to the values used by Ummel (2014), it comes out that twelve dollars spent on home maintenance and repairs everyday correspond to 10 tCO2e in indirect emissions at the end of the year, thirty dollars spent every day on beef add another 10 tCO2e to an annual individual budget. In other words, indirect emissions can be very carbon intensive and the 250tCO2e figure is an enormous one, but, again may correspond to actual emission levels of very top earners - especially if we take into account the carbon content of their investments (see the discussion in the methodology section).

Now, looking at the middle of the distribution of global emitters, say individuals emitting around 7 tCO2e per person and per annum, slightly above world average, we find groups as diverse as the top 1% earners from Tanzania, the upper middle class (7th decile) in Mongolia and China as well as poor French and Germans (respectively 2nd and 3rd income deciles) - Table 6.

Table 6 - Average world emitters in 2013

French individuals in this group (i.e. the 3rd decile of income earners) are likely to emit 2.5 tCO2e for housing (heating, furniture, home repairs, etc.), close to 1tCO2e for food (mostly at home and some outside), 2tCO2e for transport (fuel and car purchases) [92]. The 2nd decile from Germany is likely to follow a similar breakdown - though with higher emissions for housing, due to a more carbon intensive energy mix and a different climate than in France. Breakdowns for top 1% Tanzanians, or upper middle classes in Mongolia or China are likely to differ however, not only because of national level differences, but also because of different consumption patterns (rich

[92] These are derived and adapted from Lenglart et al. (2010).

Tanzanians probably have individual electric generators, Air Conditioning systems or water purifiers which low income Europeans are less likely to possess).

iv. How unequal are global carbon emissions? The "ten-fifty relationship"

In order to better represent the contribution of different groups of emitters to total CO2e emissions, we now split the world in three groups: top 10%, middle 40% and bottom 50% CO2e emitters. For each of these groups, we present the percentage of the group's emissions stemming from each region of the world.

Figure 6 - Regional composition of top 10, middle 40 and bottom 50% emitter groups.

According to our estimates, top 10% emitters account for 45% of emissions. Middle 40% emitters for 42% of emission and bottom 50% for a meagre 13% of global emissions. At the very top of the distribution, the 1% highest emitters, represent 14% of emissions while the bottom 10% less emitting individuals emit about 1% of global emissions. Indeed, assuming other elasticities would change this repartition (Table 7): with a lower elasticity assumption (say 0.7), emissions are less concentrated at the top of the distribution in each country and globally: the top 10% figure falls to 40%. Conversely, with a higher elasticity assumption (1.1), top 10% emitters are responsible for more than half of the world CO2e budget (51.3%). As a gross rule of thumb, and assuming an elasticity of 0.9, it is possible to recall the "ten-fifty" relationship, with 10% emitters responsible for close to fifty percent of emissions and the bottom fifty percent emitting slightly over ten percent of emissions.

Table 7 - GHG emissions concentration shares in 2013 (%)

Focusing on the geographical origin of emitters, it comes out that close to 1/3rd of emissions within the top 10% group are from developing and emerging countries. Clearly, industrialized countries still dominate top emissions, but the contribution of top emitters from developing countries is already substantial.

One can also compare concentration values for CO2e with income concentrations worldwide (see Appendix B Table 1). While CO2e is very concentrated, income is even more unequally distributed than CO2e: at the world level, top 1% earners concentrate close to 20% of global income, that is twice more than the bottom 50% earners who concentrate less than 10% of income. The top 10% earners captured 57% of world income before the economic crisis of 2008, and fell to 53% in 2013 following the Great Recession. It is interesting to see how income concentration at the very top of the global distribution, i.e. the top 1% earners, was only slightly hit by the financial crisis. This was not the case when we look at top 10% global earners (which include, in particular, middle classes in industrialized countries) and whose income shares in global income was significantly reduced during the recession. We stress again, however, that these estimates should be seen as provisional, in particular because available top income data for a number of countries (e.g. China) is unsatisfactory and might well underestimate the level and change in top end inequality.

v. Who benefitted from the highest growth in CO2e emissions since Kyoto?

Is the distribution of global CO2e emissions more unequal today than it was 15 years ago? If CO2e emissions had remained at the same level within each country between 2013 than in 1998, a more equal concentration of income would mean a more unequal distribution of CO2e, and vice versa. However, the answer to our question is not trivial, as not only within country income distributions evolved over time, but national emissions as well (resulting of economic development, evolutions in energy production sectors, changing consumption patterns, etc.) and so did international flows of CO2e exchanged from countries to countries. Our estimates depend not only on income inequalities within countries, but also of evolution in CO2e emissions of each countries and international trade in CO2e emissions (enabling us to account for consumption-based CO2e). As a result, it is difficult to say, *a priori*, whether CO2e emissions are more concentrated among certain individuals in the world today than 15 years ago.

Figure 7 presents "growth incidence curves" for CO2e emissions. On the x-axis, we ranked groups of synthetic individuals (fiftieths[93]) according to their per capita CO2e emission level in 2013. On the y-axis, we show by how much CO2e emissions grew for each of these groups between 1998 and 2013[94]. We observe that for the first two fiftieths of the CO2e emissions distribution, i.e. the 4% lowest emitters, emissions actually decrease over the period by more than 10%. From the 3rd to the 37th fiftieth, the growth rate of emissions rises with the position in the global distribution of emissions, among these groups, the more per capita emissions in 1998 meant the higher growth between 1998 and 2013. For groups between the 27th and 37th fiftieth (the middle 30% of the global distribution of emissions), emissions grew at a rate higher than 30% over the period.

Figure 7 - Growth of CO2e emissions from 1998 to 2013

Remarkably, emissions' growth falls back after the 37th fiftieth: low and middle income groups in rich countries exhibit a limited increase in CO2e emissions. This difference can be attributed to different factors: slowdown in growth and incomes in rich countries (as shown by Lakner and Milanovic, 2015) combined with a slowdown in energy consumption at the end of the period associated to economic slowdown, higher efficiency in energy production processes associated to energy and climate policies as well as technological change. At the top of the CO2e emissions distribution, growth

[93] i.e. fifty groups ranked in ascending per capita emission order and representing each of them 2% of the world population.

[94] We compare, for instance the CO2e emission level of the 25th percentile of the world CO2e distribution in 1998 with the CO2e emission level of the 10th ventile in 2013, in order to derive CO2e emissions growth for this ventile over the two dates. Indeed, individuals within the two groups are not the same at the two points of time.

seems to recover slightly: this reflects the very good economic situation of top income earners over the period. A similar graph, focusing on income growth rather than CO2e, is presented in the Appendix (see Appendix B Figure 2). The profile of the curve is very close to that of CO2e and confirms the pattern found by Lakner and Milanovic (2015) between 1988 and 2008.

Another way to look at the rise in CO2e emissions at different points of the world distribution is to compare different parts of the CO2e distribution with one another, i.e. focus on the evolution of percentile ratios as is often done for income or wealth inequalities. Table 8 shows that inequalities in CO2e emissions were reduced between the top and the middle of the distribution (the p90-p50 ratio falls from 6 to 4.9 over the period) whereas inequalities between the top and the bottom of the distribution increased as per the p75-p25 ratio. Inequalities also increased between the bottom and the middle of the distribution, as shown by the reduction in the p10-p50 ratio.

Table 8 - Evolution of percentile ratios for CO2e emissions

vi. Did global CO2e emission inequalities increase or decrease over the past decades?

Are the trends highlighted above the result of dynamics of CO2e emission levels between countries (toput it simply: China, as a whole, catches up with the industrialized world), or are they due to a rise in within country inequalities (the middle class is getting thinner in the USA and CO2e emissions are more unequal there)? One way to answer this question is to look at evolutions of the Theil index. This index is useful because it can be broken into two components informing the relative importance of "within-group" and "between group" inequalities: it is then possible to represent the contribution of between country differences to global GHG emissions inequalities (evolution of total emissions for each country) and the contribution of within-country differences (that is national level inequalities in CO2e emissions).

Figure 8 - Evolution of within & between country CO2e emissions inequalities

From the Kyoto protocol in 1998 to the Paris Climate Conference in 2015, three important facts must be highlighted. The first one is that overall carbon inequalities decreased over the period, as measured by the Theil index - which moves from 0.75 to 0.70. CO2e emissions are more equally distributed among world individuals and regions today than fifteen years ago. This is the direct consequence of figure 7: the middle 40% emitters caught up with the top emitters thanks to (much) higher growth rates in emissions. However, this reduction in CO2e emissions inequalities hides two opposite trends. On the one hand, we notice a clear reduction in between-country inequalities. The Theil index was 0.46 in 1998 and falls to 0.35 in 2013. This is the "rise of China effect" (and other "BRICS" countries). But we also see a clear increase in within country CO2e emissions inequalities. The within country component of the Theil index moves from 0.29 to 0.35. What is striking here is that the two lines of Fig. 8 cross each other in 2013. In 1998, between country differences contributed to about two third of overall CO2e emissions inequalities. Fifteen years later, between country and within country inequalities contribute in the same proportion to overall inequalities[95].

The evolution of within and between country *income* inequality displays similar results: i.e. a reduction in between country inequalities driven by economic development, in particular among BRICS countries, coinciding with an increase in within country inequalities over the same period. However income inequalities between countries are more important than CO2e emissions inequalities. One way to illustrate this is to compare American and Indian mean income and mean CO2e emissions: per capita emissions are on average 12 times higher in the USA, while average income is on average 15 times higher in the USA.

[95] Indeed, with different income-CO2e elasticity values, the within country component of inequality would differ. With an elasticity of 0.7, only 37% of global inequality is explained by within country differences in 2013. With an elasticity of 1.1, 62% of global inequality is explained by within country differences.

7 Financing adaptation via a global progressive carbon tax

Results from section 6 show to what extent the geography of individual CO2e emissions changed from the Kyoto Conference in 1998 to the Paris Conference of Parties. A significant number of high emitters can now be found in emerging countries. Inequalities increased between the bottom of the CO2e emissions pyramid and the middle, and were reduced between the middle and the top. Our results thus corroborate and support the key messages of Chakravarty et al. (2009), for whom all countries should contribute to climate mitigation efforts and emerging countries in particular had to stop "hiding behind their poor" (see Chakravarty and Ramana, 2011), given the presence of high emitters in China, India or Brazil. On the other hand, our results show that the vast majority of high emitters still come from rich countries (particularly North America). Thus our estimates can be used to provide a more balanced and neutral basis to approach these highly controversial issues.

Our estimates can also prove helpful to frame equity debates on the financing of a climate adaptation fund. In terms of climate mitigation efforts, emerging and developing countries have already stopped hiding "behind their poor". In fact, under the Intended Nationally Determined Contribution logic, all countries contribute to climate mitigation efforts - see for instance DDPP, 2015. This is not the case for adaptation financing, for which efforts remain concentrated among a few countries only (Fig. 1). As we have shown in section 2, the current breakdown of contributors neither reflects ability to pay principles, nor historical responsibilities[96].

In order to better align the amount of funds required for adaptation with adaptation needs, contributions to climate change and individuals' ability to pay, we

[96] historical production-based responsibilies, the estimation of historical consumption-based emissions remains to be done.

propose an equity logic in which efforts would be split among the world top current emitters - rather than countries. When it comes to equity debates, there is clearly no "good" allocation rule or formula and our objective is certainly not to discover the perfect solution. At a more modest level, we hope that our examination of the implications of a global progressive carbon tax on all world emitters can contribute to a more informed discussion. Our exercise clearly has limits - due to the assumptions made to construct our estimates and because of simplicity of the allocation logic we follow- but it also has interests: it provides order of magnitude on "who should pay what" under different options for adaptation finance.

i. Proposed strategies for climate adaptation contributions

In its simplest version, our proposed allocation rule works as follows: all individuals in the world emitting above a given emission threshold should contribute to the world adaptation fund, in proportion to their emissions in excess of the threshold. In effect, this is equivalent to a two-bracket global progressive carbon tax, with a 0% marginal tax rate on carbon emissions below a threshold, and a positive marginal tax rate above the threshold (the upper tax rate being set so as to raise the desired budget for the world adaptation fund).

We present results for four main thresholds (Table 9a-b). We first look at the case with a zero threshold: this corresponds to a flat carbon tax with a proportional rate on all world emitters, no matter how small or how large their carbon emissions (we call this strategy 0). In strategy 1, we set the threshold at the level of average world emissions above (6.2tCO2e per year per person). In effect, the top 28% emitters of the world population have to contribute. In strategy 2, we set the threshold so as to target the top 10% world emitters (i.e. individuals emitting more than 2.2 times average world emissions). In strategy 3, we set the threshold so as to target the top 1% world emitters (i.e. individuals emitting more than 9.1 times average world emissions).

For example, take a Chinese high-income urban dweller emits 10.2 tonnes of CO2e emission per year. In our "average emission threshold" (strategy 1), she would contribute to the fund on the basis of 4 tonnes of CO2e (10.2tCO2e minus the world average, 6.2tCO2e). The amount paid is then proportional to the share of the individual's emissions above the threshold in all global emissions above the threshold. We provide estimates to generate €150bn per year (about 0.2% of world GDP), clearly above the €42bn ($50bn) per year that is supposed to be raised via the Green Climate Fund, but clearly under the estimated true costs of adaptation according to the UNEP, which can be higher than €300 bn (see section 2). The reference value we take falls in the mid range of recent estimates for climate adaptation.

It has been suggested that historical responsibilities should be taken into account when attributing fair shares of climate-related efforts (Grasso and Roberts, 2014, Fuglestvedt and Kallbekken, 2015, Matthews, 2015, Raupach et al, 2014, Landis and Bernauer, 20120). We thus reproduce strategies 1, 2 and 3 on the basis of individual-level emissions corrected by historical emissions since 1990 and 1850 (Tables 9c-d). In effect, we recalculate national individual CO2e emissions averages on the basis of each country's contribution to historical emissions as per Equation 4. Doing so unsurprisingly increases the contribution to be borne by emitters in rich countries and reduces that of emitters in low income and emerging countries

We should make clear from the outset that we do not view any of these strategies as fully satisfactory. The ideal solution from a world social welfare viewpoint - whatever the way one defines such an optimum - would presumably involve a mixture of these different strategies, i.e. a many-bracket progressive carbon tax with graduated rates on the different interval of carbon emissions. Given the enormous inequality of the world distribution of carbon emissions, we feel that the flat tax (strategy 0) can hardly be regarded as an equitable solution. In our view, the best compromise probably involves a combination of strategies 1, 2 and 3. In particular, strategy 2 - with its focus on top 10% world emitters, who are responsible for nearly 50% of all world emissions - can be regarded as a reasonable middle ground and reference point. In particular, although we do not provide explicit estimates of negative externalities and associated social welfare computations, it should be noted that the tax burden imposed on this group (about 0.2% of world GDP) is much less than the reduction in welfare imposed on the rest of the world by their emissions (middle-range estimates of the long-run annual costs of global warming typically range from 2% to 10% of world GDP, and are higher under some estimates; see e.g. Stern et al., 2006).

Table 9a - Population, mean emissions and world shares in strategies 0-1

Table 9b - Population, mean emissions and world shares in strategies 2-3

Table 9c – Contributions according to historical contributions, strategies 0-1

Table 9d – Contributions according to historical contributions, strategies 2-3

The main conclusions emerging from tables 9A-9B are relatively clear. According to the flat carbon tax strategy, China and North America should both contribute about 21% of the world adaptation fund, and EU should contribute 16% (strategy 0). However most emitters in China are very low emitters, so this does not look like an equitable solution. In strategy 1, we split the burden on individuals polluting more than world average emissions (28% of the world population). The share of North America jumps to 36%, while that of China falls to 15%, and that of Europe rises to 20%. When we split the burden between top 10% world emitters, the share of North America further rises to 46%, while China stands at 12% and Europe at 16% (strategy 2). When we split the burden between top 1% world emitters, the share of North America further rises to 57%, while China falls at 6% and Europe stands at 15% (strategy 3). Interestingly, the share of China falls below that of Russia/Central Asia or Middle-East/North Africa in the most progressive strategy).

To summarize: equitable adaptation requires to define neutral criteria applying to all citizens of the world equally, whether they come from rich, emerging or developing countries. We certainly do not know with certainty how to combine the different strategies so as to reach an equitable solution to all. But the bottom line of our simulations is that, at the end of the day, by far the largest contribution to world adaption funds should come from rich countries: adaptation contributions from European countries should increase by more than 3 times and those from the USA by more than 15 times.

i. Implementation via country-level progressive taxation

Our preferred strategy for equitable adaptation finance is a global progressive carbon tax. However enforcing a progressive carbon tax at the global level seems very difficult, to say the least. Another strategy might be to use the global progressive carbon tax simulations to determine country shares in global adaptation funding, and then to let each country raise the required amount as they see fit. Ideally each country could raise the required amount via a contry-level progressive carbon tax. This is technically challenging but not impossible. In order to fix ideas, we also illustrate on table 10 how each country could raise the required amount via country-level supplement to existing progressive income taxes. To summarize: in order to raise the equivalent of 150 billions € per year (about 0.2% of world GDP), one can use income tax supplements with marginal rates around 1-2% of income on the top 10% emitters of the world, or around 5-10% on the top 1% emitters of the world. Note that the required tax rates vary across countries because the carbon intensity of income is not the same everywhere. We should stress again, however, that this is not our favoured solution: for given income, different individuals have different carbon emissions, and it is highly preferable - whenever possible - to use a progressive carbon tax, either at the country or world level.

Table 10 - Implementation via country-level progressive income taxation

ii. Implementation via a global progressive tax on air tickets

Yet another possible option to implement a tax on the world's highest emitters is to tax certain consumption items - those associated with high individual energy consumption and CO2e emissions levels. Car ownership, being an air transport passenger or possessing an AC system may constitute such markers. Indeed, none of them are ideal ways to identify high CO2e emitters or high energy consumers: car ownership is a relatively poor marker of high emitting lifestyles and this is even more true for ownership of AC system. Air transport may stand out as a relatively good marker of high income and high CO2e emitting lifestyles. It is generally associated with high living standards - at the world level at least - and it generally also operates a distinction between different income or social groups with the economy/first and business class system. A global tax on air transport could thus have two interesting properties: it would reach high-income individuals and high emitters.

Table 11 shows how each region of the world contributes to global air passengers[97] and also presents the contribution of world regions to each of the three groups targeted in section 7.1. The repartition between different regions for air tickets is relatively to each region's contribution to emissions above world average, i.e. in terms of regional efforts, taxing flights (without distinguishing business or economy, national or international) would then be close to our first strategy.

A tax on flights to finance specific development schemes was in fact discussed and established after the Paris International conference on the finance of development in 2005. Initially signed by 30 countries, the tax was implemented in 9 countries. The tax generates about €200m per year and its revenues are used to finance an international organizations (UNITAID and the International Finance Facility for Immunisation) which act in the field of vaccination and fight against epidemics. According to our

[97] The data informs on the share of flights by passengers of a given region in global air trafic.

estimates, the tax reaches about only 4.3% of flights worldwide (and much less in terms of km travelled).

One way to go forward would be to generalize such a tax to all flights in the world and increase the per ticket cost. Taxing all flights at a rate of €52 per ticket would yield €150bn, required to finance climate adaptation in our adaptation scenario. Indeed, there can be many ways to make such a tax more 'progressive': different tax levels according to regions, on the basis of their contributions to top income emissions can be thought of. A differentiation between economy class and business class is also an option - already implemented in a country like France. With simple assumptions, we estimate that taxing business class at a rate of €180 per flight and economy class at a rate of €20 would yield about the same amount of money[98]. Here, we do not differentiate between national and international flights. Indeed, the former could be taxed at lower rate, and the latter at a higher rate.

Table 11 - Who should contribute to climate adaptation funds?

8 Conclusions and prospects for future research

In this chapter, we have presented new estimates on the evolution of the global distribution of CO2e emissions between world individuals from 1998 and 2013. We then applied our findings to examine different strategies to finance a global climate adaptation fund based on efforts shared among high world emitters rather than high-income countries.

Our estimates are provisional and should be refined in many ways. In particular, world income distribution estimates need to be improved, as well as the reference values

[98] Assuming that 20% of total flights are business or premier class, which is a typical breakdown for medium size planes (Boeing 747-400 for instance).

for carbon-income elasticities and how they vary between countries. However our main conclusions appear to be relatively robust to alternative specifications.

To summarize: equitable adaptation requires to define neutral criteria applying to all citizens of the world equally, whether they come from rich, emerging or developing countries. We certainly do not know with certainty how to combine the different strategies so as to reach an equitable solution to all. But the bottom line of our simulations is that, at the end of the day, by far the largest contribution to world adaption funds should come from rich countries - particularly the USA, but also the EU. Even if high income groups from emerging and developing countries were to contribute to adaptation efforts, Americans and Europeans would need to substantially scale up their current contributions to fill the adaptation gap.

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Table 1 - Current per capita GHG emissions - production base

	tCO_2e per person per year	Ratio to world average
World average	6.2	1
N. Americans	20	3.2
Russians / C. Asians	10	1.6
West. Europeans	9	1.5
Chinese, Middle East	8	1.3
S. Americans	5.2	0.8
S. Asians, Africans	2.4	0.4
Sustainable level	1.3	0.2

Source: Authors' calculations based on CAIT (WRI, 2015). Key: South Asians emit on average 2.4tCO2e per person and per year, i.e. 0.4 times world average emissions. Note: These are "production base" GHG emissions excluding land use change, i.e. emissions produced within territorial boundaries - data for 2012.

Table 2 - Global GDP, Population and GHG coverage (%)

Year	GDP	Population	CO_2e
1988	91.8	79.1	NA
1993	97.1	89.9	NA
1998	96.7	89.4	87.2
2003	96.1	89.6	87.1
2008	93.9	87.8	89.1
2013	93.6	87.2	88.1

Source: authors. Key: The dataset covers 96.7% of world GDP in 1998, 89.4% of world population and 87.2% of world CO2es emissions

Table 3 - Current per capita GHG emissions - consumption-based

	tCO_2e per person per year	% change with production	ratio to world average
World average	6.2	0	1
N. Americans	22.5	13	3.6
West. Europeans	13.1	41	2.1
Middle East	7.4	-8	1.2
Chinese	6	-25	1
Latino Americans	4.4	-15	0.7
S. Asians	2.2	-8	0.4
Africans	1.9	-21	0.3
Sustainable level	1.3	0	0.2

Source: authors' calculations based on (Peters and Andrew, 2015) and (WRI, 2015). Key: Western Europeans emit on average 13.1tCO2e per year and per person, including consumption-based emissions. This figure is 41% higher than production base emissions and 2.1 times higher than world average. Note: data for 2013.

Table 4 - Bottom global CO2e emitters, 2013

Country	Population (million)	Group	Income PPP	CO_2e emissions (Annual tCO_2e p.c.)
Honduras	0.8	Bottom 10%	64	0.09
Mozambique	2.6	Bottom 10%	117	0.11
Rwanda	1.2	Bottom 10%	215	0.12
Malawi	1.6	Bottom 10%	72	0.14
Zambia	1.5	Bottom 10%	188	0.16

Source: authors. Key: the bottom 10% of income earners in Honduras (0.8 million individuals) earned 64€ euros on average in 2013 and emitted 0.09tCO2e per person that year.

Table 5 - Top global CO2e emitters in 2013

Country	Pop (million)	Group	Income PPP	CO_2e emissions (annual tCO_2e p.c.)
USA	3.16	Top 1%	542453	318.3
Luxembourg	0.01	Top 1%	220709	286.8
Singapore	0.05	Top 1%	25049₂	250.7
Saudi Arabia	0.29	Top 1%	569063	246.7
Canada	0.35	Top 1%	257085	203.9

Source: authors. Key: the top1% Americans earned 542453€ on average in 2013 and emitted 318tCO2e per person that year.

Table 6 - Average world emitters in 2013

Country	Pop (million)	Group	Income PPP	CO_2e emissions (annual tCO_2e p.c.)
Tanzania	0.5	Top 1%	9716	7.3
Mongolia	0.3	7th decile	3129	7.1
Germany	8.1	2nd decile	8921	7.1
China	58.5	73-77th pct.	3277	7.1
France	6.6	3rd decile	9347	6.5

Source: authors. Key: the top1% Tanzanians earned 9716€ on average in 2013 and emitted 7.3tCO2e per person that year.

Table 7 - GHG emissions concentration shares in 2013 (%)

Year	elast	top1	top5	top10	mid40	bot50	bot10
2013	0.9	13.8	31.5	45.2	41.8	13.0	1.2
2013	0.7	9.9	26.6	40.0	44.8	15.3	1.5
2013	1.1	19.0	38.0	51.3	38.0	10.7	0.9

Source: authors. Key: assuming an income-CO2e elasticity of 0.9, the top10% highest emitters are responsible for 45% of global emissions.

Table 8 - Evolution of percentile ratios for CO2e emissions

	p90/p10	p90/p50	p10/p50	p75/p25
1998	15.4	6.0	0.39	4.27
2013	15.2	4.9	0.32	4.64

Source: authors. Key: In 2013, individuals at the 75th percentile of the global CO2e distribution emit 4.6 times more than individuals at the 25th percentile of the global CO2e distribution.

Table 9a - Population, mean emissions and world shares in strategies 0-1

Region	Flat carbon tax on all world emitters (100% world population)			Strategy 1. Progressive carbon tax above average emissions (27% world population)		
	Population concerned (millions)	MeanCO_2e emissions (annual tCO_2e per capita)	Contribution to emissions (%)	Population concerned (millions)	MeanCO_2e emissions (annual tCO_2e per capita)	Contribution to emissions above average (%)
North America	351.3	22.5	21.2	316.1	24.6	35.7
EU	494.9	12.4	16.4	409.1	14.1	20.0
China	1357.0	5.9	21.5	428.1	11.8	15.1
Russia/C.Asia	222.7	10.0	6.0	123.4	14.8	6.6
Other Rich	127.3	13.4	4.6	114.6	14.4	5.8
Mid. East/N.A	310.8	7.0	5.8	108.8	14.2	5.4
Latin America	493.1	4.5	5.9	82.7	14.6	4.3
India	1252.0	2.1	7.2	37.0	10.6	1.0
S.S.Africa	610.1	1.9	3.1	31.4	13.8	1.5
Other Asia	995.3	3.1	8.3	102.0	13.6	4.7
World	6214.4	6.2	100%	1753.1	15.4	100%

Source: authors. Key: Under strategy 1 (taxing all emissions above world average), 316 North Americans would be concerned, their average emissions are 24.6tCO2e, and they represent 35.7% of all emissions above world average.

Table 9b - Population, mean emissions and world shares in strategies 2-3

Region	Strategy 2. Progressive carbon tax on top 10% world emitters (2.2 times above world avg. emissions)			Strategy 3. Progressive carbon tax on top 1% world emitters (9.1 times above world avg. emissions)		
	Population concerned (millions)	Mean CO_2e emissions (annual tCO_2e per capita)	Contribution to emissions above threshold (%)	Population concerned (millions)	Mean CO_2e emissions (annual tCO_2e per capita)	Contribution to emissions above threshold (%)
North America	210.8	32.1	46.2	32.0	85.8	57.3
EU	141.4	22.8	15.6	4.8	107.4	14.8
China	58.5	30.3	11.6	13.6	63.2	5.7
Russia/C.Asia	43.8	25.6	6.3	1.4	126.5	6.1
Other Rich	50.9	20.9	4.5	1.3	106.2	3.8
Mid. East/N.A	31.2	28.5	5.5	4.5	80.7	6.6
Latin America	36.2	23.0	4.1	3.3	65.7	1.9
India	12.5	17.9	0.7	0.0	0.0	0.0
Other Asia	33.8	23.7	4.1	1.1	98.5	2.7
S.S.Africa	9.3	26.7	1.5	0.5	89.7	1.1
World	628.4	27.0	100	62.4	82.7	100

Source: authors. Key: 58.5 million individuals living in China emit above 2.2 average emissions levels. They contribute to 11.6% of emissions over the threshold and their mean emissions are 11.6tCO2e.

Table 9c – Contributions according to historical contributions, strategies 0-1

	Strategy 0 : Flat carbon tax (Contribution to scheme %)			Strategy 1: Above world average (>6.2 tCO2e) (Contribution to scheme %)		
Region	Current emissions	Since 1990	Since 1850	Current emissions	Since 1990	Since 1850
North America	21.2	23.2	32.2	35.7	38.5	44.6
EU	16.4	15.6	26.5	20.0	17.4	31.5
China	21.5	19.9	12.2	15.1	12.3	3.1
Russia/C.Asia	6.0	9.2	11.0	6.6	12.8	12.8
OtherRich	4.6	4.2	4.2	5.8	4.8	3.7
Mid.East/N.A	5.8	4.7	3.0	5.4	3.5	1.2
Latin America	5.9	5.8	2.8	4.3	4.0	0.8
India	7.2	6.3	3.1	1.0	0.7	<0.5
Other Asia	8.3	7.6	3.5	4.7	3.8	1.0
S.S.Africa	3.1	3.7	1.6	1.5	2.0	1.1
World	100	100	100	100	100	100

Source: authors. In a contribution scheme based on Strategy 1 and on historical responsibilities since 1990, individuals living in China would make up 3.1% of the total contribution.

Table 9d – Contributions according to historical contributions, strategies 2-3

	Strategy 2: Top 10% emitters (> 2.2x world average) **Contribution to global emissions above threshold (%)**			**Strategy 3: Top 1% emitters (> 9.1x world average)** **Contribution to global emissions above threshold (%)**		
Region	**Current emissions**	**Since 1990**	**Since 1850**	**Current emissions**	**Since 1990**	**Since 1850**
North America	46.2	49.5	53.5	57.3	63.6	67.9
EU	15.6	12.5	28.6	14.8	11.5	21.3
China	11.6	9.2	2.1	5.7	3.3	<0.5
Russia/C.Asia	6.3	13.4	11.2	6.1	10.7	7.8
OtherRich	4.5	3.3	1.8	3.8	2.7	1.4
Mid.East/N.A	5.5	3.3	0.9	6.6	2.8	0.6
Latin America	4.1	3.6	<0.5	1.9	1.9	<0.5
India	0.7	<0.5	<0.5	<0.5	<0.5	<0.5
Other Asia	4.1	2.8	<0.5	2.7	1.7	<0.5
S.S.Africa	1.5	2.2	1.1	1.1	1.8	0.9
World	100	100	100	100	100	100

Source: authors. In a contribution scheme based on Strategy 3 and on historical responsibilities since 1850, individuals living in the EU would make up 21.3% of the total contribution.

Table 10a - Implementation via country-level progressive income taxation, strategy 1-2

Region	Above average				Top 10% emitters (Above 2.2x average)			
	Pop. share concerned	Mean income (€)	Marginal income tax (%)	Lower income threshold (€)	Pop. share concerned	Mean income (€)	Marginal income tax (%)	Marginal income threshold (€)
North America	90%	32600	0.6	5851	60%	43400	1.2	14278
EU	83%	18200	0.7	6155	29%	30100	1.2	13797
China	32%	5900	1.6	2730	4%	16800	2.9	6663
Russia/C.Asia	55%	15900	0.8	5904	20%	29200	1.4	14609
Other Rich	90%	19200	0.6	7083	40%	28900	1.1	17284
Mid. East/N.A	35%	18000	0.6	6512	10%	41300	1.1	16657
Latin America	17%	23700	0.5	10330	7%	37200	1	23982
Other Asia	5%	14800	0.8	5600	6%	26200	1.5	14406
S.S. Africa	10%	13200	0.9	5522	1%	29200	1.6	11051

Source: authors. Key: emitters from North America with individuals CO2e emissions levels above world average earn 32600€ per person (on average). The lower income threshold to be part of this group in the USA is 5851€. The tax would correspond to 0.6% of their income above the threshold.

Table 10b - Implementation via country-level progressive income taxation, strategy 3

Region	Top 1% emitters (Above 9.1x average)			
	Pop. share concerned	Mean income (€)	Marginal income tax (%)	Marginal income threshold (€)
North America	9.1%	130100	5.3	73218
EU	1.0%	171000	5.4	71922
China	1.0%	37300	13.9	32799
Russia/C.Asia	0.6%	168200	6.4	68377
OtherRich	1.0%	172300	5.2	85082
Mid.East/N.A	1.4%	141100	4.5	79693
Latin America	0.7%	115200	4.8	117726
Other Asia	0.2%	100000	7.9	45791
S.S.Africa	0.1%	105200	7.1	62644

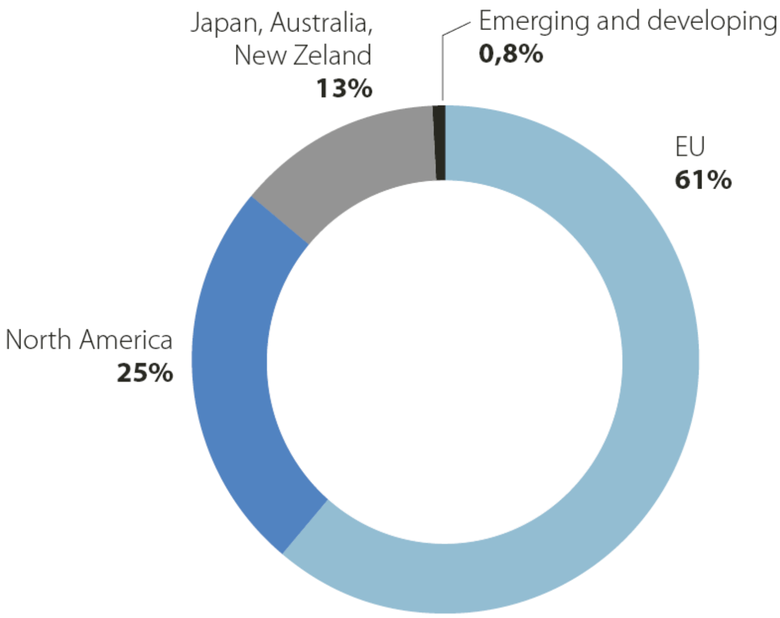
Source: authors.

Table 11 - Who should contribute to climate adaptation funds?

Regions	Effort sharing according to all emissions (flat carbon tax) (%)	Progressive carbon tax strategies			Effort sharing according to a global tax on air tickets (%)
		Strategy 1	Strategy 2	Strategy 3	
		Effort sharing among all emitters above world average (%)	Effort sharing among top 10% emitters (above 2.3x world average) (%)	Effort sharing among top 1% emitters (above 9.1x world average) (%)	
North America	21.2	35.7	46.2	57.3	29.1
EU	16.4	20.0	15.6	14.8	21.9
China	21.5	15.1	11.6	5.7	13.6
Russia/C. Asia	6.0	6.6	6.3	6.1	2.8
Other Rich	4.6	5.8	4.5	3.8	3.8
Middle East/N.A	5.8	5.4	5.5	6.6	5.7
Latin America	5.9	4.3	4.1	1.9	7.0
India	7.2	1.0	0.7	0.0	2.9
Other Asia	8.3	4.7	4.1	2.7	12.1
S.S. Africa	3.1	1.5	1.5	1.1	1.1
World	100	100	100	100	100

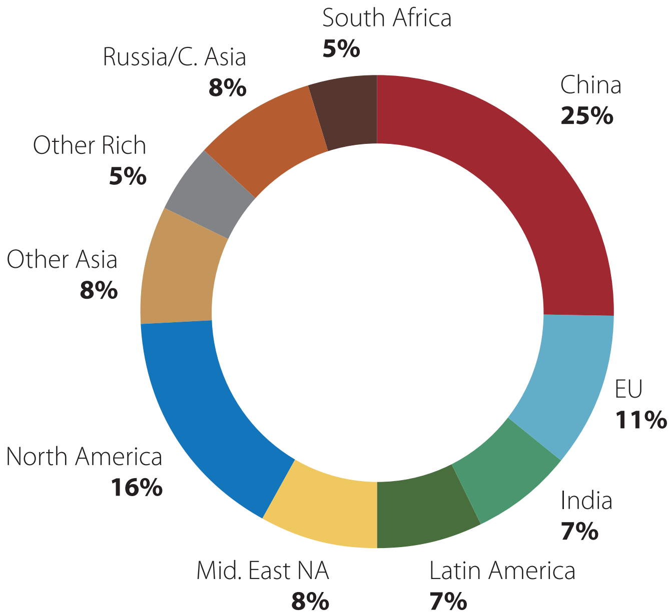
Source: Authors. Air passenger data from World Bank (2015). Key: The European Union makes up 21.9% of global air passengers. It also contributes to 20% of emissions emitted by individuals above world per capita CO2e emissions average, to 15.6% of individual emissions above 2.2 times average and 14.8% of emissions 9 times above average. Note: only consumption-based emissions are displayed.

Figure 1a - Contributors to global adaptation funds (2014)



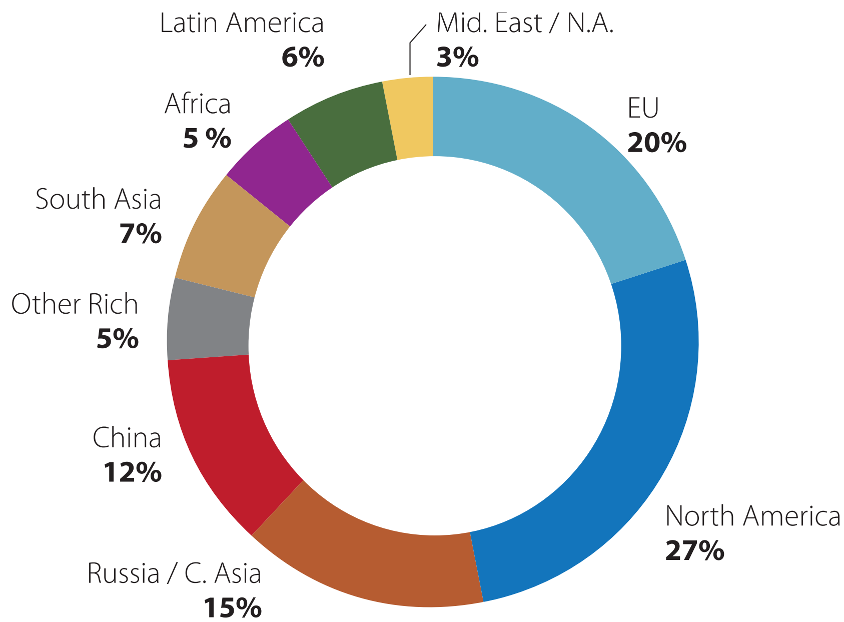
Source: Authors. Data from climatefundsupdate.org and gcca.eu. Key: Western Europe contributes to 61% of global climate adaptation funds. Note: the breakdown is based on a total value of funds of €7.5bn. The focus is solely on global funds. Bilateral funds and funds disbursed by developing countries for themselves are not taken into account.

Figure 1b - Distribution of current production-based CO2e emissions



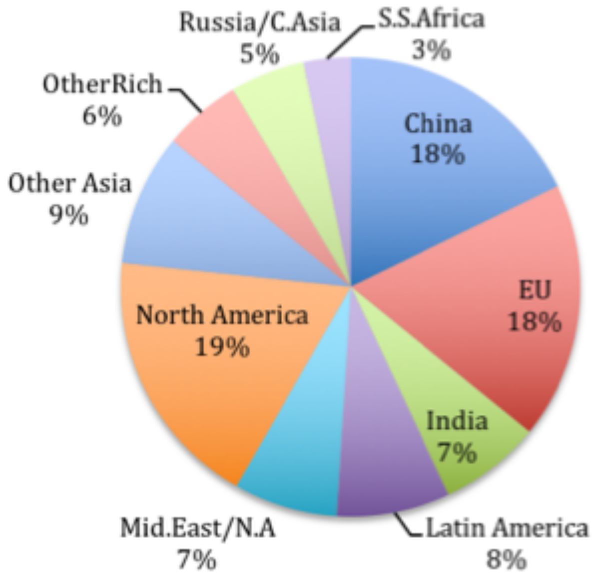
Source: authors based on CAIT (WRI, 2015). Key: China represents 25% of global CO2e emissions when measured from a production base. Note: data from 2012.

Figure 1c - Distribution of cumulated production-based historical CO2e emissions



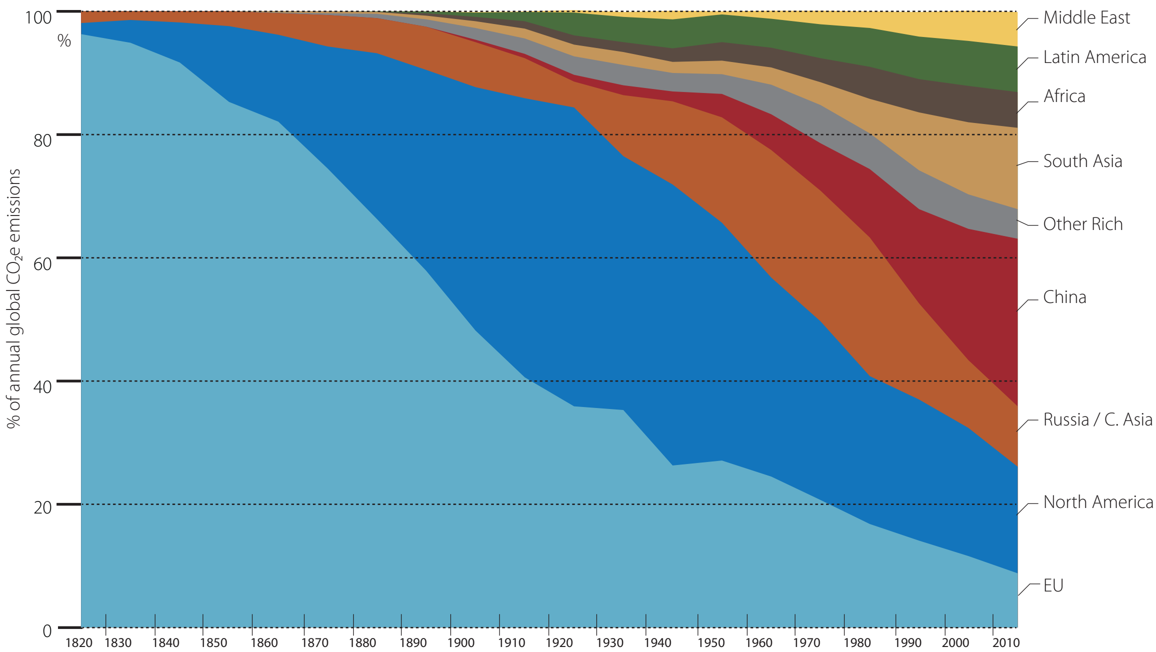
Source: authors based of CAIT (WRI,2015) and CDIAC (Boden et al, 2015). Key: Emissions from North America represent 27% of all CO2e emissions ever emitted since the industrial revolution. Note: these are production base emissions.

Figure 1d - Current distribution of global GDP



Source: authors based on World Bank (2015). Key: North America makes up 19% of global GDP. Note: 2014 current PPP values.

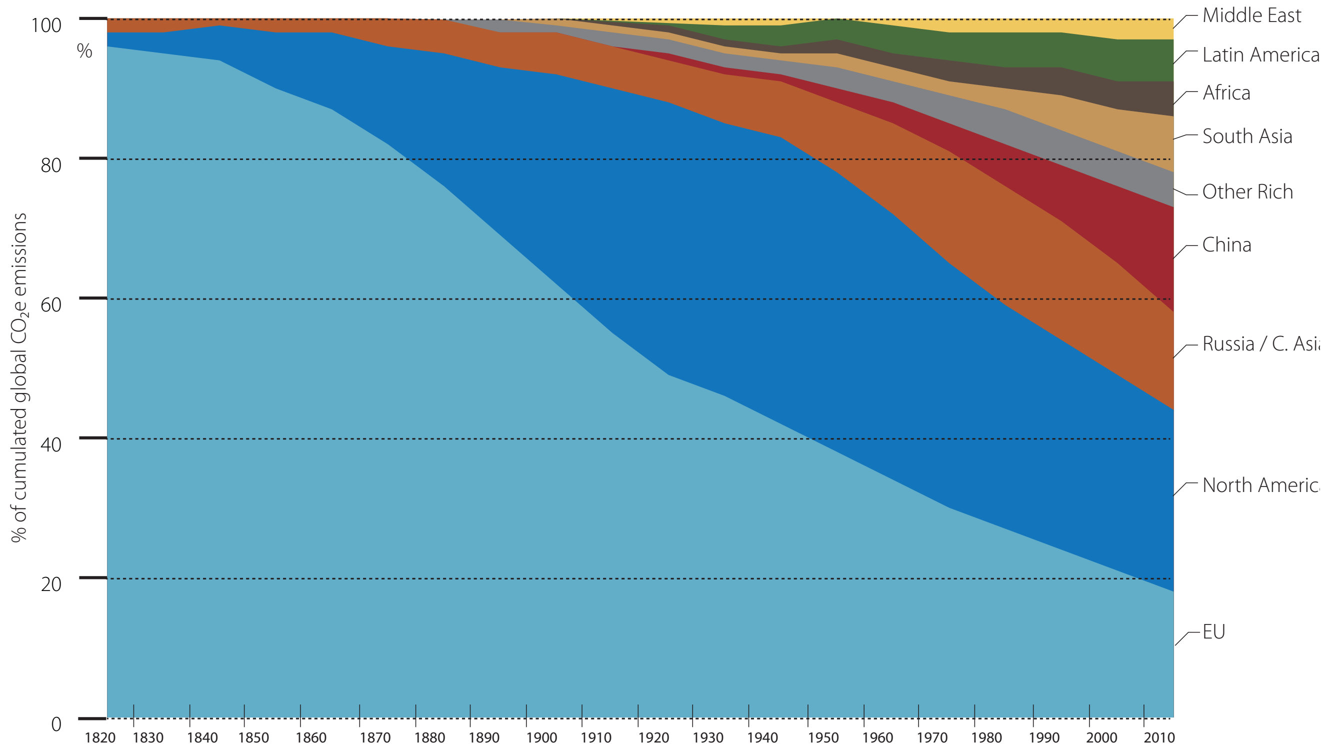
Figure 2a - Share in global CO2e emissions since 1820



Source: authors' estimates based on CAIT (WRI, 2015), CDIAC (Boden et al., 2015), Maddison (Maddison, 2013)[99]. Key: in 2010, 9% of global CO2e emissions are emitted in Western Europe. Note: data is smoothed via 5-year centred moving averages.

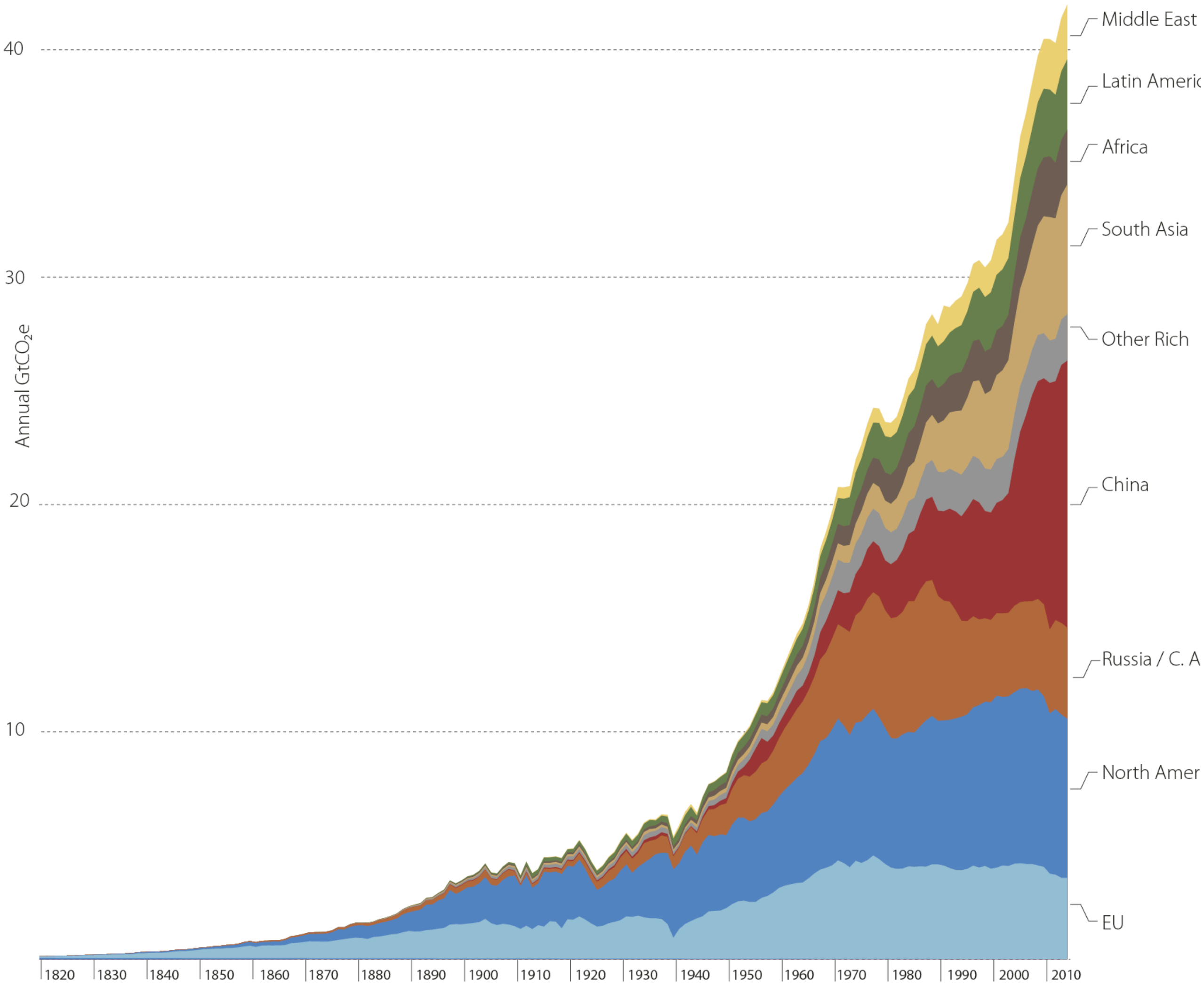
[99] Estimates for figures in this section are based on CAIT data for CO2e and GHG emissions up to 1970, Madisson and UN Stats data for population and CDIAC data for CO2e prior to 1970. We assume constant GHG/CO2e ratios to reconstruct historical GHG series.

Figure 2a - Share in cumulated global CO2e emissions since 1820



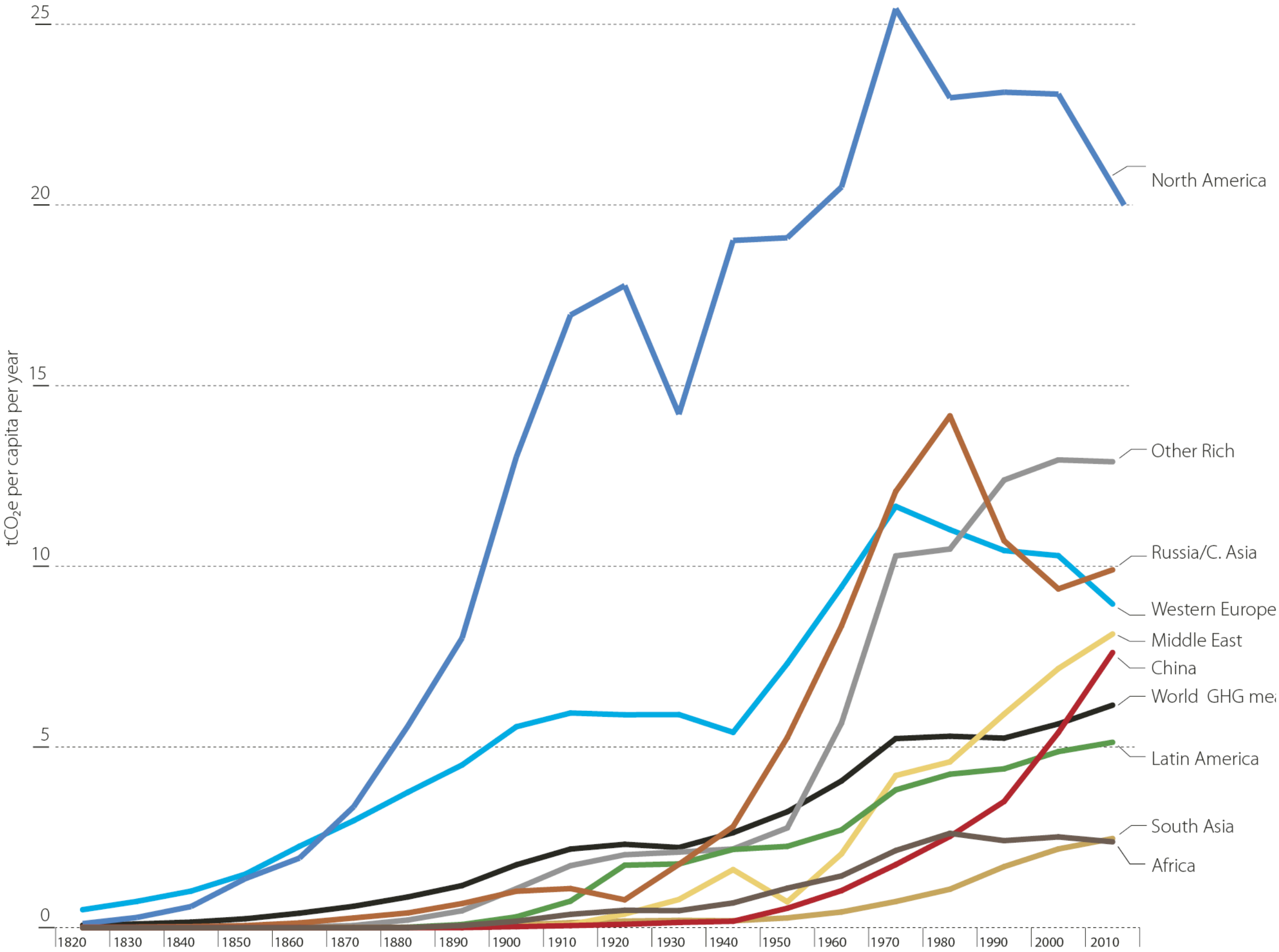
Source: authors' estimates based on CAIT (WRI, 2015), CDIAC (Boden et al., 2015), Maddison (Maddison, 2013). Key: In 2010, 12% of cumulated global CO2e emissions, since the Industrial revolutions, were emitted in China. Note: data is smoothed via 5-year centered moving averages.

Figure 3 - Global CO2e emissions per region, from 1820 to today



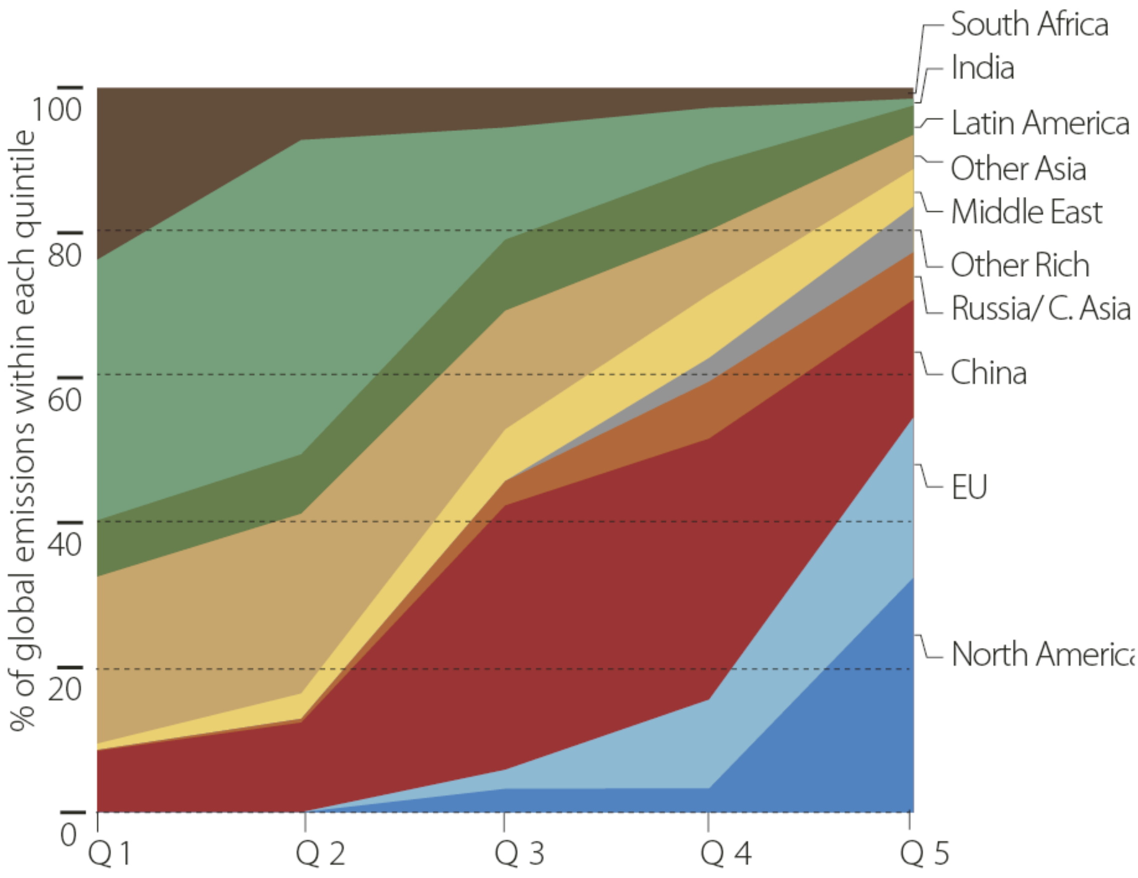
Source: authors' estimates based on CAIT (WRI, 2015), CDIAC (Boden et al., 2015), Maddison (Maddison, 2013). Key: Western European countries emit 3.5 billion tonnes of CO2e in 2012.

Figure 4 - Per capita GHG emissions per world region.



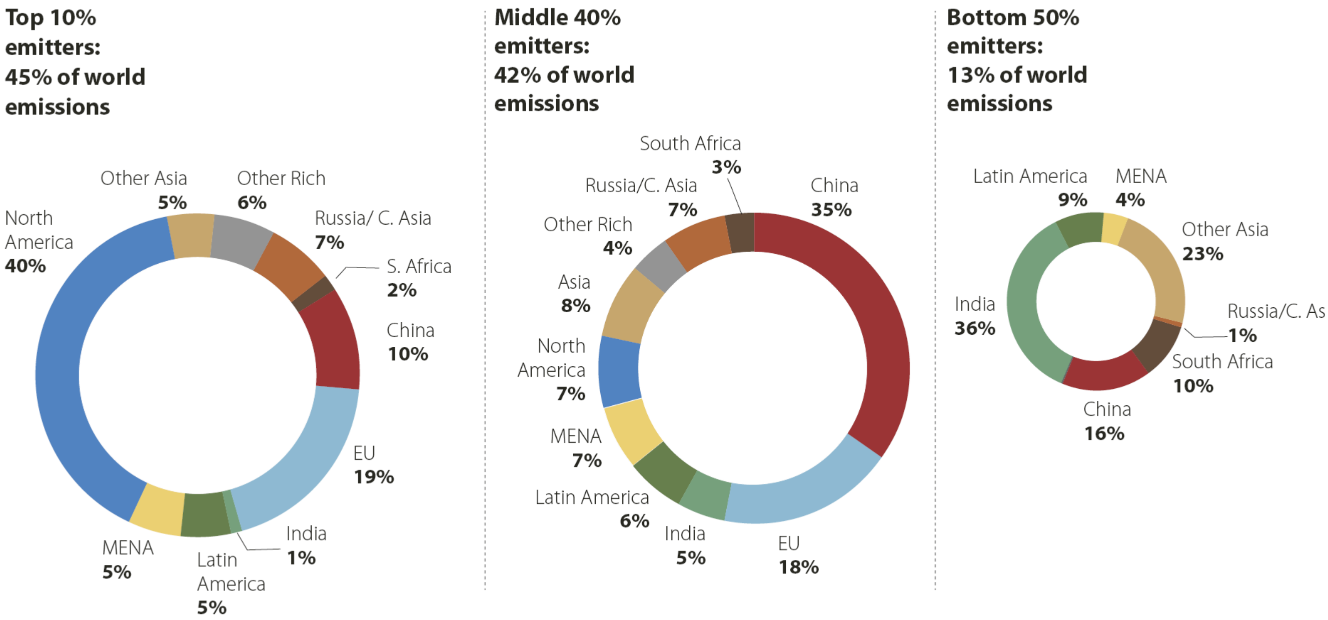
Source: Authors' estimates based on CAIT (WRI, 2015), CDIAC (Boden et al., 2015), Maddison (Maddison, 2013). Key: in 2012, the North American per capita CO2e emission average is 20.5tCO2e.

Figure 5 - Regional composition of emissions per global CO2e quintile.



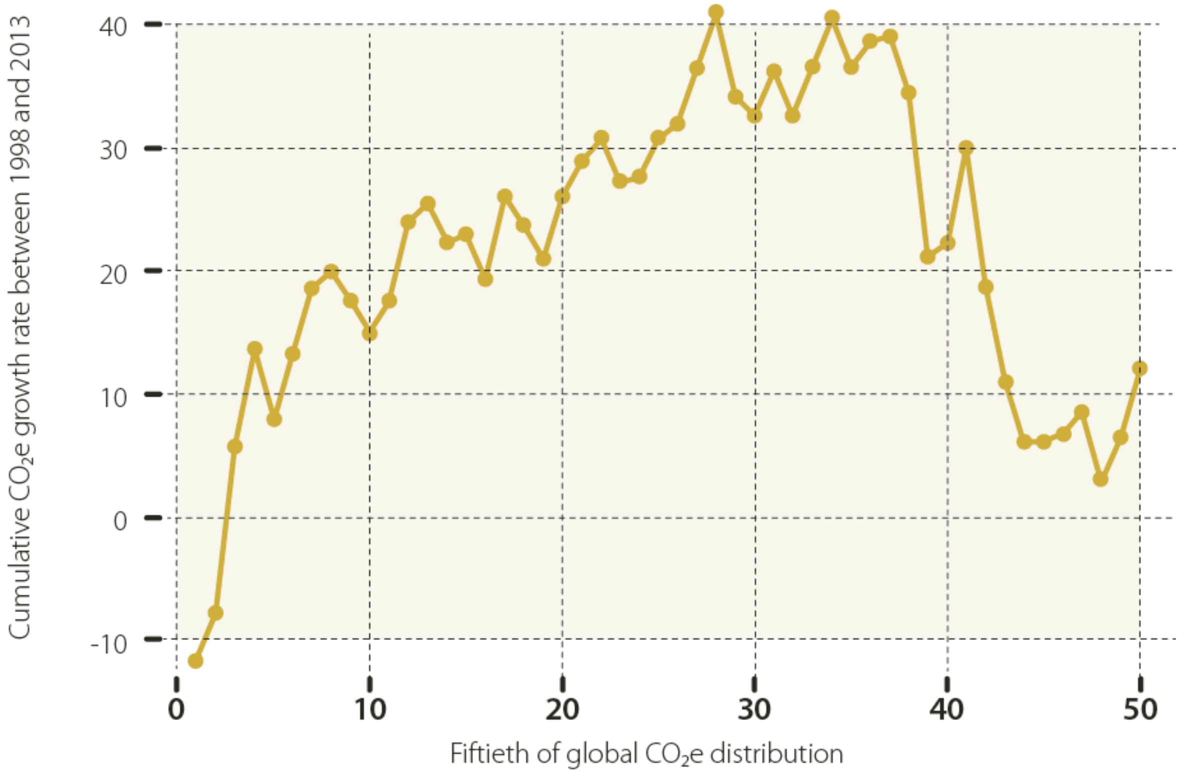
Source: authors. Key: 36% of emissions within the first decile of the global CO2e distribution (i.e. bottom 20% global emitters) come from India.

Figure 6 - Regional composition of top 10, middle 40 and bottom 50% emitter groups.



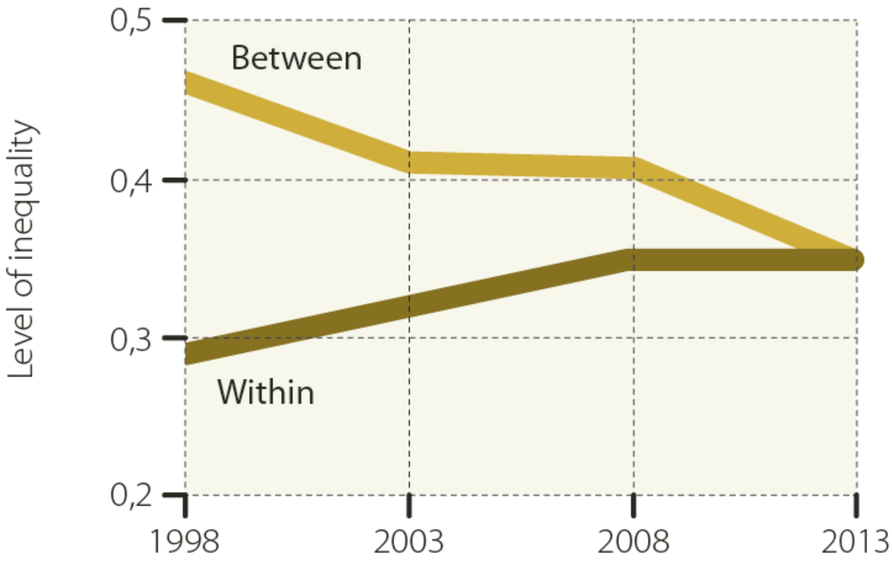
Source: authors. Key: Among the top 10% global emitters, 40% of CO2e emissions are due to US citizens, 20% to the EU and 10% from China.

Figure 7 - Growth of CO2e emissions from 1998 to 2013



Source: authors. Key: the group representing the 2% lowest CO2e emitters in the world, saw its per capita CO2e emissions level decrease by 12% between 1998 and 2013. Note that the composition of each quantile of the distribution can vary over time, i.e. the 2% lowest emitters group is not necessarily made up of the same country-income groups in 1998 and 2013.

Figure 8 - Evolution of within & between country CO2e emissions inequalities



Source: authors. Key: in 2008, the within country component of the Theil index was of 0.35 and the between-country component of 0.40.

Part III

From Measurement to policy

CHAPTER 5

The "frais réels" tax scheme: An unfair and unsustainable tax loophole?

In France, the taxable income of wage earners is based on 90% of salaried income rather than 100%. This measure was historically introduced to treat workers on a fair basis with respect to non-salaried income tax payers who do not have work-related expenses. To further guarantee a fair treatment between salaried taxpayers, the scheme makes it possible for those spending more than 10% of their income in work-related expenses, to declare the exact value ("frais réels") of these expenses. The "frais réels" scheme amounts to about an estimated €2 billion and the main source of deduction is related to transport expenses (about €1.6 billion according to our estimates).

In this chapter, we combine household transport survey data with income tax data to evaluate the social and environmental impact of the measure. We show that the scheme largely favors energy intensive and polluting vehicles, at odds with the French government's explicit objective to curb CO2 emissions related to the transport sector. In addition, by subsidizing long commuting travels, the measure is at odds with urban planning goals to limit urban sprawl. We also show that the "frais réels" cannot be justified on social justice grounds: the scheme is essentially to the benefit of richest taxpayers. The top 20% captures 50% of the gains associated to the measure, while the bottom 4 deciles are almost shut off from it. Restricting the analysis to transport-related expenses, we confirm this general pattern. The rich have more polluting cars and declare higher work-related distances, thus benefitting more from the measure than low income groups. This data adds to a growing literature on the distributional impacts of energy subsidies in rich or emerging countries (Rao, 2012; Sterner, 2012).

Two options to reform the scheme are discussed, the first one consists in revising the rules to measure transport related expenses so as to stop subsidizing polluting vehicles and high-income tax payers. Another, more ambitious reform is discussed. It calls for a better integration of fiscal policy, urban planning policy and low-income households support in the context of environmental transition policies.

This chapter is based on an article co-authored with Mathieu Saujot, entitled "Les frais réels transport: une niche fiscale inéquitable et anti-écologique", initially published as an IDDRI Policy Brief, 2012.

1 Contexte

Dans le contexte actuel de chômage de masse et de faible progression des revenus au bas de la pyramide sociale, de nombreuses voix opposent transition écologique et justice sociale, politiques environnementales et prospérité économique : les mesures pro environnementales sont souvent jugées anti-redistributives, venant gréver encore davantage le pouvoir d'achat des classes populaires.

A l'occasion du vote du projet de loi des finances de 2013, le débat sur les subventions anti-écologiques a pris de l'ampleur[100]: des acteurs associatifs ainsi que la cour des compte mettent en avant nombre d'avantages fiscaux allant à l'encontre du développement durable. Par ailleurs, de récents travaux[101] ont mis en avant le caractère inégalitaire de notre système de prélèvements, appelant à une remise à plat de ce dernier. Enfin, il apparait qu'un certain nombre d'outils fiscaux et financiers ont un impact considérable sur le développement urbain, sans pour autant qu'il y ait évaluation de leurs effets ni articulation avec les objectifs des politiques d'urbanisme[102]. C'est donc la cohérence des politiques publiques qui est ici questionnée.

Trois années après le projet avorté de taxe carbone en, début 2010[103], ces éléments ouvrent naturellement la porte à la question de la fiscalité écologique dans un contexte plus large : comment concilier équité et efficacité environnementale dans un système fiscal articulé aux politiques territoriales ? Nous nous demandons dans cet article si le remboursement par l'Etat des frais de déplacement domicile-travail, les « *frais réels* », constitue une **niche fiscale anti-écologique et inéquitable.** Pour répondre à cette question, nous analysons les effets de la niche sur le développement urbain et l'environnement d'une part et ses effets en termes de justice sociale d'autre part. A

[100] Voir par exemple l'appel du RAC et de la FNH, soutenu par un grand nombre d'association : http://www.stopsubventionspollution.fr/

[101] Cf. Landais et al. (2011)

[102] Voir par exemple les travaux de Renard(2006),

[103] Cf. Senit (2012)

travers cet exemple, il s'agit également de proposer une méthode pour analyser les niches fiscales dans le cadre d'une hypothétique réforme d'ensemble.

2 Les « frais réels », une subvention au développement non durable.

i. Description de la mesure

Afin de favoriser l'emploi et de protéger les salariés des dépenses induites par leurs activités professionnelles, l'impôt sur le revenu est calculé, pour les salariés et les exploitants professionnels, sur la base de 90% de leur revenu, et non sur 100%. Cette déduction forfaitaire de 10% est sensée couvrir les frais professionnels engagés par tous les salariés. Mais l'article 83.3 du Code des Impôts permet aux foyers fiscaux dépensant plus de 10% de leur revenu afin de satisfaire aux contraintes de leur travail, de déclarer ces frais supplémentaires. Ils ne sont donc plus soumis à la déduction forfaitaire de 10% mais à une déduction supérieure, correspondant au montant *réel* de leurs dépenses.

Ces frais peuvent être de différentes natures[104] : frais kilométriques, frais de nourriture, frais de vêtements, frais de matériel informatique.... Au total une quinzaine de types de frais sont déductibles. Ces déductions qui permettent de traiter ménages et entreprises de la même manière, selon le principe d'imposition du revenu net (les entreprises n'étant pas imposées sur leurs frais de fonctionnement) apparaissent également comme un moyen pour l'Etat de favoriser l'emploi en aidant les ménages à faire face aux dépenses qui y sont liées. Plus largement, c'est une des façons de répondre à la problématique ancienne de la prise en charge du transport des salariés, dont le « Versement transport[105] » est une autre dimension. Nous nous intéresserons à la

[104] Voir pour le détail, la brochure de l'administration fiscale : http://doc.impots.gouv.fr/aida/brochures_ir2012/ud_015.html

[105] Le Versement Transport : Les entreprises qui emploient à partir de 9 salariés dans un périmètre de transport urbain (en région parisienne ou dans le périmètre d'une autorité organisatrice de transport) sont soumises

dimension « frais kilométrique » de cette disposition fiscale[106], la principale en termes budgétaires selon nos estimations. Le barème publié annuellement par l'administration pour les calculer prend en compte l'entretien du véhicule, l'assurance et les frais de déplacement.

ii. Une mesure en contradiction avec les politiques environnementales de la France.

Le barème kilométrique est indexé sur la puissance fiscale du véhicule[107], les frais réels peuvent donc être assimilés à une subvention aux grosses cylindrées, les plus émettrices de CO2[108]. En effet la puissance fiscale du véhicule est corrélée positivement aux émissions de CO2 et aux autres formes de pollution. Toutes choses égales par ailleurs, un moteur plus puissant consommant plus de carburant rejette davantage de polluants.

Cela est contradictoire avec les engagements de la France en termes de réduction des émissions de CO_2 (l'objectif 20% de réduction d'ici à 2020 et division par 4 d'ici à 2050), les objectifs d'indépendance énergétique, et plus concrètement avec d'autres dispositifs financiers nationaux comme le bonus-malus. Par exemple, si un ménage aisé choisit une voiture de 10CV (175gCO^2/km) au lieu d'une voiture de 6CV (120gCO^2/km), cela lui coûte 750€ en malus, mais les frais réels lui rapportent 500€ sur la durée de possession du fait de l'indexation sur la puissance[109]. Les frais réels réduisent ainsi considérablement l'effet incitatif du malus.

au versement transport. Cette contribution est calculée sur la totalité des salaires soumis à cotisations ou de la base forfaitaire lorsqu'elle est applicable (sauf exceptions). Elle est recouvrée par les Urssaf au titre des cotisations sociales et est ensuite reversée aux autorités organisatrices de transports. Pour une agglomération comme celle de Grenoble, cela représente environ 80 millions d'euros par an disponible pour financer les transports en commun.

106 Les frais kilométriques sont limités à 40km quotidien, sauf justifications de conditions particulières.

107 Voir ici le barème kilométrique : http://www3.finances.gouv.fr/calcul_impot/2012/pdf/baremekm.pdf

108 Les véhicules de plus de 8CV ne représentent que 15% du parc automobile des particuliers. A titre d'exemple une Citroën C4 Picasso 110ch a une puissance fiscale de 6CV. Une Mercedes « Classe S » a entre 13 et 16 CV.

109 Comparons deux cas, dans le premier, le ménage a une voiture de 6CV et dans l'autre une voiture de 10CV. Les autres hypothèses sont inchangées : un ménage type marié avec deux enfants et un revenu net d'activité

Figure 1 - CO2 emissions and fiscal power in France, 2012

Les frais réels apparaissent d'autant plus en contradiction avec la politique environnementale lorsque l'on compare le coût d'une taxe carbone pour les ménages aux gains associés aux frais réels. Ainsi, pour un ménage aisé du 8ème décile[110], la taxe carbone, telle que proposée en 2009 aurait été de 35€ par an pour l'ensemble des transports en voiture du ménage (cf tableau 2). La déclaration des frais réels de transport lui permet d'économiser 460€ à l'année, soit treize fois plus. Le niveau des remboursements en jeu limiterait donc substantiellement l'effet de cette politique environnementale. Cela pose aussi une question sociale, un ménage pauvre du deuxième décile, parcourant le même nombre de kilomètres et payant aussi la taxe sur le carbone, n'aurait bénéficié d'aucune économie grâce aux frais réels ; nous reviendrons sur ces effets redistributifs en deuxième partie.

Les frais réels, parce qu'ils sont proportionnels à la distance parcourue pour se rendre à son travail, peuvent aussi apparaître comme une subvention à l'extension des aires urbaines. La mesure permet en effet de s'établir plus loin du lieu de travail ou d'y rester sans en subir les coûts de transport réels. Si nul ne s'amuse à calculer les gains liés aux frais réels et à les rapporter au coût du transport avant de signer un contrat d'achat ou de location, la mesure peut toutefois avoir un effet incitatif par l'intermédiaire de comportements de mimétisme, identifiés par les sociologues et les économistes comme des moteurs des choix individuels, certains ménages ayant un

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de 50 500€ (8ème décile de niveau de vie pour ce profil de ménage), avec 7400 km par an pour aller au travail pour la voiture principale (distance moyenne 8ème décile, ENTD 2008). Dans les deux cas, le ménage déclare parallèlement 2000km en frais réels pour la seconde voiture (ce qui permet de dépasser les 10% forfaitaires). Dans le cas où le ménage dispose d'une 6CV (par exemple un Picasso Hdi à 120gCO2/km, classe C), ses coûts kilométriques déclarés sont de 3561 €, selon le calculateur en ligne des impôts. Dans le second cas, le ménage dispose d'un Picasso Hdi de 10CV fiscaux (175gCO2/km, classe E pénalisé par un malus de 750€) et ses coûts kilométriques à déclarer sont de 4276€. L'impôt sur le revenu est de 2274 € d'impôts dans le premier cas et de 100€ de moins dans le second. Sur la durée moyenne de possession d'un véhicule, soit cinq ans, le gain pour le ménage à 10CV est de 500€.

[110] Le terme décile renvoie ici à chacun des dix groupes de revenu, de taille identique et classé par ordre croissant dans la distribution des revenus par unité de consommation.

raisonnement du type *« mon collègue a fait construire à 20km du travail, il est passé aux frais réels et il s'en sort… »*. Cette mesure apparait donc contradictoire avec les objectifs nationaux de développement urbain maitrisé, d'utilisation économe des espaces naturels et de réduction des émissions de gaz à effet de serre, tel qu'inscrits dans la loi SRU (2000) et les lois Grenelles et traduit dans les documents de planification (comme les SCOT).

Au regard du calcul du barème, du montant de la déduction et de l'effet incitatif qu'elle peut avoir, cette mesure n'apparait pas adaptée au contexte actuel, celui d'une hausse tendancielle des prix de l'énergie. Cependant, il convient de la replacer dans son contexte : la protection de l'environnement *n'est pas l'objet de cette mesure*, qui vise à protéger les *travailleurs*. Il s'agit donc dans un second temps d'interroger l'objectif premier de la mesure et d'étudier son impact social.

3 Les frais réels : une mesure au service des salariés les plus aisés.

i. A quoi sert la politique fiscale ?

La politique fiscale d'un Etat (menée par le biais de l'impôt, des taxes et des dépenses fiscales[111]) a trois principaux objectifs[112]. Le premier est la *collecte de fonds*, qui doit satisfaire aux besoins de la collectivité. En 2010, le montant total des prélèvements obligatoire est de 815 Mds d'euros, soit 48% du revenu national. L'impôt sur le revenu ne représente qu'une petite partie de ces prélèvements (environ 6%, cf. tableau 1). Le second objectif est *incitatif*: il s'agit, en jouant sur les prix du marché, de réguler l'activité économique en modifiant le comportement des acteurs et

[111] Une dépense fiscale est une exonération, un abattement, une déduction, une réduction de taux, une modalité particulière de calcul ou un crédit d'impôt (Guillaume, 2011 ; p 57). Dans le langage courant on parle de niche fiscale.

[112] Cf. Arkwright et al., 2012

d'encourager (ou de décourager) certains comportements. Le troisième objectif de la politique fiscale est la *correction des inégalités* : la DDHC de 1789 stipule que l'impôt doit être « *également réparti* » entre les citoyens, « *en raison de leur faculté* ». C'est l'objectif de la progressivité de l'impôt sur le revenu, des taxes sur les droits de succession par exemple.

Table 1 - Tax revenues in France, 2010

La plupart des niches fiscales s'attaque au second objectif de la politique fiscale. A titre d'exemple, la déduction de 50% de l'impôt sur le revenu du montant versé aux œuvres caritatives, a pour but de faciliter le financement de ces institutions, jugées utiles à la collectivité; la déduction de 50% sur les chèques emploi service permet de développer les services à domicile et lutter contre le « travail au noir ». Il ne faut cependant pas négliger le caractère politique et court-termiste de certains dégrèvements, qui sont mis en place pour répondre aux demandes de groupes de pression particuliers.

Les frais réels répondent au principe général d'imposition des revenus nets, tel que mentionné dans l'article 13 du Code des impôts. On retrouve notamment trace de la mesure dans le Code Général des Impôts de 1978. Alors que cette mesure constitue une déduction d'impôt sur le revenu, elle ne figure pas dans le rapport du Comité d'évaluation (Guillaume, 2011) des « Dépenses fiscales et des niches sociales »[113], qui cherche à évaluer la pertinence de l'ensemble des dépenses fiscales.

Au regard du poids de cette dépense fiscale (qui coûte chaque année, 2,1 milliards d'euros de manque à gagner à l'Etat, soit environ 1.4% de l'IR en 2010) et de ses incohérences avec les politiques environnementales identifiées précédemment, il nous semble pourtant légitime de l'interroger au regard des deuxièmes et troisième objectifs de la politique fiscale, de la même manière qu'une niche fiscale. Les frais réels

[113] Rapport du comité d'évaluation des dépenses fiscales et des niches sociales, Juin 2011

représentent en effet la moitié des niches liées à la consommation d'énergie et identifiées par le rapport du Comité d'Evaluation (2011). S'ils étaient pris en compte, ils deviendraient la 2ème dépense en montant, derrière l'exonération de la Taxe Intérieure de Consommation pour l'aviation, qui coûte chaque année, 3.5Md€.

ii. Une évaluation des frais réels

Dans un premier temps, nous nous demandons quel est l'effet incitatif des frais réels. Nous avons vu dans la première partie que la mesure constitue une subvention implicite à la conduite de véhicules énergivores et à l'étalement urbain, pratiques qui n'apparaissent pourtant négatives collectivité. Ces effets incitatifs ne justifient pas les frais réels.

Pour examiner l'effet de la mesure sur l'accès à l'emploi, il faut regarder son impact sur les différentes catégories de revenu. Le principe général du revenu net implique de retirer les dépenses contraintes du revenu imposable. Il convient donc de qualifier les dépenses contraintes liées à l'emploi. La réalité actuelle est celle d'un étalement urbain avec des franges d'urbanisation toujours plus lointaines des centres urbains qui continuent de concentrer les emplois[114]. L'émergence de la question de la précarité énergétique, dans sa dimension dépense de transport[115] est l'illustration de ces contraintes.

Toutefois, si certains ménages sont contraints, d'autres au contraire ont davantage de marges de manœuvre (Bigot, 2009), notamment dans leur choix de logement ou de véhicule. Ainsi, on peut se demander s'il est juste que la collectivité prenne en charge les frais professionnels des ménages lorsqu'ils touchent aux préférences individuelles ou au confort. Il s'agit de se demander si les frais réels sont progressifs et s'ils compensent bien les ménages dans le besoin.

[114] Insee Première, Le nouveau zonage en aire urbaine 2010, n°1375, Octobre 2011.
[115] Voir par exemple Saujot (2011), Adeus (2011)

iii. A qui profitent les frais réels ?

Nous présentons ici les gains liés aux frais réels par décile de niveau de vie[116]. Ces données transmises par le Trésor Public montrent clairement l'effet anti-redistributif de la mesure : plus le ménage est aisé, plus le gain obtenu grâce aux frais réels est élevé.

Les ménages pauvres et modestes[117] ne bénéficient presque pas de la mesure. Seuls 8% des ménages déclarent les frais réels. Ceux qui déclarent touchent en moyenne 66€ par an (soit 0,9% de leur revenu). Les ménages de la classe moyenne sont plus nombreux à déclarer (16%) et touchent en moyenne davantage, soit 385€ par an et par ménage (soit 1,9% de leur revenu). Les ménages aisés et les hauts revenus sont 12% à déclarer, ils touchent en moyenne 1063 € (soit 2,4% de leur revenu). Ces chiffres ne prennent pas seulement en compte les dépenses kilométriques mais correspondent à tous types de frais.

Figure 2 - Gains associated to the "frais réels" scheme, by income decile

La répartition des gains s'explique par le fait que les ménages les plus modestes ne sont pas soumis à l'impôt sur le revenu et sont peu nombreux à déclarer la mesure. Ceux qui déclarent sont imposés à un taux marginal faible et bénéficient peu de la réduction. Les ménages aisés doivent déclarer des montants très élevés pour bénéficier de la mesure et dépasser le seuil des 10% du revenu. Néanmoins, la répartition des gains par décile de niveau de vie reste très inégalitaire, puisque 40% des gains sont captés par les 20% les plus riches de la population française.

Ces données agrégées ont deux limites pour notre propos : d'une part elles recouvrent l'ensemble des frais réels (l'administration fiscale n'étant pas en mesure de

[116] Revenu du travail et du capital corrigé par la taille du ménage

[117] Ménages pauvres et modestes : les 30% des ménages en bas de l'échelle des niveaux de vie ; classes moyennes : 50% suivants ; ménages aisés et hauts revenus : 20% du haut de la pyramide des revenus. Grille du CREDOC (cf. Bigot, 2009)

dire précisément à quel type de frais le manque à gagner est attribué, ce qui est en soit problématique pour le suivi de cette dépense fiscale) et d'autre part, elles ne permettent pas d'expliquer finement l'inégalité observée entre les ménages. Pour approfondir l'analyse, nous croisons d'autres bases de données sur le niveau de vie des ménages (enquêtes Budget de Famille de l'INSEE) et sur leurs déplacements quotidiens pour leur emploi ainsi que sur la puissance motrice (enquête ENTD, CGDD-INSEE- Ifsttar).

Afin d'analyser l'effet distributif du remboursement des frais kilométriques, nous étudions les gains pour les dix déciles de revenu de quatre ménages types déclarant un revenu d'activité: couple marié (22% des ménages), couple marié avec deux enfants (20% des ménages), célibataire (20% des ménages), monoparentale un enfant (6% des ménages).

Pour chaque décile, nous utilisons les valeurs moyennes des distances domiciles travail et des revenus fournies par bases de données INSEE et CGDD. Ces valeurs sont introduites dans le simulateur de l'administration fiscale (Finances, 2012). Les ménages déclarant les frais réels ont probablement des distances plus grandes que la moyenne, ce qui explique leur passage aux frais réels. Nous sous-estimons donc les gains liés aux frais de déplacement pour chaque catégorie. Toutefois, même avec ces valeurs moyennes, sur chaque décile et chaque ménage type à l'exception des hauts revenus, nous retrouvons des gains liés aux frais réels proches des données de l'administration fiscale. Les frais kilométriques représentent la plus grande partie des frais réels (de 40% à 100% pour les déciles 4 à 9). En première approximation, nous estimons à 1,6 milliard les dépenses fiscales liées aux seuls frais kilométriques (Table 2)[118].

Table 2 - Total gains by income decile

Nous présentons sur la Figure 3 et le Tableau 3 les gains d'une famille de deux actifs et deux enfants, ainsi que pour les autres ménages types étudiés. Pour les déciles

118 Nous supposons que la population française est composée de quatre types de ménages (29% de mariés sans enfants, 32% mariés deux enfants, 29% célibataire et 9% adulte avec un enfant). Pour chaque ménage type, les gains sont calculés par décile de revenu. On calcule ensuite une moyenne pondérée par décile. Ce résultat est multiplié au nombre, réel, de ménages déclarant les frais réels sur chaque décile afin d'obtenir le coût total des frais kilométriques.

de la classe moyenne, ce ménage type pourrait correspondre à une famille accédant à la propriété en zone périurbaine. Les gains moyens simulés varient de 141€ à 380€ entre les 5ème et 9ème déciles. Ils culminent à 456€ pour le 8ème décile de niveau de vie. Trois facteurs expliquent les différences observées entre déciles de revenu : les puissances fiscales plus élevées chez les ménages aisés, les distances parcourues plus grandes chez ces ménages et des taux marginaux qui augmentent avec le revenu (et donc une déduction d'impôt plus importante).

Figure 3 - Gains induced by transport related "Frais réels" in euros, by income decile

Table 3 - Gains induced by the "frais réels" scheme

Pour le 10ème décile l'application de la méthode utilisée pour les 9 premiers déciles induit un gain réel lié au transport nul. En effet, le revenu moyen étant très élevé (la dispersion des revenus y est très forte), la dépense kilométrique ne dépasse pas 10% du revenu imposable pour les ménages types que nous simulons. Or nous savons que les frais réels totaux pour le dernier décile sont de 1618€ en moyenne, selon les données de l'administration fiscale. On ne peut exclure que le 10ème décile déclare 100% de frais réels hors transport, mais cette hypothèse demeure difficilement concevable. Les frais réels transport représentent en effet la totalité ou plus des trois quarts des frais réels de tous types confondus, selon nos estimations, pour les déciles 7,8 et 9. Pour le dixième décile, nous proposons donc des méthodes d'estimation complémentaires permettant d'affiner notre analyse.

Nous proposons deux alternatives pour approcher le gain lié aux frais réels transport du dernier décile, en insistant sur le fait qu'il s'agit là de premières approximations. L'accès aux micro-données fiscales permettrait notamment de mieux documenter les gains liés aux transport au sommet de la pyramide des revenus. La première stratégie alternative consiste à ne regarder que le premier tiers du dernier décile, plus homogène que l'ensemble du groupe. Du fait de la forte dispersion des revenus au sein du dernier décile, ce groupe a des revenus plus proches du revenu moyen du 9ème décile que de celui du 10ème. Pour cette catégorie, nous observons un gain lié aux frais réels proche de celui du 9ème décile. Une autre méthode consiste à supposer que les gains liés aux frais réels transport pour le dernier décile représentent la même part dans les gains liés aux frais réels totaux que pour le 9ème décile (soit 76%). Cette hypothèse mériterait d'être confrontée aux déclarations fiscales, mais en première approximation elle peut sembler réaliste. Il n'est d'ailleurs pas exclu que les enquêtes transports que nous utilisons, les plus hauts revenus sous-déclarent leurs revenus, comme c'est souvent le cas dans les enquêtes (Atkinson et al., 2011), ce qui peut avoir pour conséquence potentielle de réduire la distance domicile-travail calculée pour ce groupe (en gonflant la distance calculée pour les déciles inférieurs[119], à supposer que la distance domicile travail réel des plus hauts revenus soit plus élevée et que cette distance elle n'est pas sous-évaluée). Il n'est pas à exclure non plus que les ménages du dernier décile indiquent à l'administration fiscale des données kilométriques plus élevées que celles mesurées par les enquêtes statistiques. L'intérêt d'une telle déclaration est évident pour le déclarant et les échanges que nous avons eus avec l'administration en charge de traiter ces déclarations fiscales laissent à supposer que le taux de contrôle est faible.

iv. La mesure est-elle justifiée ?

La mesure ne semble pas correctement adaptée au niveau de contrainte des ménages. Les frais des ménages aisés, davantage remboursés que les autres, sont pourtant plus souvent le fait préférences individuelles que pour les autres ménages. Il est clair les ménages modestes ne bénéficient pas de cette aide. Par ailleurs, on peut se demander si le soutien apporté aux ménages de la classe moyenne inférieure, identifiés

[119] Dans ce cas de figure, un individu du dixième décile est alors compté dans le 9ème décile, mais avec un kilométrage élevé.

comme les plus vulnérables à des hausses des prix des carburants (CGDD, 2010 ; CERTU, 2010) est suffisant.

Il convient de replacer la mesure dans le cadre d'une réflexion plus large sur le système fiscal français. Les travaux de Landais et al. (2011) ont mis en avant le caractère inégalitaire de la fiscalité : alors que le taux global d'imposition devrait progresser avec le revenu des ménages, celui-ci ne progresse quasiment plus à partir du 5ème décile et décroît de manière significative à partir des 5% les plus riches. La déduction des frais réels renforce cette régressivité.

De plus, le fait de justifier les frais réels par le caractère contraint des dépenses de transport peut être perçu comme un aveu d'échec des politiques urbaines : celles-ci ne réussissent pas à organiser les villes de manière à limiter les coûts de mobilité pour les ménages et ce type de dispositif, subventionnant la distance, n'y est peut-être pas complètement étranger. Plus de 5 millions de personnes[120] utilisent les frais réels. Ceci révèle des formes urbaines génératrices de longs déplacements quotidiens et l'importance de cette mesure dans un tel contexte. Cette disposition fiscale sort donc du seul champ de la fiscalité pour entrer dans le domaine de la politique d'aménagement du territoire[121], et devrait donc être discutée en tant que telle.

Enfin, cette mesure est un dispositif statique qui ne propose pas d'amélioration et ne nous place pas sur une trajectoire vertueuse qui verrait le niveau de contrainte baisser. Elle encourage un statu-quo peu compatible avec les objectifs environnementaux et le contexte de hausse des prix de l'énergie.

4 Conclusion : Comment réformer les frais réels ?

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[120] Déclaration des revenus 2009, France entière « effectifs », http://www2.impots.gouv.fr/documentation/statistiques/2042_nat/Impot_sur_le_revenu.htm

[121] A ce titre, la lecture de l'argumentaire de l'amendement (retoqué) au PLF de 2006 est révélatrice. L'amendait visait à supprimer la limite des 40km et ses rédacteurs mobilisent l'aménagement du territoire (« la protection des campagnes ») pour justifier leur proposition.

Plusieurs critères doivent être pris en compte pour réformer la niche fiscale étudiée dans cet article. Les frais réels doivent soutenir les ménages qui en ont réellement besoin. D'autre part, la mesure ne doit pas contrevenir à l'objectif de progressivité de l'impôt ni aux autres outils de la politique environnementale. En règle générale, la mesure doit être mieux coordonnée avec les autres outils de la politique publique et être compréhensible aux yeux des citoyens. Remplir tous ces critères à la fois pose une double question *i) celle des modalités d'une réforme à la marge des frais réelles et ii) celle d'une réforme des dispositifs d'aides aux ménages précaires dans le cadre d'une réforme plus large de la fiscalité.* Nous proposons donc deux options de réformes, la première, améliorant le dispositif actuel de manière limitée, peut servir de prélude à la seconde, plus générale.

Première option de réforme : un plafonnement du barème kilométrique et du niveau de revenu. Le prochain projet de loi de finances pourrait redéfinir le barème kilométrique applicable aux frais réels. Comme nous l'avons montré, le barème actuel contredit les outils de la politique environnementale et bénéficie davantage aux ménages aisés. Il conviendrait donc de fixer un seuil au-delà duquel une voiture plus énergivore ne rapporterait pas davantage de déduction fiscale aux ménages. Cette limite pourrait être le seuil des 7CV (en dessus duquel on compte seulement 15% des véhicules particuliers -ENTD, 2010). D'autre part, la réforme pourrait intégrer davantage de progressivité, en indexant le taux de remboursement sur le niveau de revenu. Mais, si l'objectif des frais kilométriques est d'aider les ménages réellement dans le besoin, la conditionnalité devrait combiner un critère revenu à d'autres critères plus locaux. Or il n'est pas possible de penser cela en dehors d'une réforme systémique de la fiscalité et des outils de la politique d'accompagnement des ménages précaires.

Deuxième option: supprimer les frais réels et penser la mesure dans une réforme plus large de la fiscalité[122].

[122] Par ailleurs, dans le cadre d'une réflexion plus générale sur la prise en charge par l'Etat des frais professionnels des salariés, on pourrait également questionner le forfait de 10% applicable à tous les contribuables. Les très hauts revenus, supérieurs à 1 000 000 d'euros par an, voient leur revenu imposable déduit de 100 000 euros

Dans le cadre d'une réforme plus large de la fiscalité, qui réaffirmerait la progressivité de l'impôt et réexaminerait la justification et le coût des niches fiscales, les frais réels pourraient laisser place à des mesures ciblées d'accompagnement des frais professionnels des ménages les plus contraints. Ceci aurait l'avantage de rendre plus efficace et plus visible aux yeux de la collectivité ces mesures d'accompagnement qui coûtent cher à l'Etat et qui ne bénéficient pas forcément à ceux qui en ont besoin. La suppression des frais kilométriques nécessite donc de reposer la question des inégalités et de la fiscalité dans le cadre d'une économie où les prix de l'énergie augmentent tendanciellement. Quelles variables retenir pour satisfaire à l'exigence de justice sociale et aux contraintes de l'appareil statistique ? Cette question est délicate et nécessite davantage d'approfondissement.

Par ailleurs, cette remise à plat devra se faire avec l'Acte III de la décentralisation. Nous avons vu que les frais réels constituent d'une certaine façon une politique urbaine *implicite*. En subventionnant les coûts de déplacements, ils rendent plus accessibles la périphérie et peuvent ainsi favoriser son développement. Or cette niche fiscale a le défaut de traiter de manière très générale une question où la dimension égalitaire et territoriale devrait être étudiée plus finement. Une politique *explicite*, dirigée vers les ménages précaires ou vulnérables[123] ne gagnerait-elle pas à associer les collectivités locales ? D'une part l'identification des zones et des types de ménages les plus contraints est disponible localement[124] et s'inscrit plus largement dans une connaissance de son territoire par les acteurs locaux. D'autre part, celles-ci pourraient ajuster l'aide au niveau de l'offre de transport public (transport en commun ou nouvelles offres de mobilité) et la combiner avec une maîtrise de l'usage des sols (zonage donnant droit ou non à cette aide) : ainsi cette mesure pourrait favoriser le développement urbain souhaité par la collectivité plutôt que d'interférer avec la politique d'aménagement. Or

automatiquement, au titre de leur frais professionnels. Or il est peu probable que leurs frais professionnels dépassent cette somme.

[123] CGDD, 2010

[124] Les études citées s'appuient sur les EMD, Enquête Ménages Déplacement, menées à l'échelle des aires urbaines

les collectivités locales n'ont pas la main sur cet aspect de la fiscalité des ménages. Enfin, les collectivités perçoivent déjà le Versement Transport versé par les entreprises pour le financement des transports publics urbains. Dans la perspective de revoir les modes de financements de la mobilité de manière, et non mode par mode, une partie de la dépense fiscale pourrait être dirigée vers les territoires. On pourra alors concilier plus largement justice sociale et politiques environnementales.

Dans ce chapitre, nous avons identifié une niche fiscale en contradiction apparente avec les objectifs généraux des politiques publiques (ici, environnementale et sociale), nous avons évalué la niche au regard de son objectif principal, de son impact sur l'environnement et de son coût global. Dans le cadre de la remise à plat de la fiscalité française, ce travail doit être approfondi, et pourrait être élargi à d'autres types de dégrèvements.

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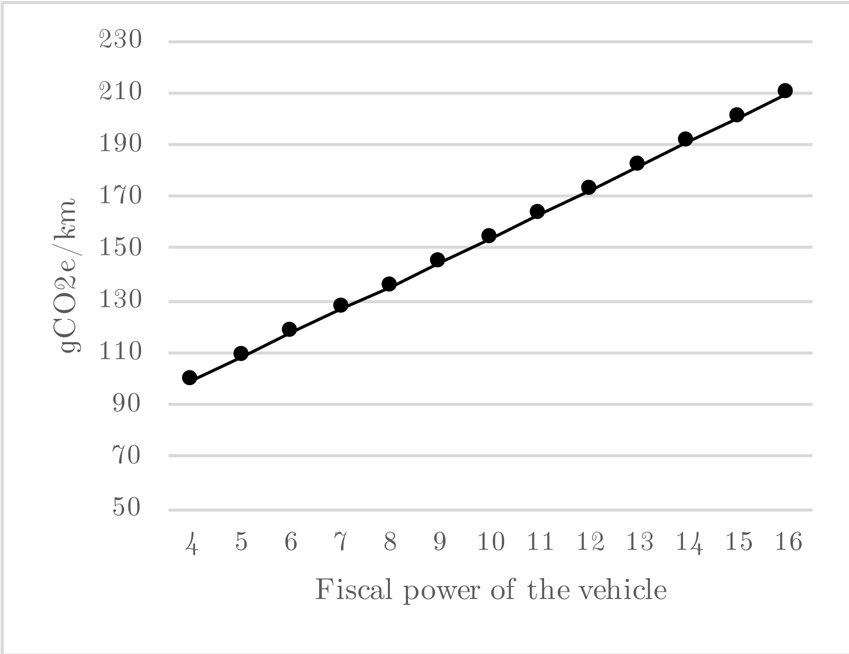
Table 1 - Tax revenues in France, 2012

	Recettes (Mds €)	% Revenu National
Impôt sur le revenu	**146**	**9%**
IRPP	*52*	*3%*
CSG	*94*	*6%*
Impôt sur le capital	**62**	**4%**
Impôt sur les bénéfices	*35*	*2%*
Taxe foncière, ISF, droits de succession	*27*	*2%*
Impôt consommation	**225**	**13%**
Cotisations sociales	**386**	**23%**
Maladie, famille	*164*	*10%*
Retraite, chômage	*221*	*13%*

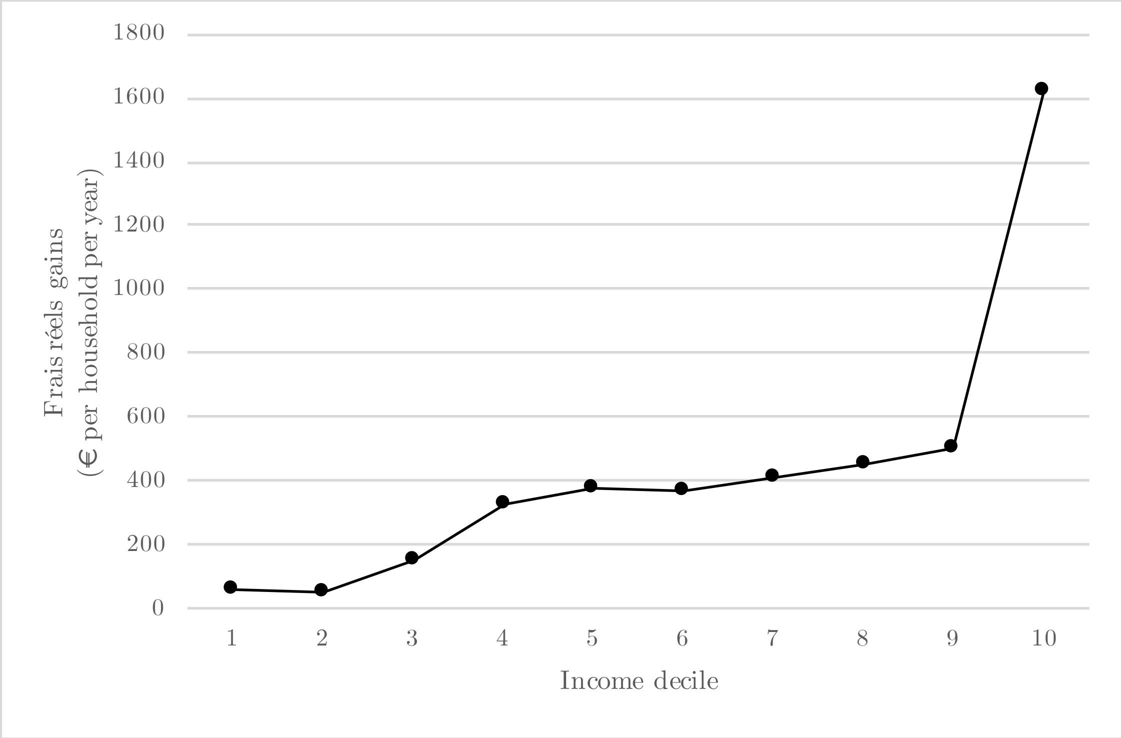
Source : Landais et al., 2011

Figure 1 - CO2 emissions and fiscal power



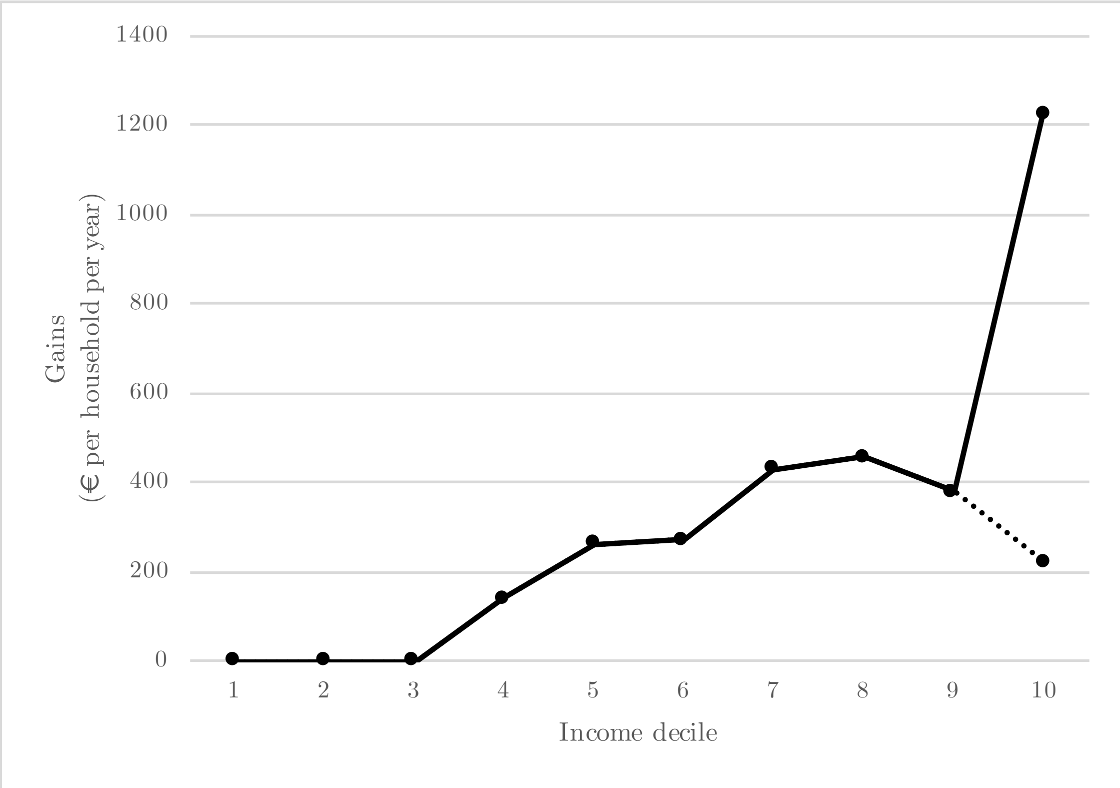
Source: Authors based on Ademe (2012). Note: the graph shows average CO2 emissions of new vehicles in 2012.

Figure 2 - Total gains induced by the "Frais réel" scheme, per income decile



Source: Authors based on DGFIP data.

Figure 3 - Gains induced by transport related "Frais réels" in euros, by income decile



Source: Authors' estimates based on DGFIP data, INSEE BDF and ENTD. The thick line represents our preferred strategy (assuming that the share of transport related frais réels in Decile 10 tax units is the same as in Decile 9). The dashed line represents the gain for the first tier of Decile 10, as described in the text.

Table 2 - Total gains by income decile

Decile	Average gain weighted by household type (€ per year per tax unit)	Number of tax units declaring "frais réels"	Total gains per decile (millions €)	% total gains
1	0	78416	0	0%
2	0	302913	0	0%
3	0	479306	0	0%
4	95	567933	54	3%
5	293	607236	178	11%
6	298	618684	184	11%
7	423	641167	271	17%
8	418	647218	271	17%
9	457	555633	254	16%
10	1258	332985	419	26%

Source: Authors' estimates based on DGFIP data, INSEE BDF and ENTD. Decile 10 gains are based on our preferred estimation strategy (assuming that the share of transport related frais réels in Decile 10 tax units is the same as in Decile 9).

Table 3 - Gains induced by the "frais réels" scheme

	Income Decile	1	2	3	4	5	6	7	8	9	90-93 percentiles (S1)	10 (S2)	10 (S0)
	Annual commuting distance (km)	4794	5781	6063	6204	6063	7097	7097	7379	7755	7849	7849	7849
	Fiscal power 1st vehicle	4	5	6	6	7	7	8	10	12	13	13	13
	Fiscal power 2nd vehicle	3	4	5	5	6	6	7	9	9	9	9	9
	Gains induced by frais réels	60	50	140	330	380	370	412	450	500	873	1618	1618
Married couple, 2 children	Net taxable income	5700	15500	21500	27700	32600	37700	43880	50650	62890	75075	103770	103770
	Estimated annual gains induced by Frais réels (all kinds) (% taxable income)	1.1%	0.3%	0.7%	1.2%	1.2%	1.0%	0.9%	0.9%	0.8%	1.2%	1.6%	1.6%
	Annual gains induced by Frais réels (transport) (€)	0	0	0	141	263	271	430	456	378	223	1223	0
Married couple, no children	Net taxable income	3900	10966	15448	19450	23202	26600	30870	36375	44600	53600	72000	72000
	Estimated annual gains induced by Frais réels (all kinds) (% taxable income)	1.5%	0.5%	0.9%	1.7%	1.6%	1.4%	1.3%	1.2%	1.1%	1.6%	2.2%	2.2%
	Annual gains induced by transport Frais réels	0	0	0	0	300	384	702	655	634	570	2052	0
1 adult 1 child	Net taxable income	4168	11043	15212	19400	23070	26560	31040	35896	43222	52000	58279	58279
	Estimated annual gains induced by Frais réels (all kinds) (% taxable income)	1%	0%	1%	2%	2%	1%	1%	1%	1%	2%	3%	3%
	Annual gains induced by transport Frais réels	0	0	0	102	197	136	100	95	141	0	456	0
1 adult	Net taxable income	2630	7638	11056	13680	16240	18826	21730	25780	30925	37760	50527	50527
	Estimated annual gains induced by Frais réels (all kinds) (% taxable income)	2%	1%	1%	2%	2%	2%	2%	2%	2%	2%	3%	3%
	Annual gains induced by transport Frais réels	0	0	0	138	349	290	232	236	463	339	1498	0

Source: Author's estimates, based on INSEE (2011), ENTD and DGFIP data. S0 corresponds to the standard method described in the text (which is irrelevant for the top decile). S2 corresponds to our preferred alternative method to measure transport related gains for the top 10%, ie. assuming that the share of transport-related frais réels gains is the same for the top decile than for the 9th decile group.

CHAPTER 6

Assessing the potential of Sustainable Development Goals

Recognizing that rising economic inequality challenge has become a universal issue, the United Nations agreed in 2015 to seventeen Sustainable Development Goals (SDGs), as part of a global agenda to transform society. Specifically, SDG Target 10 commits countries to 'reduce inequalities within and among countries'. To what extent SDGs and in particular SDG target 10 can help nations reverse inequality towards a downward trend is the question we address in this chapter.

To answer this question, we build on the theory of change underpinning the goal-based governance characterizing the SDGs, then we infer the added value of the SDGs along three criteria: the production of a common metric, the capacity to emulate peer pressure, and policy learning within and across countries. Across these three criteria, our main finding is that there is much that states can take away from the SDGs to address the problem of rising inequality, though success is conditional on achieving the buy-in of key actors and epistemic communities for which domestic inequalities remains a domestic issue and not a global sustainability one.

This chapter is based on the article entitled "Reducing inequality within countries: Assessing the potential of Sustainable Development Goals" published in Global Policy (Vol 9, issue 1), co-authored with Alex Hough and Tancrède Voituriez.

1 Introduction

Income and wealth inequality are rising in most countries around the world today as chapter 2 has demonstrated. Recognizing that this challenge has become a universal issue, the United Nations agreed in 2015 to seventeen Sustainable Development Goals (SDGs), as part of a global agenda to transform society. Specifically, SDG Target 10 commits countries to 'reduce inequalities within and among countries'. To that end, the SDG framework calls on states to articulate nationally specific implementation strategies and to put in place monitoring and review processes in order to meet the goals.

So far, country responses have been sporadic and inconsistent, and there has been little articulation about what Target 10 means in terms of national-level implementation. Reducing inequality *between* countries – that is to say, increasing the national income of poor countries relatively quicker than rich countries – has been at the core of development thinking for decades and motivated the creation of dedicated institutions such as the International Development Association (1960, as part of the World Bank Group) and UNCTAD (1964). More recently, rising inequality *within* countries, with an overall increase in top income and wealth shares particularly in high-income countries like Britain and the United States, combined with significant increases in the coverage of available data, have brought to light the need to consider within-country distributional outcomes. However, it is less immediately apparent what role an international framework can and should play in mediating within-country inequality. While some contributing factors like tax evasion, for example, readily lead to the need for a coordinated response between countries, other factors, like national taxation and social spending, are considered as domestic issues traditionally outside the remit of international governance frameworks. To what extent SDGs and in particular SDG target

10 can help nations reverse inequality towards a downward trend is the question we address in this chapter.

To answer this question, we proceed in four steps. First, we review the substantive reasons why within-country inequality has become a global sustainable development issue (section 1), and we detail the political process it underwent to become a stand-alone SDG target (section 2). We build on the theory of change underpinning the SDGs to set up a framework of analysis and infer the added value of the SDGs (section 3). Applying this framework to SDG target 10, we provide an assessment of the potential contribution of SDGs to inequality reduction within countries (section 4). We conclude by delineating consistency gaps which would need to be bridged to significantly increase the contribution of SDGs to domestic income and wealth inequality reduction. Our main finding is that there is much that states can take away from the SDGs to address the problem of rising inequality, though success is conditional on achieving the buy-in of key actors and epistemic communities for which domestic inequalities remains a domestic issue and not a global sustainability one.

2 Why inequality has become a universal sustainable development issue

After decades of divergence across countries per capita income, there is evidence of convergence at the global level since the 1990s, and in particular since the 2000s (Bourguignon, 2015; Milanovic, 2010; Stiglitz, 2013). Global convergence between rich and poor countries has been driven by Asian countries, first China and India, and now the whole Asian region, where incomes have risen rapidly relative to advanced economies. However, much remains to be done: incomes in Asia remain a quarter of those in the developed world, and convergence has been largely absent or fragile outside of Asia. Latin American and the Caribbean have shown more recent signs of income growth over the last decade, while Africa and Oceania have contributed little to global convergence. On average, in 1990, Africans earned 12% of the developed country income when adjusted for PPP; this figure remained the same in 2014 (Julca et al, 2015).

Uneven economic convergence across countries occurred alongside an unprecedented rise in inequality within countries (Atkinson, Piketty, Saez, 2011 ; Piketty, Saez, 2014). Drawing on the new World Wealth and Income Database (WID.world) database, we present the evolution of top 1% income shares – a telling metric of inequality – in developed economies and developing economies alike. The extent of the increase varies across countries, but in nearly all nations, the general tendency is one of rising top 1% income shares since the late 1970s. In the USA, top 1% fiscal income share was close to 10% forty years ago, and is now above 20%. Over the same period, top 1% fiscal income share increased from 6.5% to 13% in China.

i. Inequality as a health problem

Cross-sectional studies show a robust and statistically significant positive correlation between inequality and incidences of health and social problems in advanced countries (see for example Wilkinson and Pickett, 2009). Wilkinson and Pickett's prominent work, *The Spirit Level,* aggregates bi-variate analyses for a range of dependent variables pertaining to health and social problems. As summarised in the postscript to the second edition, they find that 'when people in the same social class, at the same level of income or education, are compared across countries, those in more equal societies do better' (Wilkinson and Pickett, 2010, 275–6). More recent work has attempted to establish causality. In a review of the literature, Wilkinson and Pickett find that the major epidemiological causal criteria are 'well supported' and that, therefore, 'narrowing the gap will improve the health and wellbeing of populations' (Wilkinson and Pickett, 2014, 316). On health, causality between inequality and health problems is relatively well supported, though it is understood to operate indirectly, through 'status anxiety', which may explain why individual level studies find ambiguous results (Bergh, Nilsson and Waldenström, 2016). On the other social problems, causality is harder to establish, owing in part to the lack of clear understanding about the causal mechanism through which inequality impacts society (Rowlinson, 2011).

However, even without the assurance of causality, the robust correlation between inequality and the incidence of health and social problems is highly consistent with the integrated SDG approach, which seeks to reinforce positive interactions across the goals.

ii. Inequality as an economic problem

Multiple studies support that inequality has a negative impact on growth (Cingano, 2014; Ostry et al, 2014). Measured by the Gini index, the impact of inequality on growth is significant. In OECD countries, a one-point decline in the Gini index would translate to an increase in cumulative growth of 0.8 percent per year for the following 5 years (Cingano, 2014). Furthermore, inequality as measured by the Gini coefficient is a significant explanatory variable of the duration of growth spells: Ostry et al. (2014) find that 'a one-Gini-point increase in inequality is associated with a 6 percentage point higher risk that the spell will end the next year' (p. 23). Dabla-Norris et al (2015) have shown that a relative rise in top quintile incomes has a negative long-term impact on growth, while growth in the bottom quintile is highly correlated with growth. This corroborates similar results produced by the OECD, that shows that the changes in the bottom quantile as a fraction of the mean are robust and statistically significant explanatory variables of national growth (Cingano, 2014).

The effect of inequality on growth can operate through multiple channels. First, the societal problems associated with inequality incur explicit remedial costs that would not otherwise have been incurred if inequality were less severe. For example, the Equality Trust (2014) estimated that, if the UK reduced inequality so that of the OECD average, expenditure savings on physical and mental illness, violence and imprisonment alone would amount to £39 billion per year. Second, inequality harms growth by reducing disadvantaged groups' access to public goods (Stiglitz, 2013). In a regression analysis framework focusing on all OECD countries, Cingano (2014) find that the negative impact of inequality on growth is essentially due to lesser access to education for disadvantaged groups, as well as to the reduced quality of education for a given year of school enrolment. This inequality in access to quality education reduces individual capabilities throughout their lifetime, and leads, in turn, to a decline in the productivity of the economy as a whole. Third, inequality can harm growth through reducing motivation at work. Using randomized control trials, Fehr et al. (2009) in Switzerland and Breza et al. (2015) in India showed that pay inequality has strong and significant impacts on labour productivity: more precisely, workers paid more than their peers do not produce more than the average, while workers paid less exhibit a strong reduction (about 30% in the Swiss case). In a similar vein, Card, Mas, Moretti and Saez (2012) show that wage inequality affects job satisfaction in California. Fourth, low income households have a higher marginal propensity to consume compared to high income households. Increase in inequality thus tends to reduce overall consumption growth (Johnson, Parker and Souleles, 2006).

iii. Inequality as a political problem

Multiple channels provide possible explanations for a link between inequality and political instability. First, the power of the wealthy extends to a measurable degree of influence in the law. Through multi-variate analysis of the United States, Gilens and Page (2014) find that 'economic elites and organized groups representing business interests have substantial independent impacts on U.S. government policy, while average citizens and mass-based interest groups have little or no independent influence' (p. 564). Second, McCarty, Poole and Rosenthal (2002) study the relationship between political polarization and inequality in the USA, through several decades of congressmen's vote records and opinion polls. They show that polarization decreased with inequality in the first part of the 20th Century and rose with it from the mid 1970s onwards. Polarization makes the Republican Party more pro-rich and less likely to adopt inequality reduction policies. A more polarized political system is also said to be less likely to adopt transpartisan, lasting policies.

In line with the polarization channel, a recent study shows that individuals with stagnant incomes over the past decades in the USA and major European countries are more likely than others to support right wing political parties and hold negative view on immigration (McKinsey GI, 2016). The causes for right wing political support are indeed diverse – but such results could support the claim that rising inequalities are challenging the foundations of open parliamentary democracies (Stiglitz, 2013).

iv. Inequality as an environmental problem

Several studies suggested a link between inequality and environmental quality via two causal channels. The 'Veblen effect' channel posits that the more unequal societies, the more individuals consume to differentiate themselves from other social groups. The mechanism of consumption as a way to mark a certain lifestyle has been relatively well established (Heffetz, 2010). Bowles and Park (2005) show that more unequal countries are countries where people work more and argue that this is due to a Veblen effect: lower ranked individuals work more to replicate the lifestyle of higher ranked individuals. When dominant lifestyles are unsustainable – which is the case, the overall environmental of such consumption dynamics is negative.

The other channel through which inequality impacts on environmental quality was introduced above: unequal societies are more polarized societies, in which agreement on trans partisan policies (such as environmental policies) is more complicated. Inequality renders more difficult the agreement on and the implementation of environmental policies (Laurent, 2014; Hourcade, 2013), such as carbon taxes. In addition, it has been argued that elites can, at least for a certain amount of time, protect themselves from environmental degradation (Boyce, 2007). That being said, empirical studies on inequality and the environment offer mixed results. While theoretical links can be convincing, more work is required to fully understand the extent of the problem raised by inequality on environmental degradation.

It should also be noted that inequality reduction can nonetheless be negative for the environment: when achieved through income growth at the bottom end of the distribution, it can lead to higher overall pollution levels. At the individual level, income is positively linked with carbon emissions (Wier et al, 2001; Lenzen et al, 2006; Lenglart et al, 2010). Therefore, under current production and consumption patterns, inequality reduction achieved through the growth of incomes among low earners would counteract carbon mitigation efforts at national and global scale (See chapter *"Carbon and Inequality: From Kyoto to Paris"*).

3 How inequality reduction has become part of the global policy agenda

In developing a response to rising inequality, policy makers and academia have sought to identify the drivers of inequality. A vast literature posits and tests theoretical drivers of inequality, and of subsequent policy areas to address these drivers (for an overview of this literature, see for example, Atkinson, 2015). The sheer scale of existing literature on this subject suggests that inaction does not derive from a knowledge-gap. After a decade of landmark research, coverage and quality of available data on global inequality have expanded significantly (Milanovic, 2013; WID, 2016). Though much remains to be learned, to a significant extent, the core drivers of inequality are known, and can guide policy response.

It has been common to divide the drivers of inequality into categories, first between technology and globalisation (for example, Katz and Autor, 1999) and then, more recently, between technology and trade openness viewed in concert, and policies and institutions (for example, OECD, 2011; Milanovic, 2016). These distinctions are partly artificial and can be, at times, misleading. The nature and extent of technological innovation and openness are, to a large extent, determined by policies and institutions, and the effect of both factors is itself contingent on national-level policies and institutions (Mazucatto, 2013 ; Atkinson, 2015). We therefore endorse the view of Atkinson (2015) and others that, based on the knowledge that we have about the drivers of inequality, the response to rising inequality should be framed around policies and institutions.

International development institutions have, until recently, paid limited attention to domestic inequality issues, considering the reduction of inequalities as a sovereign issue for each country, or positing inequalities as a necessary evil towards global improvement of wellbeing. Domestic income inequalities have been politically confined in the shadow of absolute poverty until the SDGs replaced the Millenium Development Goals (MDGs, see Kabeer, 2010; Langford, 2010; de Albuquerque, 2012). Until then, the few appearances of domestic inequalities in the global development agenda had narrowed them to inequalities of opportunities and access—without any significant mention of income or wealth (World Bank, 2006).

In this context, the unanimous endorsement of SDG Target 10.1 by the UN Member States marks an important shift. Target 10.1 explicitly includes domestic inequality reduction in the global development agenda. It states:

> "By 2030, progressively achieve and sustain a reduction in income inequality, as measured by the share of the bottom 40 percent of the population in national income, alongside economic growth".

The target was the subject to harshly contested debates in the Open Working Group in charge of establishing a list of goals and targets for intergovernmental negotiations. There were calls for a target for reducing income inequality within countries, measured by the Gini coefficient or the Palma index (Engberg-Pedersen 2013). Meanwhile, the report of the High-Level Panel argued against a target for addressing domestic income inequality on the grounds that 'countries differ widely both in their view of what levels of income inequality are acceptable and in the strategies they adopt to reduce it.' *(HLP, 2016)* Several countries such as the USA and Canada contended that a standalone goal on inequality could 'lead to a sterile debate' and that domestic inequality reduction would better be achieved through other goals such as economic growth or a fair access to productive assets. Other countries like China and Indonesia argued that within-country inequalities objectives tended to place a higher burden on developing countries than on OECD economies, and that 'promoting equality should not be a standalone goal area.' (Chancel and Voituriez, 2015).

After the target was removed from the draft-list in the course of 2014, a group of countries led by Denmark, Norway, and Brazil supported its re-inclusion. Denmark, along with Norway, argued that the rise in inequalities found its roots in 'exclusive growth' and that a specific metric should be used to ensure that growth resorbs inequalities rather than triggers them. As for Brazil, while stressing the need to reduce between-country inequalities, it also supported the inclusion of domestic inequality reduction targets. This second group of countries was successful in including the domestic target in the final list, after campaigns from NGOs and lobbying from influential academia such as J. Stiglitz (Doyle and Stiglitz, 2014).

4 Inferring the added value of SDGs: A framework for analysis

While there are diverse narratives explaining how and why the SDGs were set up, the core idea is that they were designed to fill an implementation gap (Caballero, 2015; SDSN, 2015). The 2030 Agenda calls for countries to develop action plans from their existing national sustainable development strategies and to align their policies with the SDGs and associated targets.

Though the theory of change underpinning the SDGs is not explicit when reading the Agenda 2030, it sits in a clear lineage of "goal setting" development strategies starting with the new public management principles across public administration in OECD countries in the 1980s, and also in the wake of the MDGs twenty years later. Young (2017) recalls that goal setting seeks to steer behavior by (i) establishing priorities, (ii) galvanizing the efforts of those assigned to work toward attaining the goals, (iii) identifying targets and providing yardsticks or benchmarks to be used in tracking progress, and (iv) combating the tendency for short-term desires and impulses to distract the attention or resources of those assigned to the work of goal attainment. He then infers that devising a clear-cut metric is both a requirement and expected outcome of goal-setting as a governance strategy. Following Young (2017), we identify the provision of a harmonized metric as the first contribution of SDGs to fostering action.

Furthermore, Young (2017) makes a distinction between goal-setting and rule-making:

> « The essential premise of goal setting as a governance strategy (...) differs from the premise underlying rule making. Whereas rule making features the formulation of behavioral prescriptions (for example, requirements and prohibitions) and directs attention to matters of compliance and enforcement, goal setting features the articulation of aspirations and directs attention to procedures for generating enthusiasm among supporters and maximizing the dedication needed to sustain the effort required to reach more or less well-defined targets. Moreover, whereas goal setting normally features the mounting of a campaign designed to attain goals within a specified time frame, rule making features the articulation of behavioral prescriptions expected to remain in place indefinitely. »

This distinction is particularly important in the case of the SDGs which do not contain legally binding compliance and enforcement mechanisms. Instead, what is implicitly expected is that '(o)nce the goals are established, efforts to attain goals normally proceed in *campaign mode*' (Young, 2017).

In concrete terms, the kind of campaign that can be expected to foster the achievement of goal 10 and its associated targets cannot easily be prescribed. The theories of change of campaigners would deserve a chapter in its own right. Nonetheless, some key principles to direct the campaigns can be articulated. To that end we draw on a recent paper which distilled key principles for a theory of change in the broad field of development (Valters, 2015). Valters posits that theories of change serve to support learning. Following Young et al. (2015), the purpose of learning in this context is in being 'accountable, improving operations, readjusting strategy, strengthening capacity, understanding the context, deepening understanding (research), building and sustaining trust, lobbying and advocacy and sensitising for action'. The MDGs – that proceeded the SDGS – reflect these principles: decisive in focusing policies, financing and campaigns, the first series of development goals radically changed donors' conception of development, instilling the idea of development as a trial-and-error process on the various *means* for a given end – the MDG list (Banerjee and Duflo, 2011). The simplicity of the targets that set absolute goals served as a strong conduit for state action and guided international funding organisations. Furthermore, the goals created a simple narrative, triggering self-fulfilling prophecies; they imagined a future of 'zero hunger', 'half the number of people in extreme poverty' and in doing so they shifted expectations and spread the idea that achieving the goals was not only necessary but - and more importantly - possible. We infer that policy learning across countries is another keystone of the theory of change underpinning the SDGs.

Another lesson from the MDGs is that a comparison of countries' performance is made possible by the existence of a harmonized metric. Some leading scholars denounced the MDGs on the ground that they were unfair for Sub-Saharan African countries precisely because ranking countries became an immediate by-product of the MDG targets matrix (Easterly, 2007). On the other hand, one could argue that because the SDGs were negotiated by all countries (which was not the case for the MDGs which were set by donor countries), the mere possibility of ranking them becomes an implicit driver for change.

The education survey known as the Program for International Student Assessment (PISA) is enlightening regarding the impact of international rankings. Without exaggerating its virtues, PISA has had an influence on the development of education policies in the majority of developed countries

(Breakspear, 2012) for several reasons: ranking promotes exchanges between policymakers and experts and allows the strategies of leading countries in an area to be used for comparative studies (including between countries with similar socioeconomic characteristics); it legitimizes ongoing reforms (for example the UK has used the PISA ranking to support reforms outlined in its national strategy); it strengthens the quality of national assessments (expansion of the scope of evaluation, further improvement of indicators, etc.); and it enables policy decisions to be better informed according to national and international requirements (Scotland viewed the PISA ranking as a way to measure its relative decline and to influence policy decisions, while focusing on the national context) (Breakspear, 2012). Peer pressure is the third keystone of the theory of change underpinning the SDGs.

5 Assessing SDGs contribution to policy change

We assess the specific contribution of the SDG to bridging the policy implementation gap on inequality. We ask what the practical tools offered by the SDG framework (common metric, peer review, and peer learning) can effectively contribute to fill the implementation gap in the case of income and wealth inequality. We also identify areas where the 2030 agenda falls short in terms of filling the implementation gap. Finally, we outline the conditions under which the utility of the SDG can be realised, and suggest options for state and non-state actors to realise these conditions and leverage the existing framework (Table 1).

i. Do the SDGs provide a common metric to track inequality?

The 2030 Agenda calls for an extensive set of global indicators in its outcome document (UN, 2015) that would be "*simple yet robust, address all SDGs and targets including for means of implementation.*" The framework, the resolution notes, requires that there be "*timely, reliable, and disaggregated data to support the implementation of the ambitious 2030 Agenda*".

A common set of 230 indicators was agreed in 2016 at UN level as the backbone of monitoring the SDGs at local, national, regional, and global levels. They will serve as a management tool to help countries develop implementation strategies and allocate resources accordingly, and as a report card to measure progress towards achieving a target and to ensure the accountability of governments and other stakeholders for achieving the SDGs.

Table 1 - Converting debates into action: Assessing SDGs contribution

Target 10 satisfies the broad principles of the SDG framework to develop action plans from existing national sustainable development strategies. Over the past decades, an increasing number of countries have adopted so-called "beyond GDP" indicators to complement GDP and better measure social, environmental and broader economic factors. A close look at national beyond-GDP initiatives shows that inequality featured prominently amongst them prior to the finalisation of the SDGs (Chancel, Thiry and Demailly, 2015). The additional value of the SDGs, in this context, is to provide a common, universal metric. The metric carries particular weight as it has been unanimously endorsed by the UN Member States.

That being said, the metric for measuring inequality in Target 10.1 has potential descriptive drawbacks. By ensuring that the bottom 40% does not lose out, the target clearly reflects the SDG principle to 'leave no one behind'. However, the indicator is blind to changes at the apex of the distribution (in situations where top earners' and bottom earners' incomes grow while the middle shrinks, for instance). This amounts to more than an innocuous oversight. Rising top income shares drove income inequality dynamics in the past decades (Atkinson, Piketty and Saez, 2011 ; Piketty, 2014).

Table 2 shows the performance of three countries (China, France, USA) on the SDG target, over the past 15 years (2000-2015 period) and in the longer run (1980-2015, time span with available and comparable data). The table revises previous results by Chancel and Voituriez (2015). In the earlier results, including a more extensive list of countries, the results showed that countries variously passed and failed the SDG test over different periods. In the updated data, all three countries considered failed to meet the SDG target 10.1, suggesting that the target is more ambitious than previously assumed. Still, the target remains feasible. France came very close to achieving the target over the 1980-2015 period, for example. In France, over the 1980-2015 period, the bottom 40% is not far from average growth but the top 0.1% earners enjoy a growth rate that is more than five times higher. In China and the USA as well, the gap between average growth rate and top 0.1% income growth rate (respectively 776 % vs. 2271% and 70% vs. 343% for the 1980-2015 time period) shows the need to complement the bottom 40% target.

Table 2 - Growth and inequality in China, France, USA

We therefore suggest that countries interested in inequality reduction employ a complementary statistic, comparing, when available, the evolution of top incomes (top 1% or top 0.1% income shares) to average growth, in order to capture important changes at the apex of the income distribution. The use of complementary metrics, in addition to the global indicators list adopted by the General Assembly, is explicitly foreseen in the SDG framework. Paragraph 75 of *Transforming Our World : The Agenda 2030 for Sustainable Development* states: "The Goals and targets will be followed-up and reviewed using a set of global indicators. These will be complemented by indicators at the regional and national levels which will be developed by member states, in addition to the outcomes of work undertaken for the development of the baselines for those targets where national and global baseline data does not yet exist" (UN, 2015). The inclusion of complementary statistics is voluntary, based on the discretion of states. In this case, epistemic communities have already contributed a great deal: data about the income and wealth of the top 1% produced by academia and civil society have been harnessed by activists and NGOs to increase awareness in the issue of rising inequality. The uptake of this complementary indicator will therefore depend on the continued participation of civil society actors and academia.

Table 3 informs us on another important dimension of the debate: the source of data used to check whether countries meet the SDG objective is crucial. In Table 3, we compare the data source used in Table 2 (coming from WID.world, which combines fiscal sources and surveys), with survey data from the World Panel on Income Distribution (Lakner and Milanovic, 2013).

Table 3 - Who is virtuous? On the importance of data source used.

The main insight from this comparison is that growth rates vary substantially according to the two sources. The USA would pass the test according to Lakner Milanovic data over 1988-1998 while it clearly does not qualify in the WID.world source. In this example, the survey data does not capture all income growth in the US in 1988-1998, particularly at the top of the distribution.

How best tackle the data source issue, given that the UN has so far not provided specification on data source types that member states should use (UN, 2017)? Survey data is well-known for its inability to capture top income dynamics in a satisfactory way, because of underreporting and undersampling issues (Atkinson and Bourguignon, 2015). Additionally, in the case of the widely used World Panel on Income Distribution (Lakner and Milanovic, 2013), the surveys variously refer to consumption and to income. The level of consumption inequality is always lower than income inequality because of differential in savings rates across households. Mixing the two concepts is thus problematic.

The SDG test will need to be based on standardized and comparable concepts of income. The most promising way to deal with data limitation seems to reconcile within a harmonized framework the different sources available, namely tax data, national accounts and household surveys (Alvaredo et. al, 2016). This is the approach which pursued at WID.world.

ii. Can SDGs create peer pressure and increase political will for change?

The SDGs indicator not only provides a harmonized metric, it also sets a threshold for the income growth of the bottom 40%. The monitoring is carried out through an annual reporting system, under the aegis of the UN Secretary General, based on indicators and national statistics. Nothing in Target 10.1 constrains the speed of inequality reduction, nor the optimal range of outcomes that countries should aim to achieve. Nevertheless, to reach the target, several countries in the developed and developing world will have to invert current inequality trends (Chancel and Voituriez, 2015).

Increasing inequality can reflect the preference (or indifference) of a given society, even though it is intrinsically contrary to its own interests, as discussed in the first section of this chapter. How preferences and interests are shaped and evolve over time is a question which has spurred passionate debates in social sciences. The bedrock of our approach is that additional knowledge on the state of the problem and on the solutions space contributes to altering preferences and the distribution of interests across stakeholders likely to influence the policy process. The success of this approach depends on multiple factors. Many countries – and OECD countries in particular - have for many years submitted their national sustainable development strategies to the critical scrutiny of other countries ("peer reviews"), but these assessments have only had a limited influence on national policy. It is indeed particularly difficult to satisfy the conditions necessary for these peer reviews to have an impact: high-level political commitment, adequate budgetary resources, involvement of non-state actors, and timeliness, among other factors (Vaillé and Brimont, 2016). While acknowledging these limitations, we nonetheless assume in the following paragraphs that the dissemination of the pass and fail tests enabled by Target 10.1. is likely to trigger peer pressure that leads to action at the national level.

Is PISA-like ranking conceivable within the SDG framework? PISA benefits are maximised when stakeholders recognize the indicators as legitimate, when monitoring and reporting mechanisms are in place—as planned in the 2030 Agenda—and when evaluation results are disseminated to the media (McGee, 2010). The political appeal of ranking is particularly striking during national election campaigns – at least among EU 27 countries. In particular, GDP growth, unemployment rate and public spending as a share of GDP have pervaded across continental Europe in national debates on welfare state reforms over the last two decades. Beyond-GDP-indicators which have been developed and included in the national jurisdiction of a few countries rest on a similar rationale of country-to-country comparison (Chancel, Thiry, Demailly, 2014). The interactive OECD Better Life Index tool for instance *enables people* " to express what matters most to them (...), share and compare their answers with people across 38 OECD member and non-member countries" (OECD, 2016).

Practically, ranking countries could be done by comparing the year-on-year difference between the annual growth rate of the average income per capita and the annual growth rate of income per capita among the bottom 40% on a country basis. Countries with the highest difference would rank highest.

Table 4 - Ranking countries along target 10.1 year-on-year values

Table 4 encapsulates year-on-year values of target 10.1 and top 1% per adult pre-tax income growth for China, France and the US, from 2010 to 2013 (last available year-on-year WID.world data) and for year 1999-2000. It provides four snap-shots of countries' performance on the official (bottom 40%, "Test 1") and complementary (top 1%, "Test 2") inequality targets and makes a ranking of countries along the bottom 40% income convergence speed, as well as along the gap between average and top 1% growth. Looking at what dub the Test 1, China ranked first in 2011 and 2012 and passed the SDG test, but failed in 2013. The other way round, the US failed in 2011 and 2012 but toped in 2013, displaying sharp year-on-year changes in inequality pattern. Test 2 shows that the ranking of countries can be modified when focusing on top 1% income growth rather than bottom 40%. In 1999-2000 for instance, France passes Test 1 but fails on Test 2.

Country ranking will be technically feasible thanks to national statistical reports on SDGs. We must be clear however that it remains politically tricky. Ranking countries according to their performance in achieving specific goals and targets is very unlikely to become part of the mandate of the UN High Level Political Forum (HLPF). This ranking could be produced instead by coalitions of Think Tanks, research institutions and civil society organizations (CSO) outside of the UN system. Some initiatives are underway. Taking a comprehensive approach of the SDGs, the SDSN has developed a SDG index and dashboard for country ranking (SDSN, 2016). The Migration and Development Civil Society Network (MADE) in cooperation with Cordaid has drafted "Proposals for Shadow Reporting on SDG implementation" (MADE, 2015). Transparency International issued a methodological Note for SDG shadow reporting questionnaire to "help assess progress towards three SDG targets linked to anti-corruption and government transparency" and make comparisons across countries (Transparency International, 2017). In this context there both a clear need and a space for inequality ranking across countries that could be filled by the economic inequality and environmental inequality communities together.

iii. Can SDGs provide a platform for learning?

A third contribution of SDGs in converting policy discourses into action is the opportunity they provide to compare policy performance across countries, and learn from both successes and failures. The simple fact of providing a platform for comparison of countries' performance and to derive applicable policy solutions in different contexts does not guarantee that this process will take place, as it depends to a large extent on political will. Recent evidence from climate change policies tend to suggest that countries can learn from one another and reduce their own risk aversion toward sustainable development policies (Colombier, 2015; Henry and Tubiana, 2018). By making the case that reducing inequality is *feasible*, one country's success can elicit political traction in another country and realize the ambition of the 2030 Agenda to make SDG implementation a genuine experimentation process.

There are already dedicated platforms to enable mutual learning among countries. At the opening of the 2016 High-Level Political Forum (HLPF) on the Sustainable Development Goals, Under-Secretary-General Wu Hongbo commented that 'the lessons you have offered, the actions you have showcased, and the gaps you have identified, they are what this Forum is about: Advancing the SDGs through sharing of experiences, and mutual learning' (UNDESA, 2016). The Forum included SDGs Learning, Training and Practice sessions 'providing capacity building, networking and experience-sharing opportunities on crucial topics related to the implementation of the 2030 Agenda'.

The issue of inequality is highly suited to this kind of platform. An expanding literature has identified an extensive range of national level policy responses that states may adopt in addressing high or rising inequality, and furthermore, many countries have successfully implemented policies to reduce inequality. Some preeminent examples, like the case of Chile since the middle of the 2000s, offer scope for learning and adoption by other countries and the sustainable development platform provides a dedicated platform to that end (Martinez-Aguilar, Fuchs, Ortiz-Juarez, Del Carmen, 2017). Examples such as the case of Chile where fiscal interventions covering a wide range of instruments also support a process of South-North learning. It is hoped that such a process would increase the buy-in for the broader goals amongst countries in the Global South.

However, much remains to be done to increase the functionality of the mutual learning process – of genuine peer learning. Greater focus is required to encourage and vitalise the learning process beyond current state practice at UN HLPF which is overly permissive of countries "showcasing" national strategies and anecdotal successes, as it was the case at the time of the UN Commission on Sustainable Development which preceded the HLPF. Forums cannot simply serve as platforms for states to boast about their individual successes while overshadowing and overlooking areas of inaction or underperformance. Building on Chancel, Hough and Voituriez (2017), we thus propose i) the publication of an annual statistical and policy report ranking countries over their performance on SDG target 10.1. This report could include contributions from academia but should eventually be endorsed by the United Nations Statistical Agency. G20 countries could take the lead on this. ii) This report would contain – or would be supplemented by a side-report on – a discussion of successful and less successful policies implemented in different countries to tackle inequality. iii) The report would be presented and discussed at an annual global inequality conference. These conferences could be kickstarted by civil society, the academia or G20 hosts, but they should be eventually organized by the United Nations.

6 Conclusion

As progresses made in the field of inequality measurement, revealing the extent of the rise in income and wealth inequality, a growing body of literature highlighted the negative impacts of domestic inequality on a wide number of political, social, economic and environmental problems – thus rendering domestic inequality a key sustainable development challenge. However, over the past decade, despite growing concern, it is fair to say that debates have not been converted into sufficient and effective action. Domestic inequality keeps rising.

The inclusion of inequality within the Sustainable Development Goals framework shows that the United Nation member States are formally committed to tackle this problem. One can wonder however what could be the effective contribution of a United Nations process which does not have any binding mechanism. What comes out of our research is that the SDGs provide three levers to turn the global inequality debate into action: peer focus (a common metric), peer pressure (a ranking of countries) and peer review (mutual learning of policies). The contribution of SDGs to each of these levers is however not equal. While the common metric exists, only significant involvement from civil society, epistemic communities which were more concerned so far with domestic economic debates surrounding inequality, and the commitment from governments will make it possible for peer pressure and learning to become effective. These three effective and potential contributions of SDG stand out as necessary conditions to transform the global inequality debate into action. But they are far from sufficient: in particular, the relationship between SDGs and international trade, investment deals and fiscal agreements will also need to be clarified – replacing such discussions at the centre of the policy agenda is another potential side-effect of the SDG impetus.

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Table 1 - Converting debates into action: Assessing SDGs contribution

	SDGs EFFECTIVE CONTRIBUTION	SDGs POTENTIAL CONTRIBUTION	CONDITIONS NEEDED TO REALISE THE POTENTIAL	LEVERAGING OPTIONS
METRIC	Inequality metric Indicator with threshold (Bottom 40% income growth must be higher than average)	Can be complemented by Top1% income and wealth share, or middle 40% income/wealth share.	Broaden the country coverage and dissemination of income data on the full distribution Combination with national BGDP frameworks	Reference academic data report Unification of national BGDP indicators frameworks and SDG indicator
PEER PRESSURE	Country reports and secretary general report on inequality at HLPF 2019 Country annual statistical reporting	Ranking countries could be done by comparing the year-on-year difference between the annual growth rate of the average income per capita and the annual growth rate of income per capita among the bottom 40% on a country basis. Countries with the highest difference would rank highest Inequality reduction "champion" country to	Serious lobbying towards the HLPF to devote panel discussion during HLPF 2019 on country inequality ranking	Global Think Tanks Report on Inequality Changes & Policies (ICP) Civil society implication via name and shame NGO campaigns

		choose HLFP 2019 for accounting progress		
LEARNING FRAMEWORK	Global Sustainable Development Report (GSDR - "the IPPC of SDGs") Reporting on Inequality (HLPF 2019) to be made on a voluntary basis	GSDR dedicates one annual issue on policy learning Inequality reduction "champion" country to choose HLFP 2019 for accounting progress	Serious lobbying towards GSDR Clarifying political and policy conditions which led to successful reduction of inequalities in successful countries	Institutional framework for an inequality reduction policies forum (think tanks, civil society, administrations) Unpacking the toolbox: A guide to policy makers

Source: Authors. Legend: Major contribution | Minor contribution . BGDP : Beyond GDP. GSDR: UN Global Sustainable Development Report. HLPF: UN High Level Political Forum.

Table 2 - Growth and inequality in China, France, USA

Country	Period	Per adult pre-tax income total growth (%)				SDG TEST
		Bottom 40%	Top 1%	Top 0.1%	Average	
China	1980-2015	332	1800	2271	776	FAIL
	2000-2015	182	379	450	257	FAIL
France	1980-2015	17	84	155	32	FAIL
	2000-2015	-4	38	82	-1	FAIL
USA	1980-2015	0.4	221	343	70	FAIL
	2000-2015	-6	22	31	10	FAIL

Data source: WID.world (2017). Note: growth in pre-tax per adult income. Authors' computations. Key: Average per adult income of the bottom 40% group increased by 332% in China over the 1980-2015 period. Average per adult growth rate was 776% over the period. All figures are net of inflation.

Table 3 - Who is virtuous? On the importance of data source used.

Country	Period	WID.world Dataset: Pre-tax income growth (%) Bottom 40%	WID.world Dataset: Pre-tax income growth (%) Full population	WID.world Dataset: SDG Test	Lakner-Milanovic Dataset: Survey income growth (%) Bottom 40 %	Lakner-Milanovic Dataset: Survey income growth (%) Full population	Lakner-Milanovic Dataset: SDG Test
China	1988-1998	-0.2	19	FAIL	24	73	FAIL
	1998-2008	55	118	FAIL	44	145	FAIL
France	1988-1998	5	13	FAIL	65	17	PASS
	1998-2008	8	11	FAIL	28	30	FAIL
USA	1988-1998	5	22	FAIL	19	13	PASS
	1998-2008	2	11	FAIL	5	25	FAIL

Data source: WID.world (2017) and World Panel on Income Distribution (Lakner and Milanovic, 2013). Authors' computations. Note: WID.world is based on consistent combination of tax, survey and national accounts data; the figures report the evolution of pre-tax per adult national income. The Lakner and Milanovic Dataset reports survey data on income or on consumption.

Table 4 - Ranking countries along target 10.1 year-on-year values

Country	Period	Full pop.- income growth (%)	Test 1: Bottom 40% - income growth (%)	Test 1: Difference to full pop. (p.p)	Test 1: SDG Test	Test 1: Rank	Test 2: Top 1% - Income growth (%)	Test 2: Difference to full pop (p.p.)	Test 2: SDG Test	Test 2: Rank
USA	2012-2013	0.0	3.9	3.9	PASS	1	-5.7	6	PASS	2
France		-0.2	2.7	2.9	PASS	2	-14.6	14	PASS	1
China		9.0	7.6	-1.4	FAIL	3	9.5	-1	FAIL	3
China	2011-2012	8.2	10.9	2.7	PASS	1	1.9	6	PASS	1
France		-2.7	-2.1	0.6	PASS	2	-3.1	0	PASS	2
USA		2.2	-0.3	-2.5	FAIL	3	8.4	-6	FAIL	3
China	2010-2011	7.2	9.7	2.5	PASS	1	3.4	4	PASS	1
France		3.7	0.4	-3.3	FAIL	2	28.0	-24	FAIL	3
USA		1.5	-1.9	-3.4	FAIL	3	0.4	1	PASS	2
France	1999-2000	2.7	2.7	0.0	PASS	1	5.1	-2	FAIL	1
USA		3.5	2.0	-1.5	FAIL	2	6.8	-3	FAIL	2
China		2.2	-5.3	-7.5	FAIL	3	6.8	-5	FAIL	3

Source: Authors' estimates. Data source: WID.world (2017). Income growth rates correspond to real per adult pre-tax national income. Figures are net of inflation.

Concluding remarks

This thesis presented new methodological and conceptual frameworks developed to track systematically the historical evolution of economic and environmental inequality. This work can be seen as a first step towards the integration of Distributional National Accounting and Environmental Accounting. The thesis discussed a series of new results, based on the application of these methodologies.

In terms of income inequality, we showed in Chapters 2 and 3 that while inequality is on the rise in most countries since the 1980s, this rise occurred at different speeds, highlighting the absence of deterministic forces driving these dynamics and revealing the importance of national-level policy choices and institutional changes.

Regarding the inequality of carbon emissions, it was shown in Chapter 3 that it is largely driven by income dynamics, even if other technological and cultural factors play a role. While between-country environmental inequality diminished since the late 1990s, environmental inequality within countries is on the rise (Chapter 4). This has important implications for environmental policies at the national or global level.

Chapter 5 showed, with the case of France, that much can be done to improve fiscal systems so as to take into account the joint objective of inequality reduction and environment protection. Chapter 6 discussed the various roles of inequality metrics in public debates and in policy, in the context of the new inequality target established by the UN Sustainable Development Goals. It was shown that this target can be useful for peer pressure, peer review and mutual learning across countries.

Several limitations of the results presented were discussed and should be stressed once again here. The focus on income inequality is indeed an important restriction given the much wider scope of economic and social inequality. Future work should also focus on wealth inequality and introduce gender, political, racial inequality in the scope of analysis. Similarly, the focus on carbon emissions is also an important limitation if we take into account the diversity of environmental degradations (other forms of air, soil and water pollution, biodiversity loss, etc.) and of the resulting environmental inequality (which can indeed be understood not only as an inequality among polluters, but also among victims). That said, the restrictions operated in this thesis were necessary to establish standards and move forward in our understanding of inequality and (un)sustainability. Lifting these restrictions will indeed open areas for exciting future research.

It must also be stressed that some of the estimates presented in this thesis are, by essence, perishable. As discussed in the appendices of the different chapter, their revision is unlikely to modify the conclusions presented, but should help us refine our understanding of the dynamics at stake (at the national level in particular). We are currently revising the work presented in Chapter 2 on global income dynamics, thanks to new work on national-level income distributions for countries which had missing detailed country-level data so far. The work presented in chapter 4 on the inequality of carbon emissions, will also soon be updated in light of new methodological developments including those presented in Chapter 2.

This dynamic process, rhythmed by methodological innovations and the release of novel information by public authorities or other actors (such as leaked bank information for instance, in the case of income or wealth inequality data), should be seen as a natural part of a research process that seeks to address issues on the basis of their relevance, rather than simply on the basis of the data availability at a given point of time.

Beyond improvements in the field of measurement, much also remains to be done. Existing data can already be used to refine our understanding of the different channels through which economic inequality affects sustainability, and vice versa. The political economy of social and environmental policies also deserves more attention in the years to come, in order to identify and lift brakes to policy or behavioral change[125]. In summary: research on (in)equality and (un)sustainability has bright days ahead.

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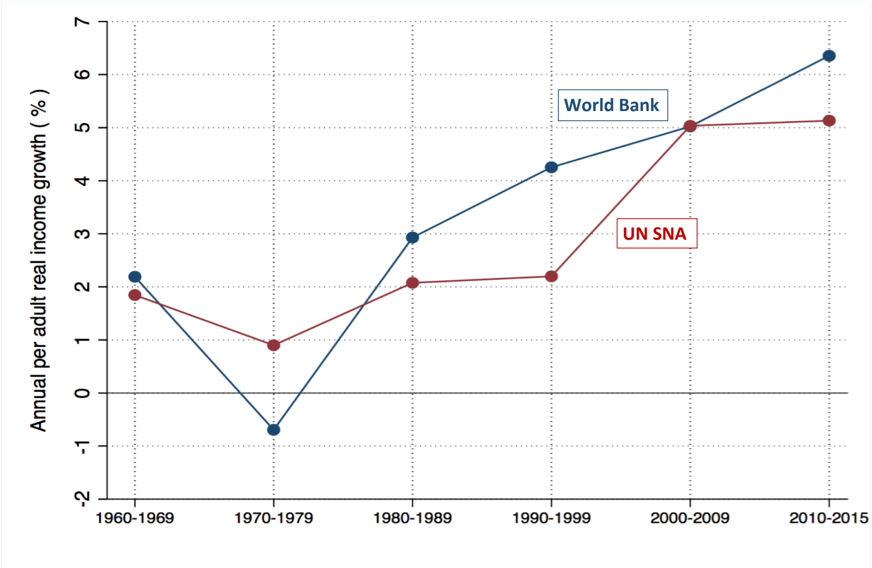
[125] See Chancel, L. (2017), "Insoutenables inégalités: pour une justice sociale et environnementale." Les Petits Matins, Paris. (forthcoming Harvard University Press, 2019)

Appendices

Indian income inequality 1922-2015: From British Raj to Billionaire Raj? Appendix

This methodological appendix presents additional graphs and tables referred to in the chapter *"Indian income inequality 1922-2015: From British Raj to Billionaire Raj?"*.

Appendix 1 – GDP growth in India, 1960-2015



Source: Authors' computations based on World Bank and UN SNA online databases. Note: Figures are deflated using the GDP deflator. Adult population is taken from UN population data.

Appendix 2 - List of corrections done to raw tax files

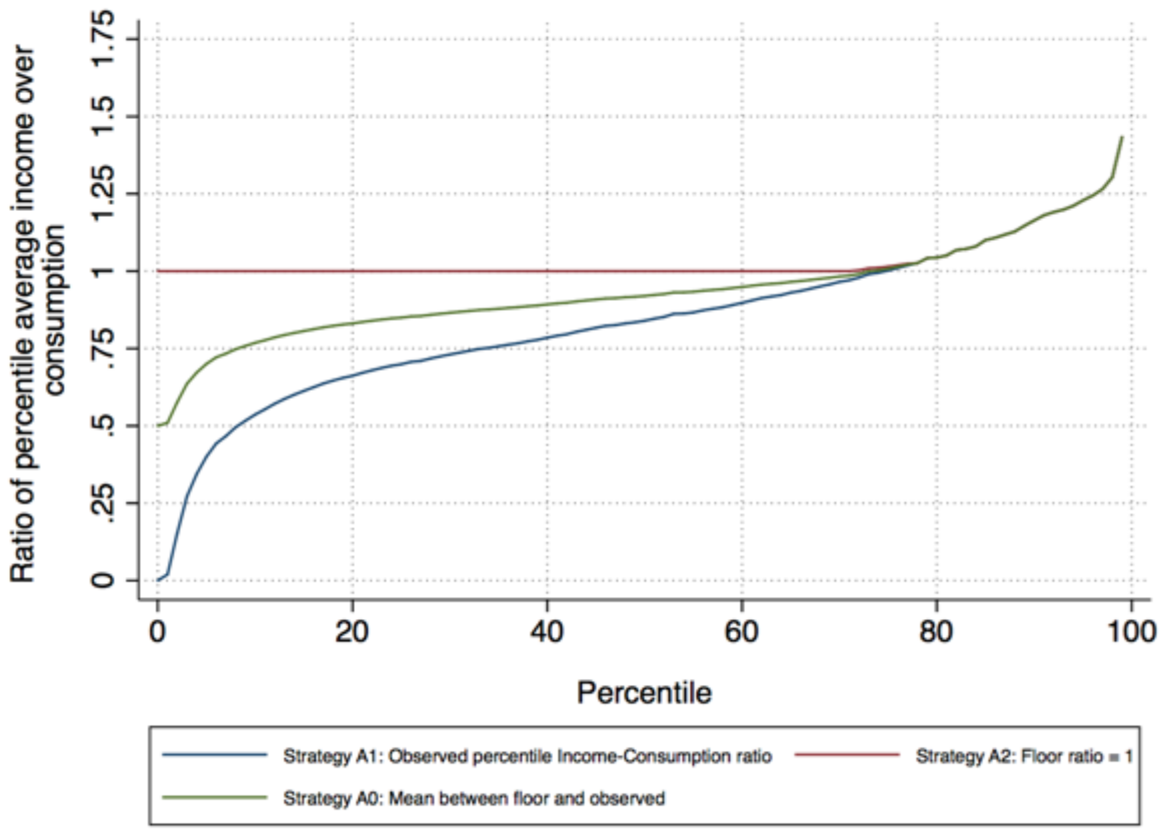
Year	Correction
1948-1951	The first bracket of 1000 is removed altogether
1951	Merging of 70k and 60k brackets into 50k to 100k brackets
1965	Merging of 15k and 17.5k brackets into 12.5k to 20k brackets
1979	Merging of 40k bracket into 30k to 50k brackets
1994	Merging of 400k and 500k brackets into into 300k
1997	Not used for the analysis due to assumed erroneous values
2013	In the first version of the paper, a correction was made to correct what was assumed to be a typo in the very top bracket. Revisions of the raw tabulations published by the Income Tax Department are in line with our early correction, but we now use the value corrected by the ITD.

Appendix 3 - List of NSS consumption surveys and summary statistics

NSS Round	Year	Mean consumption - survey	Mean income - strategy A1	Mean income - strategy A2	Mean income - strategy A0	Gini consumption - survey	Gini income - strategy A1	Gini income - strategy A2	Gini income - strategy A0	p90/p10 ratio consumption - survey	p90/p10 ratio income - strategy A1	p90/p10 ratio income - strategy A2	p90/p10 ratio income - strategy A0
3	1951	483	480	528	504	0.36	0.48	0.40	0.44	4.8	10.6	5.5	7.3
4	1952	421	417	460	438	0.35	0.48	0.40	0.44	5.0	10.8	5.8	7.5
6	1953	425	420	463	441	0.35	0.47	0.39	0.43	4.1	9.0	4.7	6.2
7	1953-54	341	338	373	355	0.35	0.48	0.40	0.44	4.5	9.8	5.2	6.8
9	1955	313	311	342	327	0.36	0.48	0.41	0.44	4.7	10.0	5.4	7.1
10	1955-56	357	355	391	373	0.36	0.48	0.41	0.45	4.7	10.4	5.5	7.2
12	1957	359	358	395	376	0.36	0.49	0.41	0.45	4.2	9.3	4.9	6.4
13	1957-58	377	373	412	393	0.35	0.47	0.40	0.44	4.6	10.0	5.3	7.0
14	1958-59	412	409	451	430	0.35	0.48	0.40	0.44	4.0	8.9	4.6	6.1
15	1959-60	413	406	451	429	0.33	0.46	0.38	0.42	3.9	8.5	4.5	5.9
16	1960-61	441	434	481	457	0.34	0.47	0.38	0.43	4.2	9.2	4.9	6.4
17	1961-62	454	446	496	471	0.34	0.46	0.38	0.42	4.0	8.8	4.6	6.1
18	1963-64	471	459	512	485	0.32	0.45	0.37	0.41	3.6	7.7	4.2	5.4
19	1964-65	555	541	603	572	0.32	0.45	0.36	0.41	3.7	8.1	4.3	5.6
20	1965-66	591	576	643	610	0.31	0.45	0.36	0.40	3.7	8.2	4.3	5.7
21	1966-67	649	631	704	668	0.31	0.44	0.36	0.40	3.9	8.4	4.5	5.9
22	1967-68	701	680	760	720	0.31	0.44	0.35	0.40	3.7	8.1	4.3	5.6
23	1968-69	702	687	765	726	0.32	0.46	0.37	0.41	3.8	8.2	4.4	5.7
24	1969-70	739	722	805	764	0.32	0.45	0.37	0.41	3.9	8.4	4.5	5.8
25	1970-71	757	737	823	780	0.31	0.45	0.36	0.40	3.8	8.1	4.3	5.7
27	1972-73	929	910	1013	962	0.33	0.46	0.37	0.42	3.9	8.5	4.5	5.9
32	1977-78	1444	1442	1594	1518	0.36	0.49	0.41	0.45	3.9	8.6	4.5	5.9
38	1983	2479	2435	2699	2567	0.33	0.46	0.38	0.42	4.2	9.1	4.8	6.3
43	1987-88	4157	4095	4540	4317	0.34	0.47	0.39	0.43	4.2	9.3	4.9	6.4
50	1993-94	7299	7169	7961	7565	0.33	0.46	0.38	0.42	4.1	9.0	4.8	6.3
55	1999-00	12804	12484	13914	13199	0.32	0.45	0.37	0.41	3.9	8.6	4.5	5.9
61	2004-05	12549	12454	13782	13118	0.35	0.48	0.40	0.44	4.2	9.1	4.8	6.3
66	2009-10	20322	20301	22402	21352	0.36	0.50	0.42	0.46	4.3	9.4	5.0	6.5

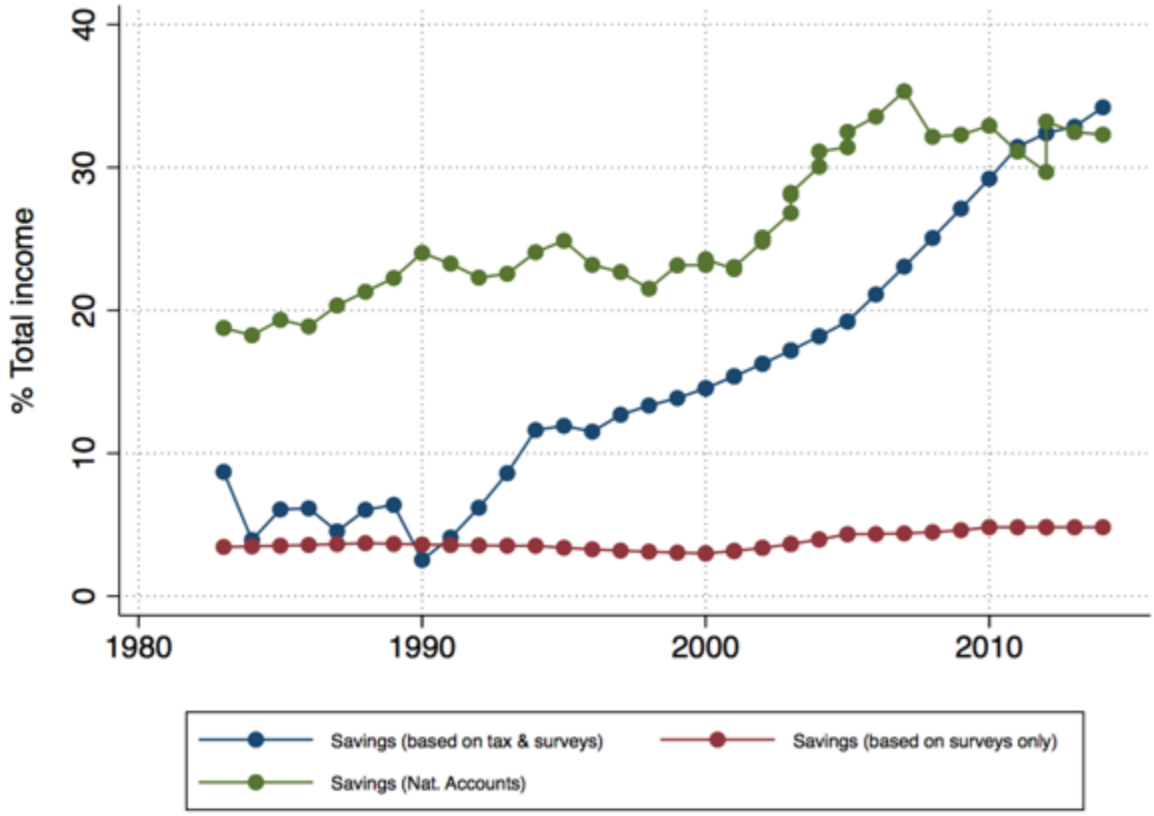
Source: Authors' computations using NSSO data, based on micro data obtained directly from NSSO (1983-2010) or from the Poverty and Growth in India Database of the World Bank (Ozler et al., 1996). Strategies 1, 2, 3 refer to strategies A1, A2, A3, respectively, discussed in the paper (Section 2.2.2). Consumption expressed in current INR.

Appendix 4 - Income-consumption profiles by percentile



Source: Authors' computations using IHDS data. Note: Strategy A1 corresponds to observed IHDS ratios, Strategy A2 corresponds to observed ratios when values are above 1 and constrained to be equal to 1 otherwise, Strategy A0 corresponds to the mean between profile A1 and profile A2 when observed ratios are inferior to 1.

Appendix 5 – Aggregate savings in India, 1983-2015



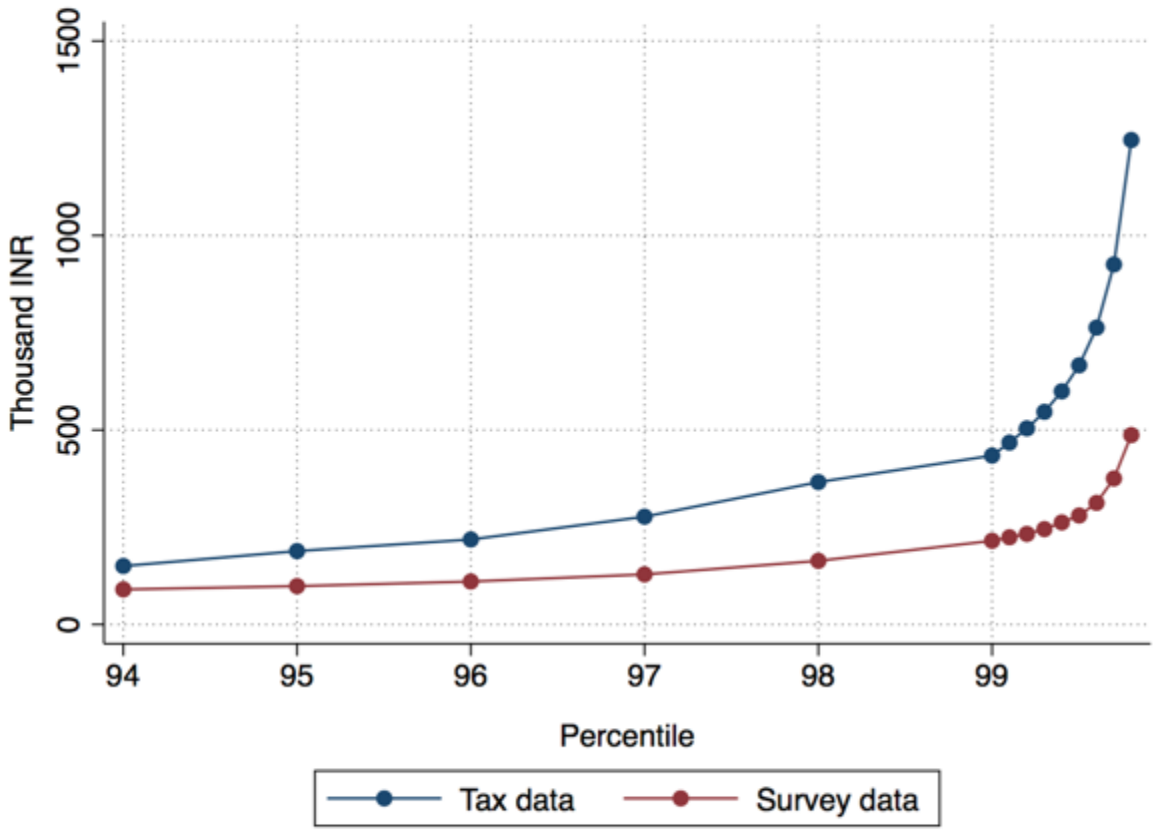
Source: Authors' computations using tax, survey and national accounts data. Note: Savings as per National accounts showsgross savings as a share of gross disposable income.

Appendix 6 – Junction percentile, fiscal years 1922-23 to 2014-15

Year	Percentile	Year	Percentile	Year	Percentile
1922	99.8	**1949**	99.8	**1979**	99.7
1923	99.8	**1950**	99.7	**1980**	99.7
1924	99.8	**1953**	99.8	**1981**	99.7
1925	99.8	**1954**	99.8	**1982**	99.8
1926	99.8	**1955**	99.8	**1983**	99.6
1927	99.8	**1956**	99.7	**1984**	99.7
1928	99.8	**1957**	99.6	**1985**	99.6
1929	99.8	**1958**	99.6	**1986**	99.5
1930	99.8	**1959**	99.6	**1987**	99.5
1931	99.7	**1960**	99.6	**1988**	99.4
1932	99.7	**1961**	99.6	**1989**	99.3
1933	99.7	**1962**	99.5	**1990**	99.2
1934	99.7	**1964**	99.4	**1991**	99.1
1935	99.8	**1965**	99.4	**1992**	99.0
1936	99.9	**1966**	99.4	**1993**	99.0
1937	99.9	**1967**	99.3	**1994**	98.8
1938	99.9	**1968**	99.3	**1995**	98.7
1939	99.9	**1970**	99.3	**1996**	98.4
1940	99.9	**1971**	99.3	**1997**	98.1
1941	99.9	**1973**	99.3	**1998**	97.6
1943	99.8	**1974**	99.3	**2011**	94.5
1944	99.8	**1975**	99.3	**2012**	93.9
1945	99.8	**1976**	99.3	**2013**	93.6
1947	99.8	**1977**	99.5	**2014**	93.1
1948	99.8	**1978**	99.3		

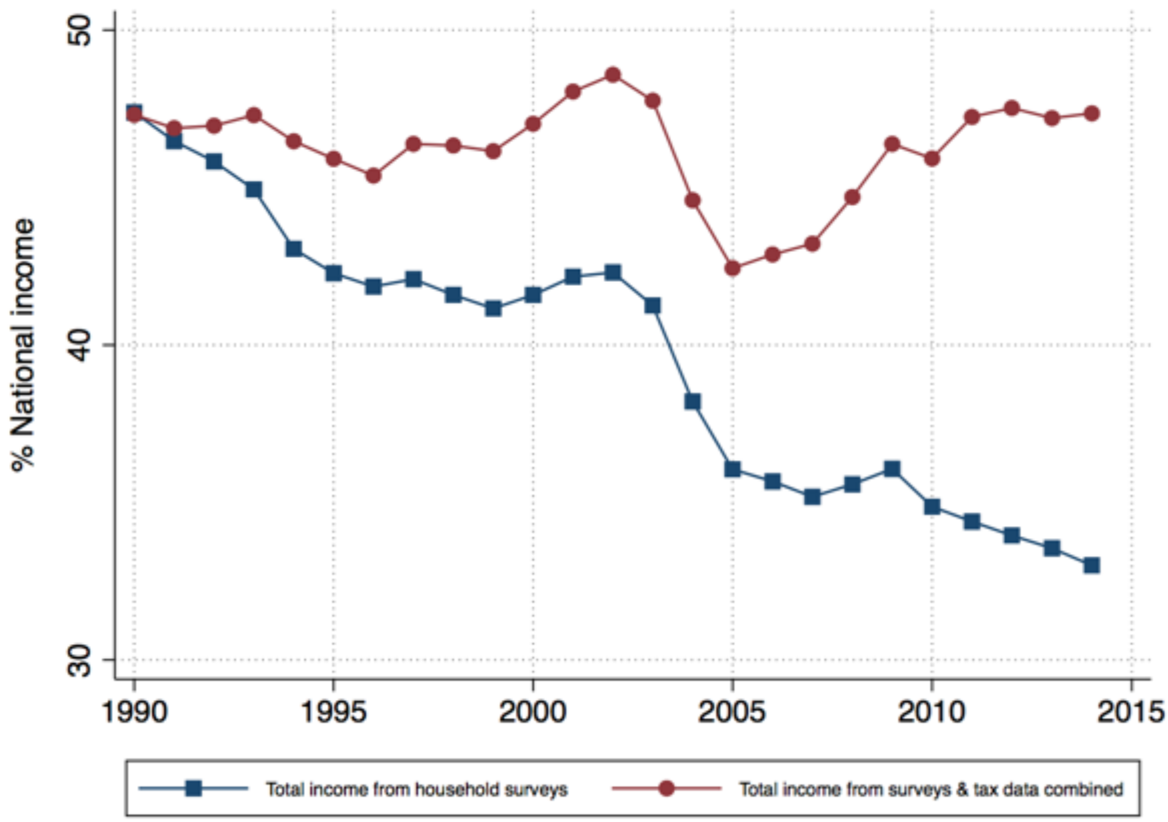
Source: Authors' computations using ITA tax data and UN Population Stats. Percentiles refer to the distribution of per adult pre-tax income.

Appendix 7 – Income levels in India, 2011: survey vs. tax data



Source: Authors' estimates based on ITA data for tax data, IHDS and NSS for survey data. Notes: Distribution of pre-tax per-adult income, scenario A0B1C1. Values expressed in current INR.

Appendix 8 – Total survey income with and without tax corrections in India, 1990-2015



Appendix 9 – Average annual per adult income growth by income group in India, 1980-2015

Income group (distribution of per-adult pre-tax national income)	**Total real per adult income growth (1980-2015)**
Full population	**3.3 %**
Bottom 50%	1.9 %
Middle 40%	2. %
Top 10%	5.1 %
incl. Top 1%	6.6 %
incl. Top 0.1%	7.7 %
incl. Top 0.01%	8.9 %
incl. Top 0.001%	9.4 %

Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Growth rates are net of inflation.

Appendix 10 – Average annual per adult income growth by income group in India, 1951-1980

Income group (distribution of per-adult pre-tax national income)	**Average annual real per adult income growth (1951-1980)**
Full population	**1.7%**
Bottom 50%	2.2%
Middle 40%	1.9%
Top 10%	1.2%
incl. Top 1%	0.2%
incl. Top 0.1%	-1.0%
incl. Top 0.01%	-1.9%
incl. Top 0.001%	-2.0%

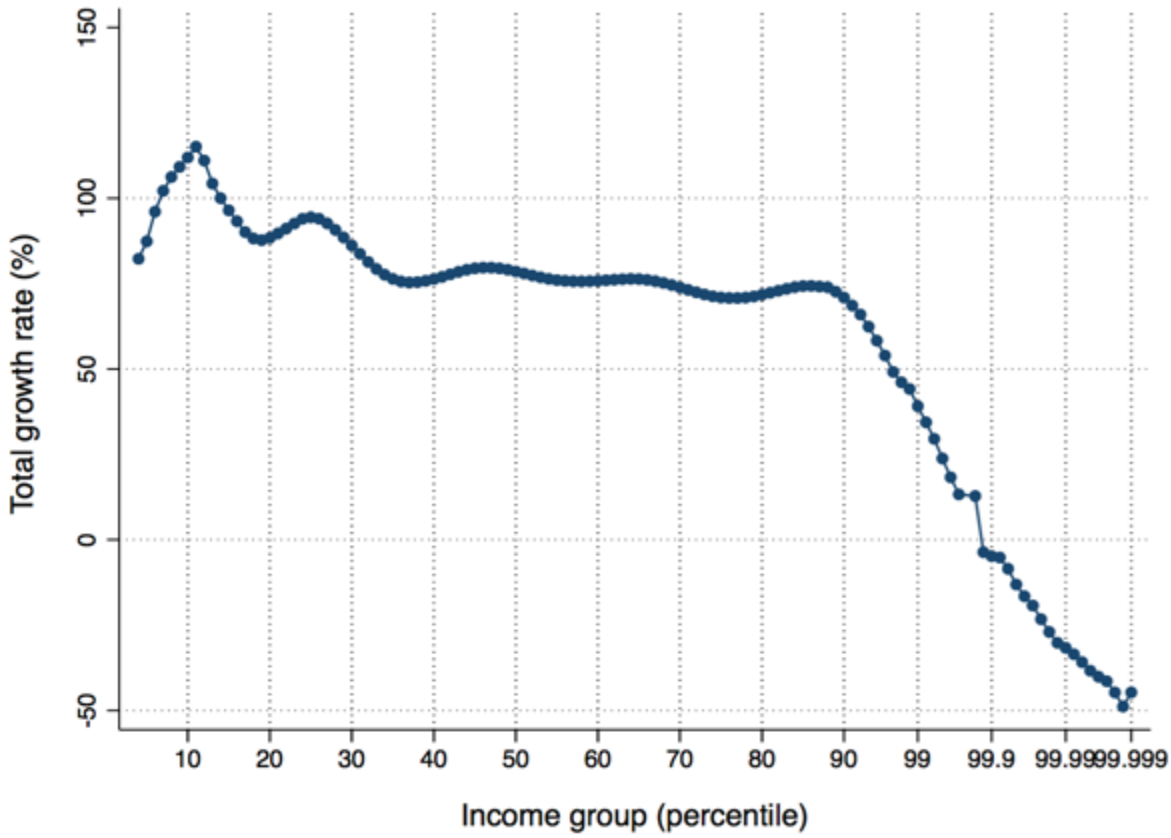
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Growth rates are net of inflation.

Appendix 11 – Share of growth captured by income group in India, 1951-1980

Income group (distribution of per-adult pre-tax national income)	**Share of income growth captured (1951-1980)**
Full population	**100 %**
Bottom 50%	**28 %**
Middle 40%	**49 %**
Top 10%	**24 %**
incl. Top 1%	**.9 %**
incl. Top 0.1%	**-1.8 %**
incl. Top 0.01%	**-1.0 %**
incl. Top 0.001%	**-0.4 %**

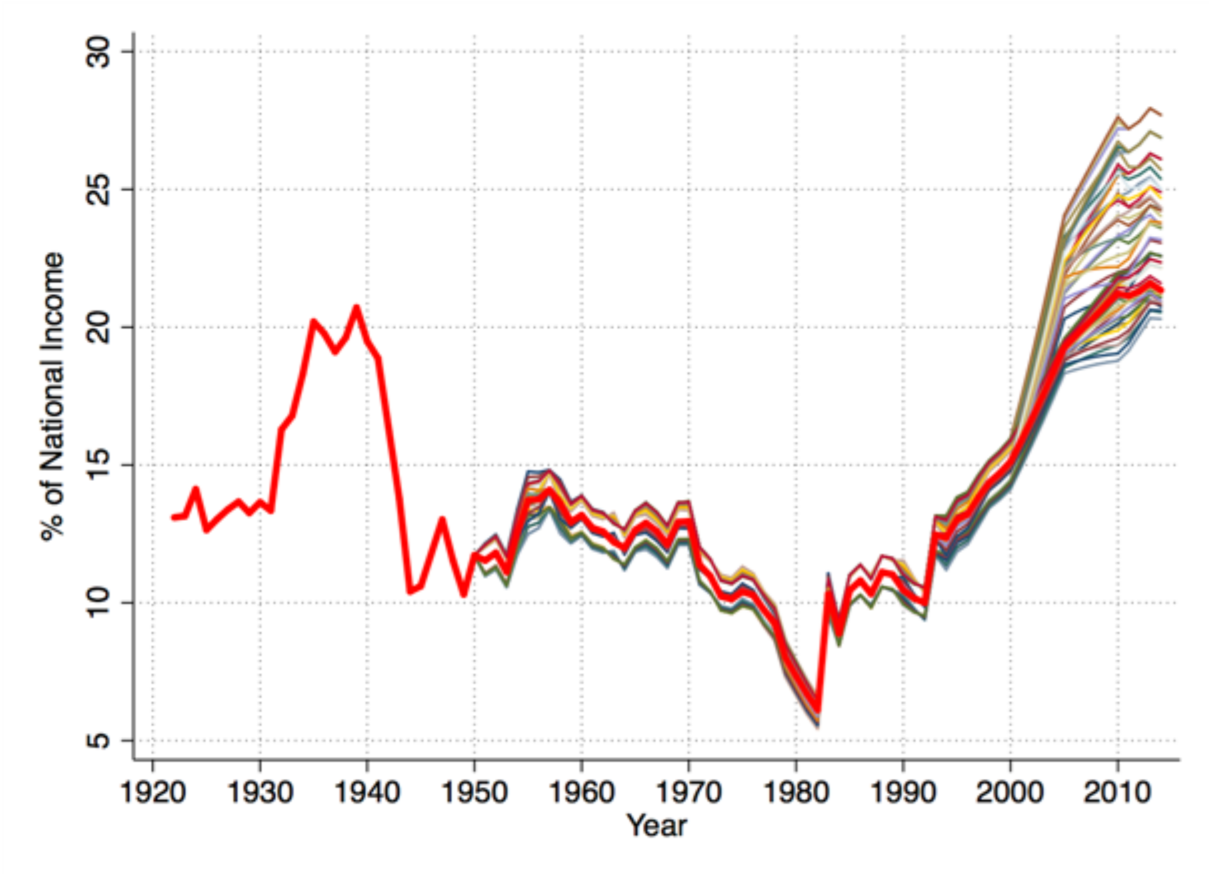
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Growth rates are net of inflation.

Appendix 12 – Income growth by percentile in India, 1980-2015



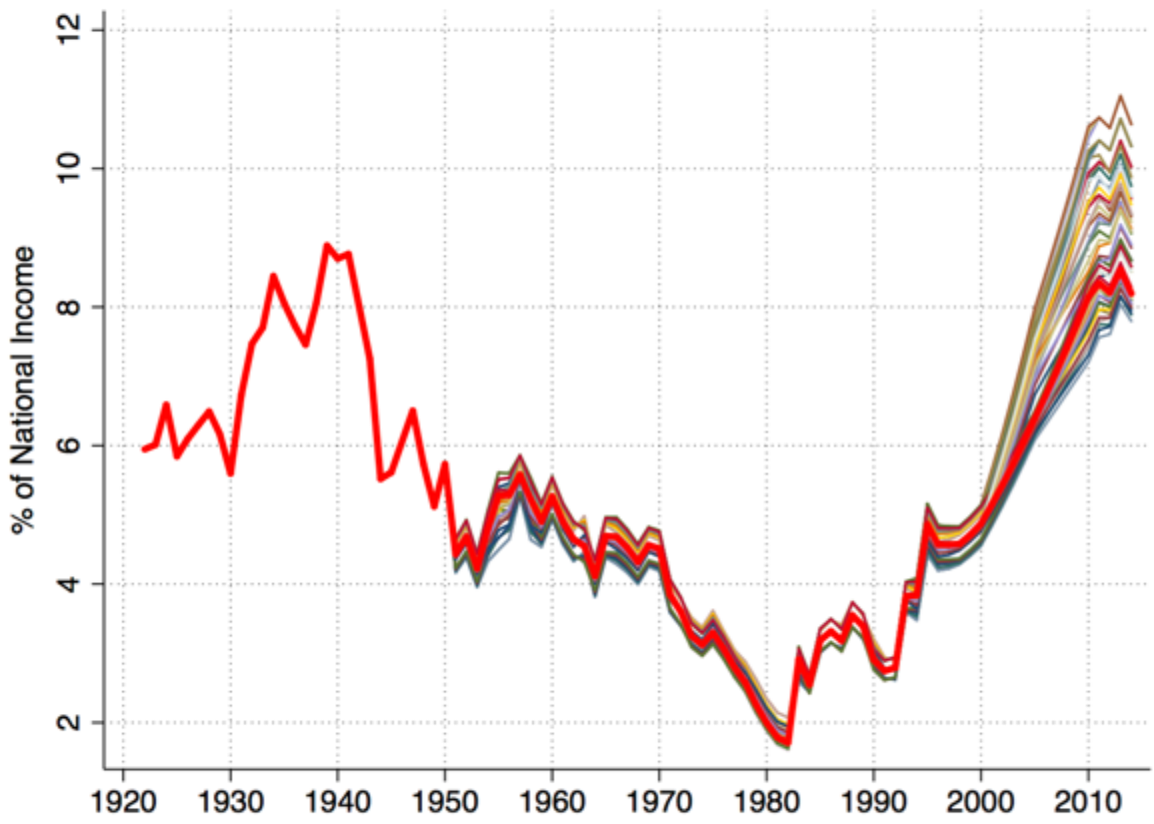
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income, benchmark scenario (A0B1C1D1). Growth rates are net of inflation.

Appendix 13a – Top 1% national income share in India, 1922-2015: results from 54 alternative scenarios



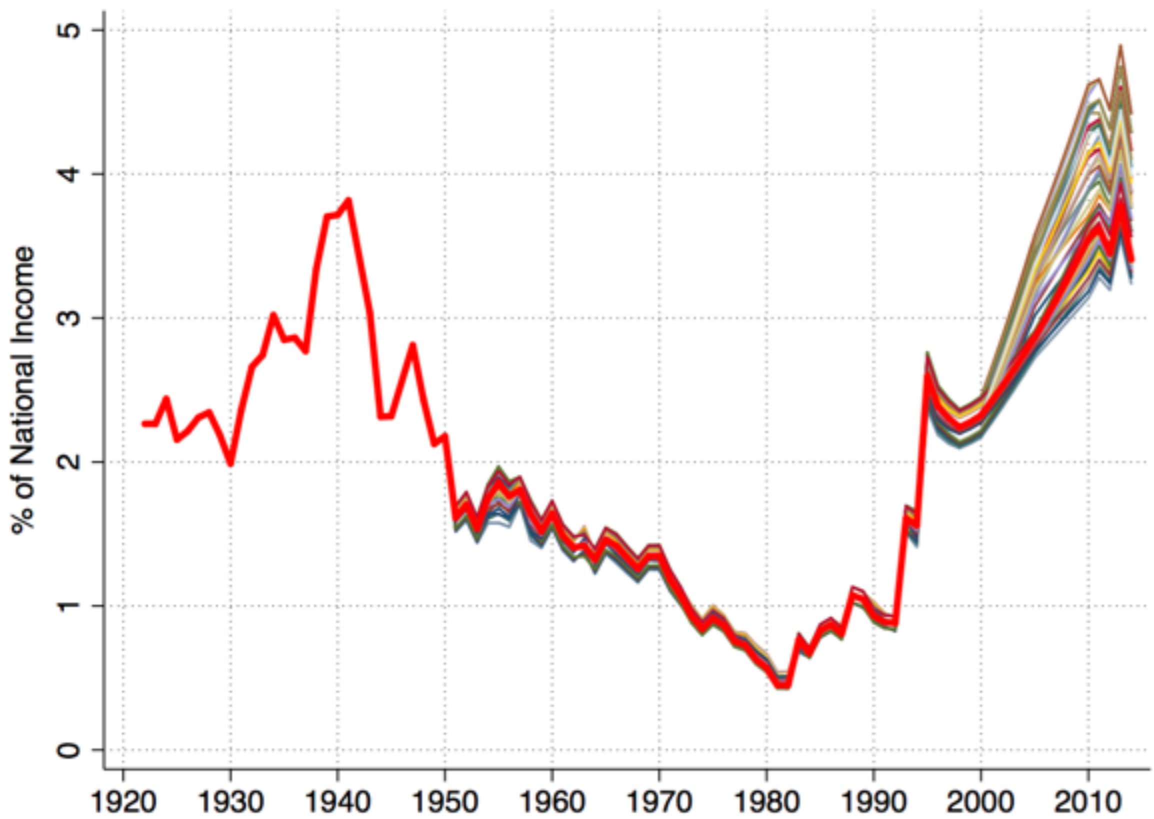
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. From 1922 to 1951, only tax data is available. Thick red line represents benchmark scenario (A0B1C1D1).

Appendix 13b – Top 0.1% national income share in India, 1922-2015: results from 54 alternative scenarios



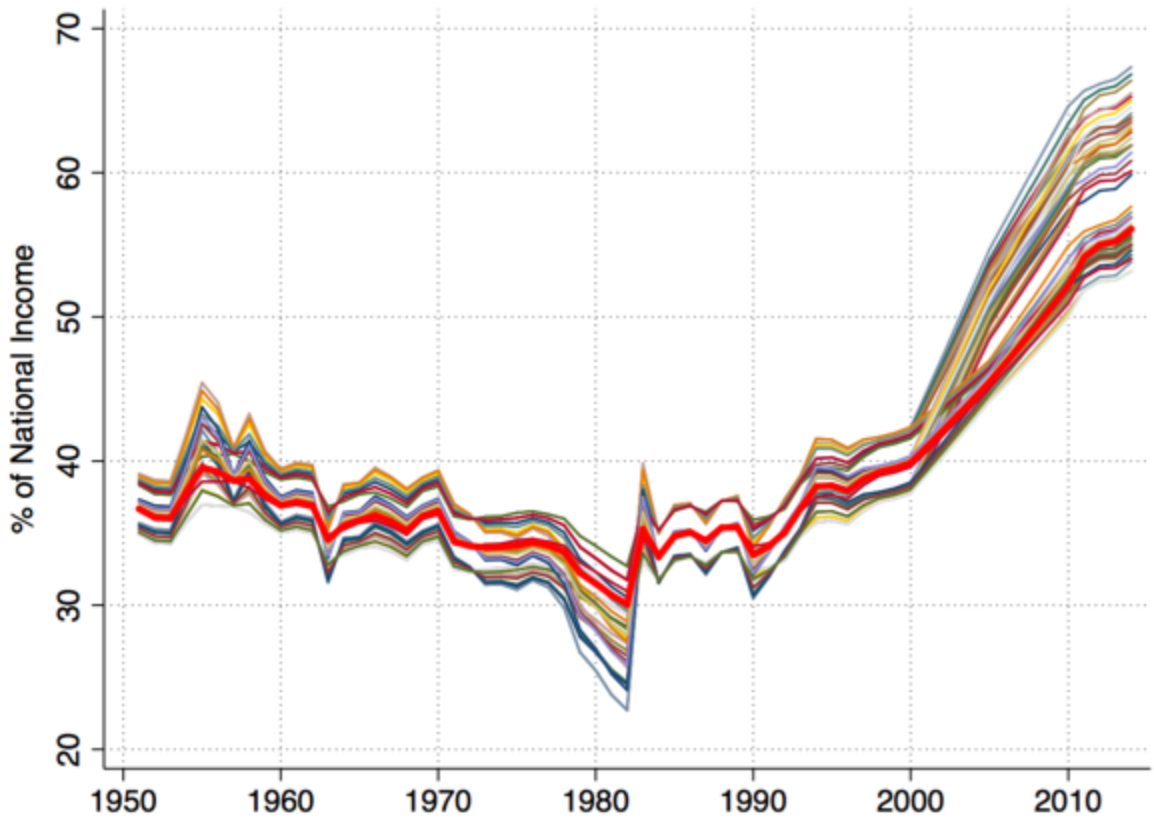
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. From 1922 to 1951, only tax data is available. Thick red line represents benchmark scenario (A0B1C1D1).

Appendix 13c – Top 0.01% national income share in India, 1922-2015: results from 54 alternative scenarios



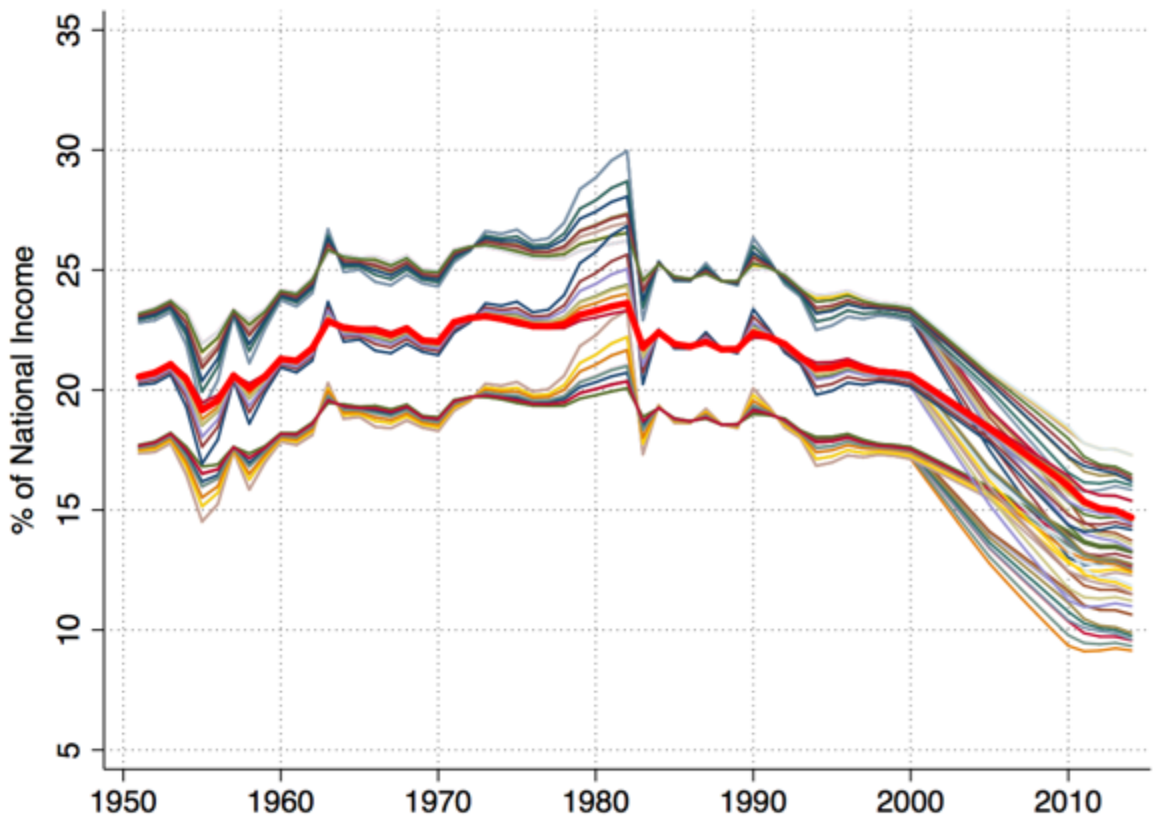
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. From 1922 to 1951, only tax data is available. Thick red line represents benchmark scenario (A0B1C1D1).

Appendix 14a– Top 10% national income share in India, 1951-2015: results from 54 alternative scenarios



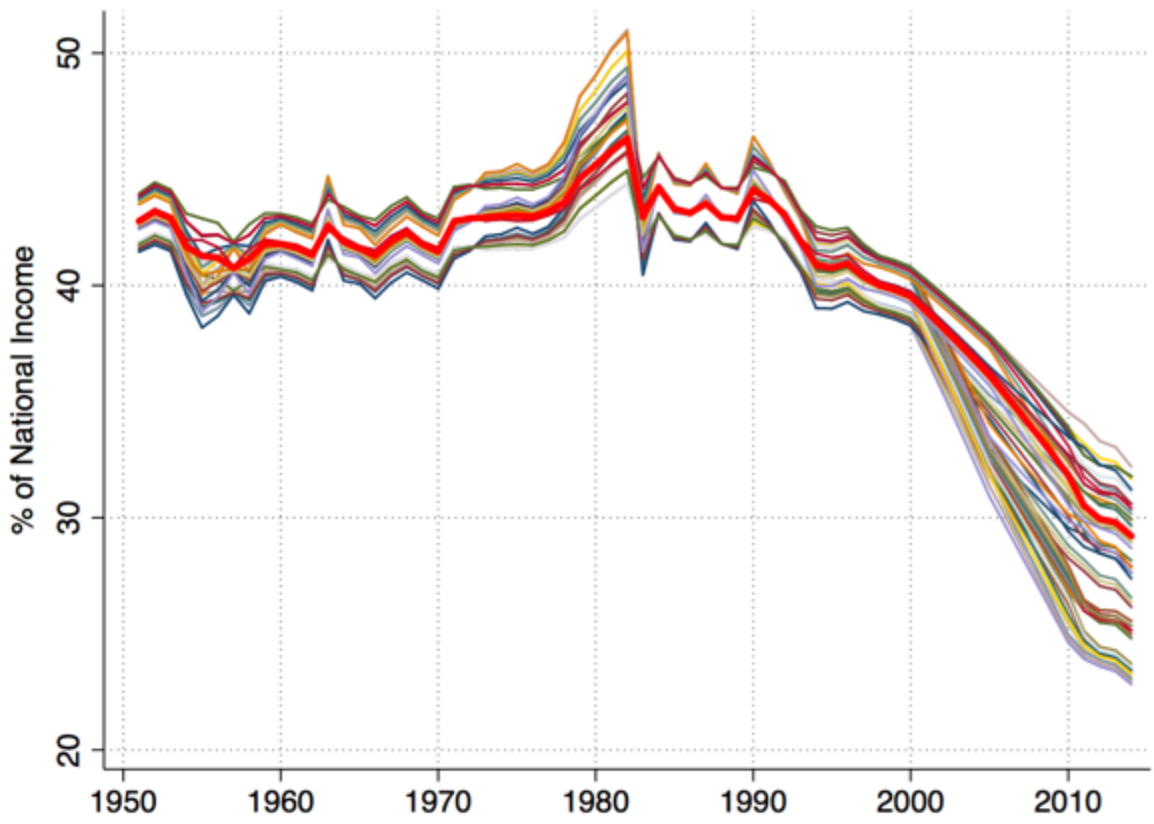
Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. Thick red line represents benchmark scenario (A0B1C1D1).

Appendix 14b– Bottom 50% national income share in India, 1951-2015: results from 54 alternative scenarios



Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. Thick red line represents benchmark scenario (A0B1C1D1).

Appendix 14c– Middle 40% national income share in India, 1951-2015: results from 54 alternative scenarios



Source: Authors' estimates combining survey, fiscal and national accounts data. Notes: distribution of pre-tax per adult national income. Thick red line represents benchmark scenario (A0B1C1D1).

Building a global income distribution brick by brick: Appendix A

This methodological appendix presents the methodology followed to construct homogeneous series of national accounts presented in this thesis and on WID.world (i.e. series of net national income, gross domestic product, net foreign income, consumption of fixed capital and population) covering (almost) all countries in the world, from at least 1950 to today. This appendix draws from "National Accounts Series Methodology", WID.world Technical Notes 2016/1, co-authored with Thomas Blanchet.

This appendix is structured as follows: we define the concepts used and detail our raw sources (1), describe the methodology followed to harmonize series (2) and the estimations performed to fill data gaps (3). We then discuss the most salient results of these new series (4) and key issues for future work (5).

1 Concept definitions, scope and data sources.

Population

In WID.world, the population of a country is defined as the *de facto* population of a country in the 1st of July of the year indicated. We use in priority the population data provided by the WID researchers, which usually come national demographic or fiscal institutes. Otherwise, the population series come from the United Nations World Population Prospects (WPP) (2015), providing total population, as well as population by age group and by gender, for all countries, from 1950 to 2015. In a few cases, we also use the population series published by the UNSNA in its Main Aggregates database.

Gross domestic product

Gross domestic product is defined, as in the UNSNA, as the value of final goods and services produced in a country. Here again, our priority source is the data sent by WID.world fellows, directly collected from countries' National Accounts tables. Otherwise, we use the series from the UNSNA, the World Bank, the IMF, or Maddison (2004). The UNSNA database is divided in two parts. The *Detailed Tables* contains highly detailed data on GDP and its subcomponents, going back to 1946 at the earliest. It distinguishes series based on the various reviews of National Accounts System (the major UN SNA rounds are 1947, 1953, 1968, 1993 and 2008), and other secondary methodological aspects. Although rich in information, this data source provides series with many breaks. The *Main Aggregates Database* provides fewer series over a shorter time span (1970–2014), but covers the entire period without any breaks. The World Bank website provides GDP series, usually back to 1990, and sometimes 1960. A secondary source from the World Bank, distinct from its main data portal, is the World Bank Global Economic Monitor. It provides some of the most up to date economic data for most countries, so it can be a precious source in the most recent years. However, probably because it relies on preliminary estimates with partial coverage of the economy, it tends to give lower GDP in levels than other sources. The IMF GDP data come from its biannual publication World Economic Outlook. The database only starts in 1980, but provides forecast of GDP for the most recent years, which can be useful when no better option is available. Finally, Maddison (2004) provides data of GDP worldwide until the year 0, although we only use its post-1950 estimates. The Maddison database is used for some of the oldest GDP estimates.

Net foreign income

Net foreign income (NFI) is equal to net property income received from abroad (property income received minus property income paid) and net compensation of employees received from abroad (compensation of employees received minus compensation paid to foreign countries). Property income covers investment income from the ownership of foreign financial claims (interest, dividends, rent, etc.) and nonfinancial property income (patents, copyrights, etc.). Net foreign income is also termed as “Net primary income from abroad” in Balance of Payments tables. The raw NFI series we use come from two sources: the IMF Balance of Payments statistics and Piketty and Zucman (2013).

Consumption of fixed capital

Consumption of fixed capital is the decline, over a year, in the current value of the stock of fixed assets owned and used by a country as a result of physical deterioration, obsolescence or normal accidental damage. As in the standard UNSNA definition, our CFC definition takes into account the depreciation of tangible assets owned by producers and of fixed assets constructed to improve land. It also takes into accounts losses of fixed assets due to normal accidental damage, interest costs incurred in acquiring fixed assets as well as certain insurance premiums related to the acquisition or maintenance of fixed assets. Our definition however does not take into account the value of fixed assets destroyed by war or major natural disasters which occur only very rarely, the depletion of non-produced assets such as land, minerals or other deposits, losses due to unexpected technological developments that render existing assets obsolete over a very short time span (United Nations Statistics Division, 2009, pp. 211, C10.156). As reminded by Piketty and Zucman (2013), the risk of measurement error in CFC series is relatively high, given the various assumptions national accountants must make. (Piketty and Zucman, 2013, Data Appendix, pp. 151). Our raw consumption of fixed capital series either come from national statistical institutes (when sent by WID.world fellows) or the UNSNA.

Deflator and PPP

To compare values over time we use, when available, GDP deflator series. When they are not available we use the Consumer Price Index. These come from the UNSNA, the IMF, the World Bank, Global Financial Data, National Statistical Institutes and country specific studies. To compare values over space, we use PPP indices published by the ICP.

Net national income

Net national income is equal to GDP minus CFC plus NFI. As stated above, NNI is a better measure of income than is GDP, since we correct the latter for the money that is spent to replace the depleting capital stock and the net income received from foreign countries. NNI series combines all the raw GDP, CFC and NFI sources presented above. Table 1 presents the breakdown of raw data sources used for each concept.

Table 1 – Coverage of raw sources used for the construction of WID.world National Accounts series

2 Harmonization of raw data sources

As highlighted in section 1, we use a variety of sources to reconstruct complete time series. Different series must be harmonized between sources and sometimes within each institutional source. For instance, the UN SNA tables provide, for a given concept, several series corresponding to the various reviews of National Accounts System (the major UN SNA rounds are 1947, 1953, 1968, 1993 and 2008). Each of these series often cover only a limited segment of the time period we consider. We discuss below how different series are combined with one another.

GDP

The GDP series are constructed in two steps. First, we pick the GDP *level* in a given year and from a given source. For countries which have GDP data send by a WID.world fellow, we use that GDP level in the most recent year available. Otherwise, we use the most recent data from one of the other sources. In case of conflict, we give priority the UN SNA, then the World Bank, then the IMF. When using the UNSNA, we give priority to the Main Aggregates Database, then to the detailed tables, from the most exhaustive series to the least ones. We do not use either the IMF forecasts or the World Bank Global Economic Monitor when fixing the GDP level.

Second, we construct a continuous series of GDP *growth rates*. As before, we use in priority the data of the WID.world fellows, then the UN SNA, then the World Bank, then the IMF. If none of those sources has any data, which can be the case in the most recent years, we use the growth rates from the World Bank Global Economic Monitor, the IMF forecasts, or as a last resort we carry forward the growth in the last available year. All those sources typically provide data until 1970 (UN SNA), 1960 (World Bank) or 1980 (IMF). For earlier years, we use the real GDP growth rates from Maddison (2004).

In China, the official GDP growth figures has been subject to criticism. Therefore, we use corrected GDP estimates from Maddison and Wu (2007). Finally, we combine the GDP growth rates with the GDP level to get a unique GDP series covering the entire time period.

Population

We always give priority to the data provided by the WID.world fellows, when available, and extend those data for the most recent years using the population growth rates from the UN WPP. Otherwise, we use UN WPP estimates. We also estimate the share and the size of population groups by age and gender from the UN WPP.

There are some cases where the geographical areas of the WPP do not match the UNSNA. In France, the national accounts include the oversea territories, which are counted separately in the WPP. Also, the WPP calculates its series according to the present borders, while the UNSNA tend to provide series according to the borders of each years: that problem concerns Sudan and South Sudan, Ethiopia and Eritrea, Indonesia and East-Timor, and economies of the former Eastern Bloc. In all those cases, the UNSNA refer to larger entities than the WPP, so population series were simply aggregated to reflect the entity used in the national account series. There are other situations where the UNSNA refer to smaller entities than the WPP. In Cyprus, the WPP provides estimates for the whole Island, while the national accounts exclude the northern part. The WPP also include the Kosovo in Serbia, while they each have their own series in the UNSNA. The same problem happens with Tanzania and Zanzibar after 1990. In each of these cases, we correct the population estimates using the population series provided directly by the UNSNA. The UNSNA series, however, only provide estimates for the whole population, without any breakdown by age or gender. Hence, we assume that the population has a similar structure in the whole area and attribute to each geographical area a share of every population subcategory equal to its share of the whole population.

3 Data gaps and global (in)consistency

i. Consumption of Fixed Capital

The UN SNA tables provide consumption of fixed capital estimates in 12% of the cases only over the 1950–2015 period[126]. Hence we chose to reconstruct missing UN SNA CFC estimates ourselves.

To do so, we develop a statistical model that incorporate three stylized facts about CFC:

- CFC tends to represent a higher fraction of GDP in more developed countries, which can be explained by the fact that the larger the share of industrial and

[126] The World Bank covers fewer years than the UN SNA (their data ranges from 1970 to 2008). WB data is itself based on several reconstructions done by WB staff, which yield odd value at times, comforting our choice to reconstruct CFC series of our own.

tertiary sector, the stronger the need to replace machinery, computer equipment, etc.

- Some countries have structurally high (or low) levels of CFC. This can be due to regional or climate differences, even though regional variations did not appear to account for CFC differences in the analyses we performed.
- CFC as a share of GDP is persistent: that is, if CFC is particularly high in year t, it will generally also be high in year $t+1$. This due to the fact that CFC seems to depend essentially on the structure of the economy and not on exogenous shocks.

We thus model CFC as a share of GDP as a function of GDP per capita at PPP, using a log-log specification. The model includes a random effect that capture constant country characteristics. Using the index t for the years, and i for the countries, we have:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 x_{it}^2 + u_i + \varepsilon_{it}$$

where y_{it} is the logarithm of CFC as a fraction of GDP, x_{it} is the logarithm of GDP per capita at PPP, u_i is the random effect term, and ε_{it} is the error term. The square of x_{it} lets us capture the concavity of the relationship between CFC and GDP per capita. We smooth the GDP using the Hodrick-Prescott filter before performing the analysis to avoid capturing short term variations of output, which would make CFC countercyclical. As in any random effect model, we assume:

$$\mathbb{E}[u_i | x_{i1}, \dots, x_{iT}] = 0$$

To take into account the persistence of CFC, we model the error term ε_{it} as an AR(1) process:

$$\varepsilon_{it} = \rho \varepsilon_{i,t-1} + \eta_{it}$$

where η_{it} is and i.i.d. white noise. The model can be estimated by generalized least squares using Stata's `xtregar` command, which yields the following estimates:

Table 2 - CFC estimation model

We can check on the following autocorrelogram that ε_{it} does exhibit persistence, but that the error term is correctly whitened once we take the AR(1) process into account:

Figure 1 - Autocorrelation residuals

We impute missing CFC values in the data using the model's best prediction, using all the information at our disposal. When we know part of the CFC series, we can estimate the country's random effect u_i, so we use it in the imputation. Given the persistence of the error term, the imputed CFC series slowly go back to their long-run expected value given the development level and fixed country characteristics, at a rate ρ^t, without any sharp break. When no CFC is available for any year, we simply assume $u_i = 0$ and impute the CFC value based solely on the level of development.

ii. Net foreign income

Net Foreign income measures net capital or labor income received by a country from nationals living abroad. While reconstructing global NFI series a problem arises: the sum of all foreign incomes does not sum to zero. This is likely due, in part, to measurement errors but also very plausibly due to the fact that a non-negligible share of global wealth is still undeclared (Zucman, 2014). This results in a significant share of global foreign income that is also undeclared. We proceed as follows, on the basis of data expressed in US dollar at *market exchange rates* of *each year.* Indeed, there is no reason why data expressed in *Purchasing Power Parities* should sum to zero.

Different discrepancies are observed: global foreign wage income is negative, as well as foreign investment income. However, foreign direct investment income is positive, while portfolio and other investment income is negative at the global level. While the discrepancy observed on portfolio and other investment income can be attributed to missing wealth, it is hard to explain the positive net global foreign direct investment income figures. It thus calls for different foreign income reallocation strategies, depending of the type of income reallocated.

Missing income reallocation

We use IMF NFI data from the Balance of Payments Statistics to compute global missing property income, i.e. the sum of all net foreign property incomes throughout the world. In the same way, we compute missing global foreign compensation income.

Figure 2 - Missing net foreign income, 1975-2015

We then allocate the global property missing income to countries or geographical regions on the basis of their share of global offshore financial wealth, based on Zucman (2014) (see table 3). Within each geographical area, we attribute missing income to countries as a fraction of their share of GDP.

Table 3 - Offshore wealth estimates

Neutral reallocation

We allocate global missing (or excess) compensation of employees' income to countries and excess Foreign Direct Investment as a function of gross domestic product shares. Global FDI excess could in fact be explained by the fact that developing countries measure FDI at their book values rather than at their market values, as suggested by Zucman (2013). Following this argument, we one could allocate excess

FDI to developing countries only (i.e. increase their liabilities). However, there is no sufficient data to prove this, we thus follow a more conservative and neutral approach.

iii. PPP and Price indexes

Price indexes

The WID.world database stores constant/real terms in "hard" (in local currency), while on the fly computations allow to move back to current/nominal values, using a national income price index (NIPI) based on GDP Deflator series when available and CPI series otherwise. We prefer the deflator as it is generally better than consumer price index (CPI) series at accounting for changes in consumer preferences over time — the so-called "substitution" bias. When such changes are not taken into account, inflation can be overestimated. GDP deflator series, in general address this issue by using chain-weighting techniques, i.e. indexes in which quantities' weights can vary over time (Piketty and Zucman, 2013, Technical Appendix, pp. 39). On the opposite, CPI series generally use Laspeyres indexes, i.e. indexes in which quantities' weights are fixed at the base year and which do not allow for changes in consumers' preferences. This choice is consistent with "Capital is back" (Piketty & Zucman, 2013) (see Technical Appendix, pp. 39).

In a few countries, neither official deflator nor CPI data can be found. In these cases, we use country specific case-studies. In other countries, the official inflation series have been subject to criticism: in such cases, we use alternative estimates. In particular, our inflation series for China come from Maddison and Wu (2007), and our inflation series in the recent years for Argentina come from ARKLEMS[127].

[127] https://arklemsenglish.wordpress.com/

PPP and market exchange rates

WID.world stores constant local currencies and computes on the fly purchasing power parity estimates (PPP) and market exchange rates values. Our general rule for exchange rates is to preserve growth rates of series expressed in constant local currency, i.e. to convert an entire series of country A in euros at market exchange rate, we use the series stored in WID.world (expressed in constant local currency) and divide all the values by the market exchange rate between local currency and euro in the reference year (2015). We thus store only one market exchange rate value for each country and international currency.

The same method is used for PPP conversions. We use the latest PPP round (ICP 2011, published in 2014). Let us remind that previous official PPP estimates (ICP 2005, published in 2008-2011) led to a significant lowering of China's, India's and other developing countries' GDP levels compared to previous ICP estimates. The growth rates were unchanged, but official PPP GDP series for China and India were adjusted downwards. This opened-up a controversy: Angus Maddison for instance refused to make this adjustment, arguing that the new PPP estimates lead to implausibly low per capita GDP estimates for China in 1950 (below subsistence level). See his "Background Note on Historical Statistics" (2010). In *Capital in the 21st Century*, Piketty uses Maddison's estimates except for China and India which are corrected to match key international organizations estimates — the official source of economic data.

Table 4 – ICP controversy

	Year	2005 ICP	2011 ICP	Implied re-evaluation
India	2005	14.67	11.3	30%
China	2005	3.45	2.8	23%

The latest round (ICP 2011) re-evaluated China and India' PPP, along with other developing countries' PPP, and revealed that price levels were apparently too high in the 2005 round, compared what comes out from 2011 round's methodology. One of the reason was the use, in the 2005 round, of several uncommon, expensive goods in developing countries which artificially increased the price levels in such counties — e.g. a bottle of Bordeaux. In the 2011 methodology, it was easier to avoid unrepresentative, expensive goods in the methodology used to compute price levels of developing countries. This led to the reduction in the price levels of such countries and thus in the relative strengthening of developing countries' currencies.

In this thesis and on WID.world, we use the 2011 PPP round and use the same extrapolation method as the World Bank to obtain 2016 PPP conversion rates: that is, we correct the 2011 PPP rate with the relative evolution of local National Income Price Index to that of the US dollar:

$$PPP_{2016}^{LCU/USD} = PPP_{2011}^{LCU/USD} \frac{\left(\frac{NIPI_{2016}}{NIPI_{2011}}\right)}{\left(\frac{NIPI_{2016}^{US}}{NIPI_{2011}^{US}}\right)}$$

4 Discussion

i. CFC and NFI dynamics

Main results for National Income are presented in the main text of this thesis. We discuss below CFC dynamics in Europe, North America, Southern Asia and Africa as well as NFI dynamics in two countries which illustrate two very different trajectories followed by countries over the past decades.

CFC increased relatively steadily in Western Europe, rising from 11% of GDP in 1950 to more than 16% of GDP today. Consumption of Fixed Capital in North America also rose from about 10% of GDP in 1950 to about 14-15% today, even though the trend is not as steady as in Western Europe. The trajectories are notably different in Southern Asia and Africa as expected: in Southern Asia, CFC is around 7% at the beginning of the period and reaches barely 10% at the end, that is European and North American levels in the 1950s. African CFC is slightly below 10% of GDP in 1950 and slightly above 10% in 2015, showing almost no evolution in sixty-five years.

Figure 3 – Regional CFC evolutions from 1950 to 2015

The evolution of Norwegian NFI is illustrative of the country's industrial trajectory and investment strategy. Following the development of oil production in the Scandinavian country in the 1990s, its negative NFI (about 3% of GDP in the 1970s) was progressively transformed into a positive NFI of about 3% of GDP today. This is due to Norwegian investments in foreign assets made possible by oil money, largely via the Norwegian Oil Fund. Brazil NFI evolution shows another story, with a large drop in the early 1980s at the time of the Brazilian economic turmoil (recession, high inflation, foreign debt crisis). These two examples indeed confirm the importance to take into account Net Foreign Incomes when comparing macro economic or individual incomes over time and countries.

Figure 4 – NFI evolution from 1975 to 2015 in Norway and Brazil

ii. Issues and further work

Our data contains Net National Income, GDP, CFC and NFI series for all countries in the world from 1950 to today. We tried to harmonize the data as much as possible but several limitations indeed remain. One key issue relates to PPP estimates: our methodology assumes that the modification of production and consumption structures in two countries are well taken into account by the evolution of relative national income price indices. There are indeed strong arguments suggesting that this is an over simplification (McCarthy, 2011). We could use instead previous ICP rounds to readjust PPP values on the ICP survey years, as it is done in the Penn World Tables. More precisely, instead of assuming that Australia national income in 1970 expressed in 2015 PPP euros is a function of 2011 European and Australian production and consumption structures and price levels (as measured by the latest ICP round), and of the relative evolution of national income price indices between 1970 and today, we could use the 1980 ICP round to get closer to the "true" PPP correspondence between Australian Dollars and Euros in 1970. Given that there are few countries with relevant PPP data before 2005, this would not change the results in older time periods. However, it would give a lot of importance to variations in hard-to-measure purchasing power parities in the assessment of a country's growth performance in recent years (see for example the ICP controversy for China and India in section 4.1.1). We thus preferred to rely solely on the most recent ICP round, and use the evolution of the price index to extrapolate in previous years.

Another issue relates to the treatment of ex-USSR countries during the soviet period. From 1950 to 1991, we only have national accounts data for USSR as a block, except for one single year, 1973, for which Maddison provides GDP values for USSR countries. This allows us to plot ex-USSR countries national income series from 1973 onwards, but we did not reconstruct national level series before this date. In order to derive robust estimates at the national level before 1973, a much closer focus on national economic and social histories is required.

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Table 1 – Coverage of raw sources used for the construction of WID.world National Accounts series

Series	Source	Period covered	Data use (%)	Data coverage (%)
Population	UN WPP	1950–2015	96,8%	98%
	UN SNA main aggregates	1970–2014	1,0%	63%
	WID.world fellows	n/a	2,2%	7%
GDP	UN SNA main aggregates	1970–2014	68,4%	72%
	UN SNA detailed tables	1946–2014	0,2%	20%
	World Bank Data	1960–2015	9,0%	72%
	IMF World Economic Outlook (excl. forecasts)	1980–2015	0,05%	48%
	World Bank Global Economic Monitor	1997–2015	0,3%	13%
	IMF World Economic Outlook (forecasts only)	1980–2015	0,8%	2%
	Angus Maddison	1950–2008*	15,8%	98%
	WID.world fellows	n/a	5,5%	5%
NFI	UN SNA main aggregates	1970–2014	42,7%	73%
	IMF Balance of Payments statistics	1945–2015	27,4%	30%
	WID.world fellows	n/a	4,7%	5%
	WID estimates	n/a	25,3%	n/a
CFC	UN SNA detailed tables	1946–2014	12,0%	15%
	WID.world fellows	n/a	4,8%	5%
	WID estimates	n/a	83,2%	n/a
Price index	UN SNA main aggregates	1970–2014	67,7%	80%
	World Bank Data	1960–2015	11,7%	83%
	IMF World Economic Outlook (excl. forecast)	1980–2015	0,3%	53%

IMF World Economic Outlook (forecasts only)	1980–2015	0,1%	13%
Global Financial Data	n/a	1,1%	n/a
WID.world fellows	n/a	15,8%	16%
Country specific studies	n/a	3,3%	n/a

Source: Authors. * Maddison (2004) provides GDP data until year 0, but we only use his post-1950 estimates. *Key: 12% of our CFC values come from UN SNA detailed tables and 83% of the values are reconstructed by us. UN SNA raw series cover only 15% of countries and years over the 1950-2015 period.*

Table 2 - CFC estimation model

Parameter	Estimate
$\boldsymbol{\beta_0}$	-5.89*** (1.16)
$\boldsymbol{\beta_1}$	0.63** (0.25)
$\boldsymbol{\beta_2}$	-0.25* (0.14)
$\boldsymbol{\rho}$	0.91

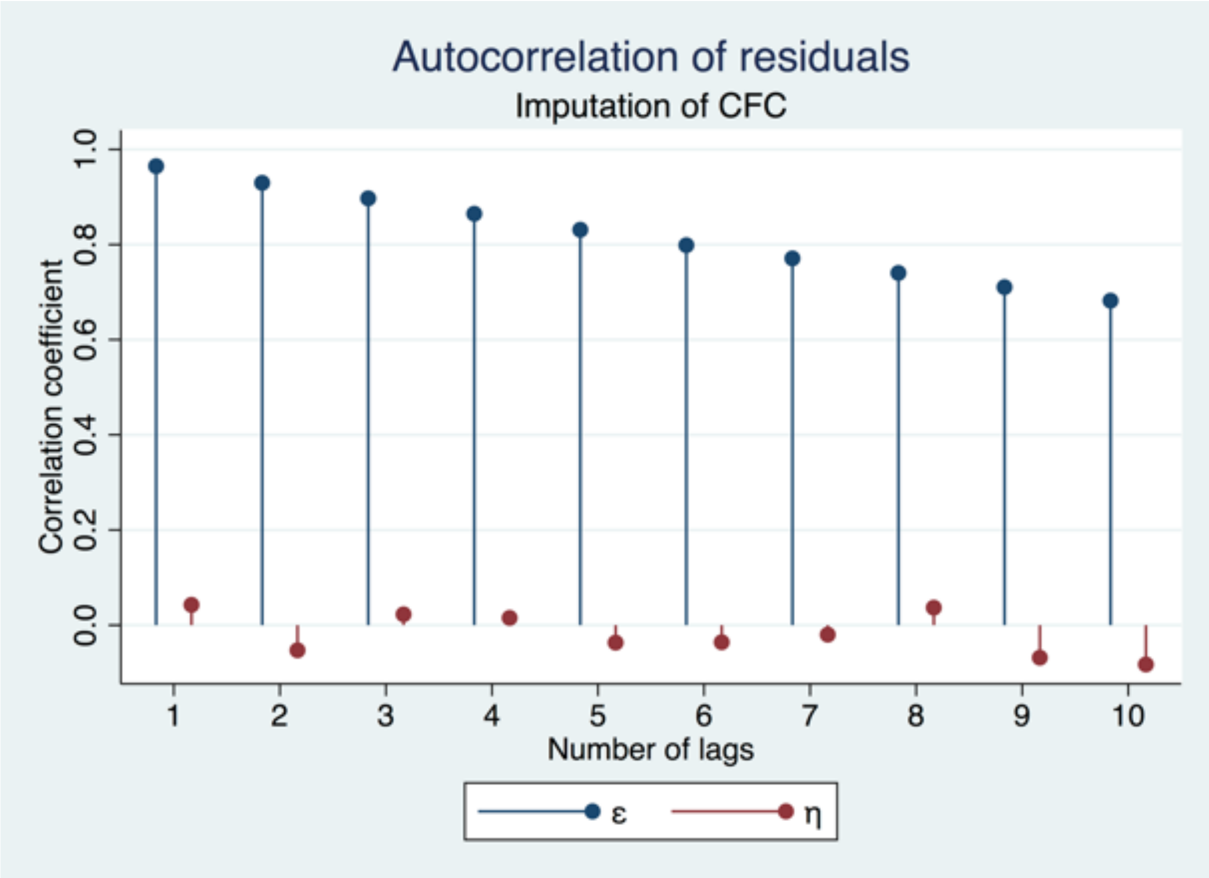
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 - Offshore wealth estimates

Geographical area	Offshore wealth	
	Value	Share
Europe	2000	34,5%
incl. Germany	*400*	*6,9%*
incl. France	*360*	*6,2%*
incl. Italy	*240*	*4,1%*
Incl. United Kingdom	*220*	*3,8%*
incl. Spain	*160*	*2,8%*
incl. Greece	*120*	*2,1%*
incl. Belgium	*120*	*2,1%*
incl. Portugal	*60*	*1,0%*
incl. Poland	*20*	*0,3%*
incl. Sweden	*20*	*0,3%*
incl. Norway	*20*	*0,3%*
incl. Other	*280*	*4,8%*
Gulf countries	580	10,0%
Asia	980	16,9%
Africa	390	6,7%
North America	1130	19,6%
incl. USA	*920*	*15,8%*
incl. Canada	*220*	*3,7%*
South America	550	9,4%
Russia	160	2,8%
Total	***5800***	***100,0%***

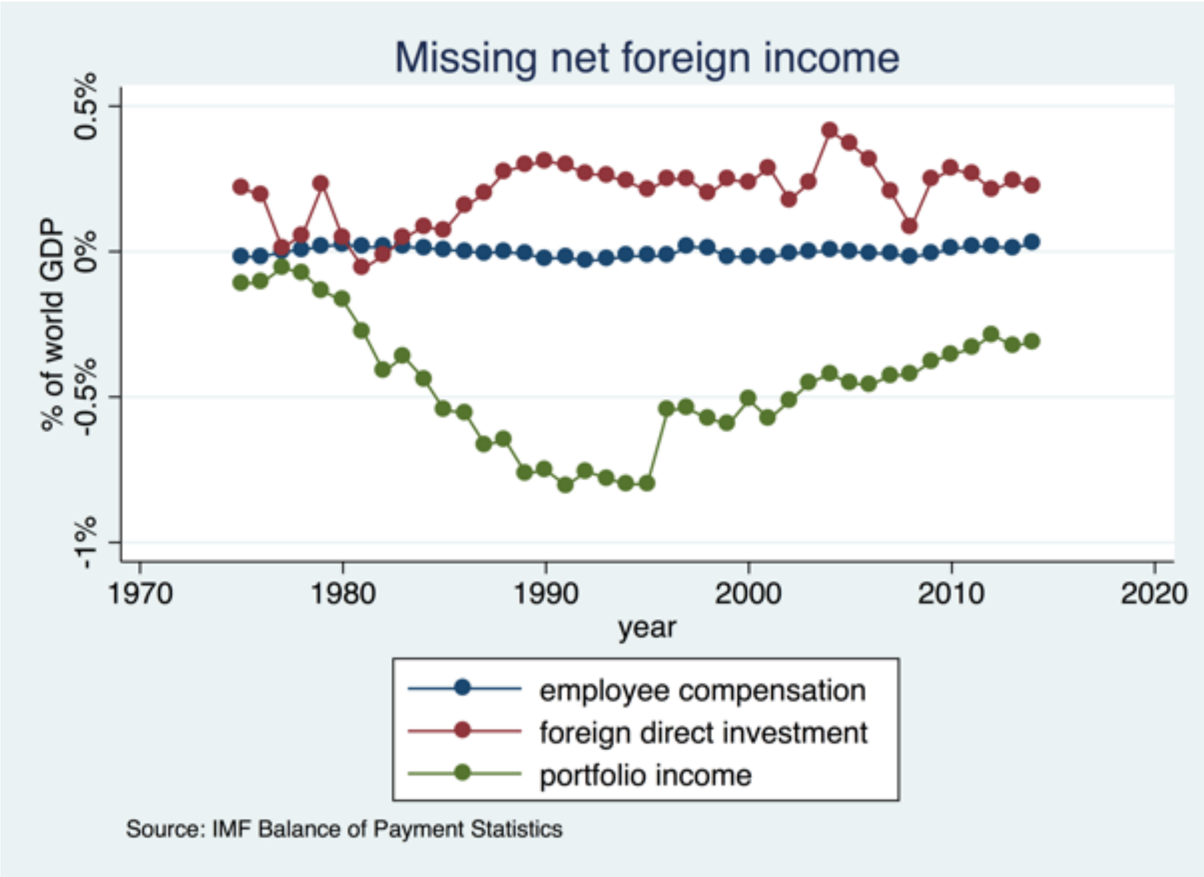
Source: Zucman (2014), JEP, Data Appendix

Figure 1 - Autocorrelation residuals



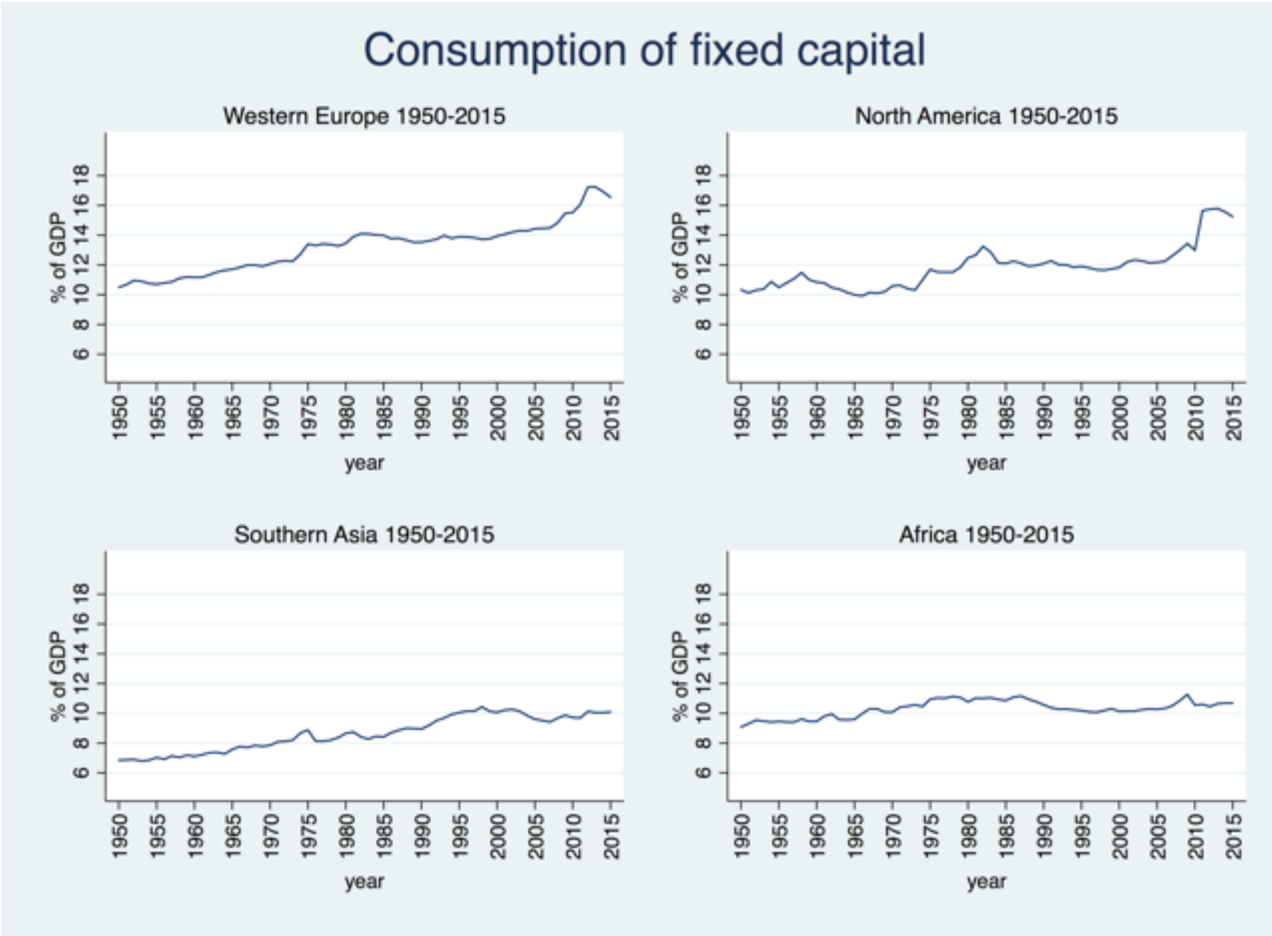
Source: Authors.

Figure 2 - Missing net foreign income, 1975-2015



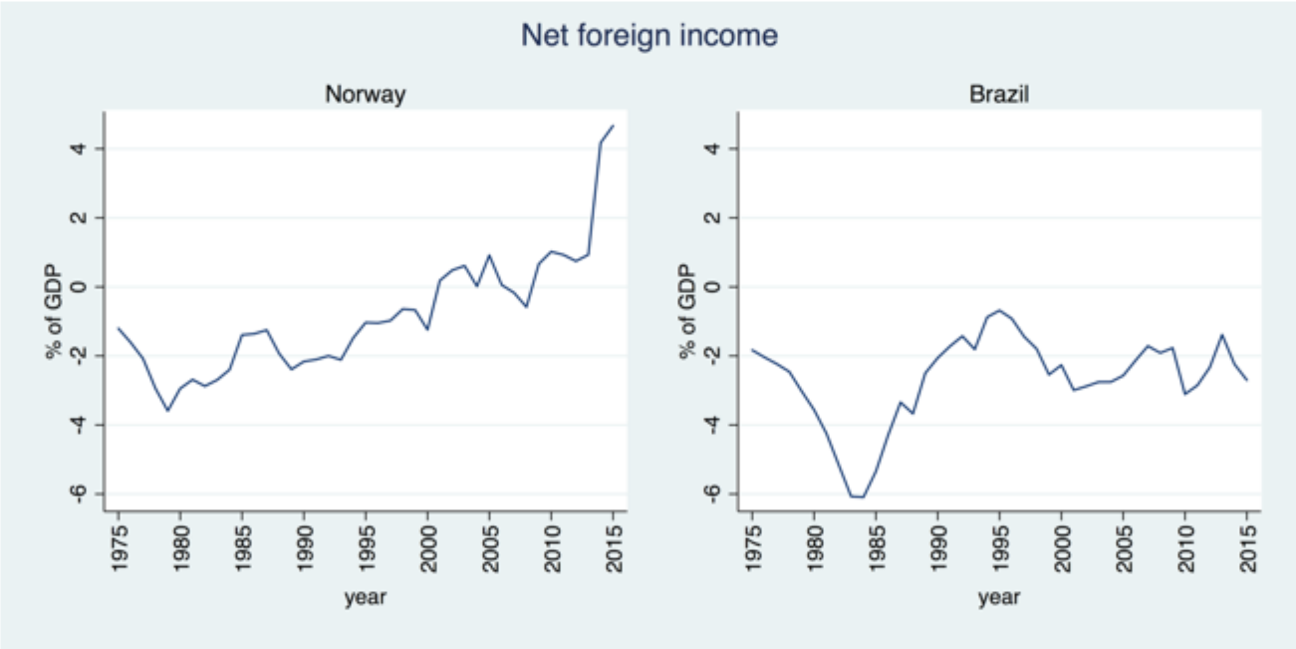
Source: Authors.

Figure 3 – Regional CFC evolutions from 1950 to 2015



Source: Authors.

Figure 4 – NFI evolution from 1975 to 2015 in Norway and Brazil



Source: Authors.

Building a global distribution of income brick by brick: Appendix B

Abstract. This appendix provides detailed information on the methods used to estimate global income inequality dynamics in the chapter "Building a global distribution of income brick by brick" and in the World Inequality Report 2018 (Alvaredo et al., 2018). We show that income inequality at the world level can be relatively well estimated from 1980 to 2016, by combining data on national incomes and available Distributional National Accounts. Our contribution is threefold. First, we attempt to go beyond country-level inequality data by comparing inequality dynamics between and within large geographic aggregates such as Europe, North America or Asia. Second, we combine data on income inequality within these aggregates to estimate a global distribution of income since 1980. We discuss the impact of several alternative methodologies to measure global inequality and show they have limited impacts on our overall results on the evolution of global inequality. Finally, we estimate the future evolution of global inequality between 2016 and 2050 by testing several assumptions about national income and population growth rates and inequality dynamics. This note also includes in its appendix a number of figures and tables, which summarize the key results of our analysis. We also provide a "Global Inequality User Guide" for readers seeking to reproduce our results. As data for more countries becomes available, we hope to be able to gradually improve our estimates of global inequality by testing more scenarios on the evolution of past and future global inequality.

This Appendix is based on “Building a global income distribution brick by brick”, WID.world Technical Note 2017/9, co-authored with Amory Gethin.

This appendix is structured as follows: Section 1 presents the main concepts used in the construction of global income inequality estimates. Section 2 describes the list of countries included in the analysis and the adjustments made to cover the 1980-2016 period. Section 3 details the steps used to aggregate country-level data into a global distribution of income inequality. Section 4 provides information on the method and scenarios used to predict global inequality trajectories between 2016 and 2050.

1 Concepts

i. Pre-tax national income

The income distribution concept used to estimate global inequality is pre-tax national income. Pre-tax national income is the sum of all pre-tax personal income flows accruing to the owners of the production factors, labor and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of the pension, unemployment and other social insurance systems. A more detailed description of the concepts and methods used in the WID.world project and the Distributional National Accounts (DINA) methodology is available in Alvaredo et al. (2016). [128]

ii. Adult population

Our benchmark population is the adult individual. For nearly all countries, this corresponds to individuals aged 20 or more (see WID.world for country-specific details). Similarly, when aggregating country-level or regional-level distributions to produce

[128] See also Box 2.4.1 of the World Inequality Report 2018 for a discussion on pre-tax and post-tax national income estimates.

global inequality estimates, we use the adult population of the corresponding aggregates.

iii. National income

As described in Appendix A, National income aims to measure the total income available to the residents of a given country. It is equal to the gross domestic product (the total value of goods and services produced on the territory of a given country during a given year), minus fixed capital used in production processes (e.g. replacement of obsolete machines or maintenance of roads) plus the net foreign income earned by residents in the rest of the world.

For any given pre-tax income distribution, we systematically rescale the averages of different income groups to match the national income of the corresponding aggregate. This means that we distribute the total national income produced in the economy to different income groups based on the relative share of total income they owned.

Example: in 2015, the Top 10% earners in terms of pre-tax income among the adult population in China earned 41.4% of total income. Given that the average national income per adult in China was € 13 144 at the time (in Purchasing Power Parity), the average income of the Top 10% was therefore:

$$\frac{€\ 13\ 144 \times 41.4}{10} = €\ 54\ 416$$

Table 1 – Share of world population and total national income (€ PPP 2016) covered by global inequality scenarios

iv. Market Exchange Rate and Purchasing Power Parity

We provide two versions of global inequality estimates depending on whether country-level and regional-level national incomes are converted to market exchange rate 2016 euros, or purchasing power parity 2016 euros.

The Market Exchange Rate (MER) is the rate at which one currency can be exchanged for another. Purchasing Power Parity (PPP) is the exchange rate that equates the price of a basket of identical traded goods and services in two countries. Converting values to PPP therefore accounts for differences in costs of living between countries, enabling comparisons between income levels in different countries. Given that market exchange rates do not take into account these differences (1€ converted in Indian rupees at market exchange rates enables a consumer to buy more goods and services in India than if it was spent in France, for instance), global inequality is likely to be higher when estimated at market exchange rates. In both MER and PPP estimates, all country-level distributions are first converted to constant local currency values using the corresponding national income deflator. Therefore, figures account for inflation.

2 Countries and regions included

i. Countries with full DINA available from WID.world

At the time of writing, all countries for which distributional national accounts (full income distribution from the poorest to the richest individuals) are available are used to estimate global inequality: Brazil, China France India The Middle-East Russia The United States[129]:

[129] For the US, many percentile groups at the bottom of the distribution have negative thresholds While this is fully relevant when analysing income inequality (see Piketty, Saez and Zucman 2016), it may be

For all these countries or regions, distributions are based on estimations combining fiscal, survey and national accounts data. Specific details on estimation of income inequality for these aggregates can be found in original articles available from the WID.world library.

ii. UK and Germany

At the time of writing, DINA estimates are not complete for the UK and Germany, but detailed estimates on top income shares, levels and thresholds are available for these countries on WID.world. This provides a rich source of information on the overall distribution of national income in these countries. We thus infer preliminary DINA estimates for the UK and Germany, based on known top income shares in these two countries and the distribution of national income in the remaining part of the distribution. For these two countries, we have data on the Top 10% of the distribution, but no data on the distribution of income within the Bottom 90%. We infer the whole distribution by using the following method:

We keep Top 10% income shares (and thus Bottom 90% income shares) as they are provided in the WID.world database. We know the average income of the bottom 90%, which differs in Germany, the UK and France. We infer the distribution of income within the Bottom 90% in Germany and the UK by assuming that its composition (*relative* to the Top 10%) is the same as in France.

This method is indeed not fully satisfactory and will be refined when DINA estimates are available for Germany, the UK and other European countries. However, alternative specifications used to infer the distribution of incomes within the bottom 90% in Germany and the UK had only very little impacts on the distribution of Western

misleading when aggregating several countries, since other countries could also have negative thresholds but these would be normalized to 0 due to data quality or estimation procedures in these countries. Therefore, we choose to systematically normalize negative thresholds and averages to 0.

Europe as a whole. This suggests that our general conclusions on Western Europe, and hence on broader global regions, will be robust to future country-level improvements. Indeed, such improvements will be important to better assess the evolution of inequality at the country level rather than at the global or regional level (which is our focus here).

iii. Sub-Saharan Africa

For Africa, full distributional national accounts are only available for Côte d'Ivoire at the time of writing and fiscal income shares are available for a handful of countries. WID.world fellows are currently working on DINA estimates for several African countries. In order to approximate the whole distribution of income in Sub-Saharan Africa, we use available survey data and correct these estimates at the top with available tax data estimates in these countries or in other African countries, with Ivory Coast as a useful benchmark (Czajka 2017). For more information on the procedure followed, see the Chancel and Czajka (2017)

iv. Adjustments

Our aim is to track the evolution of global inequality over the whole 1980-2016 period. Yet, inequality estimates for certain countries display temporal gaps. We fill these gaps by using the following method:

We interpolate linearly all gaps between two years. If the Top 1% income share in unavailable for 1991, but was 20% in 1990 and 22% in 1992, for instance, we fill in the gap by assuming that it was the mean between 1990 and 1992 levels, i.e. 21%.

In the case of gaps between 2016 and the most recent year available, we extrapolate all missing years by holding income shares constant and letting the average income of different income groups follow the growth of the average national income per adult. If data is available for 2015 but not for 2016 in a given country, for instance, and that the average national income per adult in this country grew by 2% in 2015, then we let the average income of all income groups grow by 2% between 2015 and 2016. The same procedure is applied backwards when inequality data is missing between 1980 and the earliest year available. In the context of a general rise in inequality since the 1980s, this assumption is conservative.

3 Estimating global inequality

Given the available distributions listed above, we use a two-step procedure to estimate global inequality. First, we combine country-level distributions in order to estimate income inequality dynamics in subregions of the world for which we have no data. We then merge all subregions and calibrate the resulting distribution to the average national income per adult of the world.

i. From countries to subregions

While all the countries or regions listed above cover an important share of the world adult population, important geographical areas are still missing in our analysis. In particular, this might result in seriously underestimating global inequality, since we would omit world regions who differ greatly in their average income. Given that we have data on national incomes for nearly all countries in the world (see Appendix A), it seems plausible to add missing regions to our estimation by using a gross approximation of income inequality within these areas. Put it differently, the between-country component of inequality is properly estimated (thanks to available aggregate national income data for close to 100% of global income), while the within-country component of global inequality relies on a more assumptions, somehow acceptable given that we already cover close to 75% of world income with relatively precise within-country inequality estimates. For a complete list of subregional aggregates, see Table 2.

This approximation is done by merging data from neighbouring countries, rescaling the predicted aggregate to its national income, and then predicting new income inequality dynamics within this aggregate from its growth path between 1980 and 2016. All distributions are merged using a mixture model (see the Generalized Pareto Interpolation tool, "gpinter", available online). Gpinter uses the average national incomes per adult, the adult populations and the thresholds and averages of different income groups in two (or more) countries and returns the income distribution and average income of the aggregate composed of these countries.

More precisely, we use the following method to infer the distribution of income within subregions for which we have no data:

1) We create two merged distributions using Gpinter: one composed of France, Germany and the UK, and the other composed of China and India.

2) We duplicate specific distributions to obtain new world subregions:

"Other Western Europe" is the France-Germany-UK merged distribution.

"Eastern Europe" is the France-Germany-UK merged distribution.

"Other Asia" is the China-India merged distribution.

"Other North America" is the distribution of the US.

"Other Latin America" is the distribution of Brazil.

For Russia, we simply rescale the distribution to the average national income of Russia and Ukraine combined.

3) We calibrate the income distributions of "Other Asia", "Eastern Europe", "Other North America", "Other Latin America" and "Other Western Europe" by rescaling averages to the national income per adult of the corresponding subregion. Therefore, we assume inequality and inequality dynamics to be the same in the projected region, but projected regions differ in the level and evolution of average income per adult. The final "Other Asia" aggregate, for instance, has the same income shares as the merged distribution of China and India, but has the average national income per adult of the rest of Asia (excluding Russia) across the whole 1980-2016 period. From this aggregate,

we finally build “Asia” (excluding Russia), which is the merged distribution of China, India and Other Asia.

Similarly, “Other Western Europe” is the merged distribution of France, Germany and the UK, rescaled to the average national income of the rest of Western Europe (25 countries). From this aggregate, we finally build “Western Europe”, which is the merged distribution of France, Germany, the UK, and “Other Western Europe”.

Table 2 – Composition of world subregions

ii. From subregions to regions

After having predicted income inequality in subregions of the world for which we have no data, we are left with 15 countries or subregions. In the same way as above, we merge again different subregions together to get inequality estimates at the level of world regions:

Europe is the merged distribution of France, Germany, the UK, the rest of Western Europe and Eastern Europe.

Asia is the merged distribution of China, India and the rest of Asia.

US-Canada is the merged distribution of the US and of Canada.

Latin America is the merged distribution of Brazil and the rest of Latin America.

If we add Subsaharan Africa and the Middle East, we now have six world regions, which together covering close to 100% of world population and national income. These aggregates are useful to capture broad evolutions of inequality within and between the main geographical areas of the world, bearing in mind the limits of our method associated current lack of inequality data.

Figure 1 – Share of world population by region in 2016

Figure 2 – Share of world national income by region in 2016

iii. From regions to global inequality

As highlighted in this introduction, we merge five different combinations of subregions in order to apprehend how one can gradually build a global distribution of inequality from our procedure, and to compare the results obtained from our scenarios.

Scenario 1: the US and Western Europe are merged. Western Europe is the merged distribution of France, Germany and the UK, rescaled to the national income and adult population of Western Europe as a whole[130].

Scenario 2: China, India, the US and Western Europe are merged.

Scenario 3: Brazil, China, India, the Middle East, Russia, the US and Western Europe are merged.

Scenario 4: all 15 subregions or countries are merged. These are Africa, Other Asia, Brazil, China, Germany, Eastern Europe, France, the UK, India, the Middle East, Other North America, Russia, Other Latin America, the US and Western Europe.

Scenario 5: all subregions are included, except Other Asia and Other Latin America.

Figures 8-13 provides results for the different scenarios. Our baseline scenario is Scenario 4 in 2016 PPP Euros. It combines all countries and subregions available to estimate a global distribution of income that has the largest geographical coverage. Note that in estimating global inequality, we combined all subregions and countries rather than directly merging the 6 world regions defined above. This is because using

[130] Western Europe here is therefore not exactly the same as "Western Europe" detailed in 3.1. More precisely:

- For scenarios 1, 2, 3, Western Europe = France + Germany + UK.
- For scenarios 4 and 5, Western Europe = France + Germany + UK + Other Western Europe.

Both versions of Western Europe are rescaled to the national income of Western Europe as a whole (28 countries, including France, Germany and the UK).

all the information available (at the country level, subregional level and regional level) rather than merging distributions which are already aggregated gives us a slightly more precise estimate.

Figure 8 – Global inequality dynamics in four world aggregates, 1980-2016

Figure 9 – Cumulative share of growth captured by income group in four world aggregates, 1980-2016

Figure 10 – Top 10% share of global income in four world aggregates, 1980-2016

Figure 11 – Top 1% share of global income in four world aggregates, 1980-2016

Figure 12 – Bottom 50% share of global income in four world aggregates, 1980-2016

Figure 13 – Middle 40% share of global income in four world aggregates, 1980-2016

In theory, given that we have data on the national income per adult in most countries around the world, inferring inequality in each country with the same method as above and then merging all countries would have produced even more precise estimates. Yet, this would be computationally very intensive and would not add much to the analysis, since we are already covering an important share of global income and global population with available distributional national accounts (respectively about

75% and 65%), and differences in income levels between our subregions are already sufficiently large to capture the main differences in average incomes between most countries in the world. We performed tests where we combined a larger number of countries, and as expected, results were very similar.

iv. Distinguishing inequality between and within countries

Increasing inequality at the world level comes from differences in average national incomes per adult *between countries*, as well as from differences in average income between individuals *within countries*. We attempt to separate these two dimensions by using a very simple procedure.

Inequality within countries: to estimate the degree of inequality within countries, we attribute to each subregion the average national income of the world and re-compute the average income of each percentile group by using income shares (see formula in 1.3). We then merge all subregions to get a counterfactual global distribution of income. For each year, this corresponds to the level of income inequality that would exist if all countries in the world had the same average national income per adult.

Inequality between countries: to estimate the degree of inequality between countries, we use country-level data on average national incomes per adult. We consider each country to be an observation, and we perform a simple percentile analysis based on the country-level distribution of average income, weighed by adult population. For each year, this corresponds to the level of income inequality that would exist if for any given country around the world, all individuals living in this country would earn exactly the average national income per adult.

v. Robustness check: alternative calibration method

Assuming that inequality levels and trends are approximately the same within world regions seems to be a reasonable procedure. Yet, differences in growth rates between projecting and projected regions may lead to inconsistencies. In “Other Asia”, for instance, national income growth was lower than in China or India, so assuming that income shares grew at the same rate could lead to underestimating the growth rate of the average income of the Bottom 50% across the period in this region. The publication of new DINA estimates for "Other Asia" countries, on which WID.world fellows are currently working, will allow us to better assess this question.

For the 2018 World Inequality Report, we use the calibration procedure described in 3.1. Below, we present an alternative method for inferring inequality in subregions (Figures 9-12). By contrast with the method in 3.1 which uses *levels* (income shares) to compute inequality in projected subregions, the following two-step method is based on inequality *dynamics*. Rather than assuming that the share of *income* captured by income group is the same in the projected region (“Other Asia”) as in the projecting region (the merged distribution of China and India) over 1980-2016, this procedure assumes that inequality levels are the same in 1980, but after 1980 only the share of *growth* captured by income group is the same:

1) For each distribution, we compute the share of growth captured by income group between 1980 and 2016. Consider that the average income of the Top 1% grew from $a_{top1}^{1980} = €1000$ to $a_{top1}^{2016} = €5000$ between 1980 and 2016, while the average national income per adult grew only from $avg^{1980} = €500$ to $avg^{2016} = €600$. Then the share of growth captured by the Top 1% is equal to:

$$Share\ of\ growth\ captured = 0.01 \times \frac{a_{top1}^{2016} - a_{top1}^{1980}}{avg^{2016} - avg^{1980}} = 0.01 \times \frac{4000}{100} = 0.04 = 4\%$$

2) We then start from the distribution of income in 1980 (obtained from the method described in 3.1), and predict income inequality dynamics by combining the share of growth captured by income group with the evolution of the average national

income per adult in these subregions. Formally, the average income $ainc_p^{t+1}$ of percentile p at time $t+1$ is equal to:

$$ainc_p^{t+1} = ainc_p^t + \frac{sharegrowth_p}{size_p} \times (avg^{t+1} - avg^t)$$

Where $sharegrowth_p$, $size_p$ and avg^{t+1} are respectively the share of growth captured by percentile p, the population size of percentile p (1% for the Top 1%, for instance), and the average national income per adult at date $t+1$.

Some key results obtained with this calibration method are available (Figures 9-12). Results are qualitatively similar to those obtained with static calibration. When calibrating income shares based on the share of growth captured by income group, income is higher at the bottom of the distribution and is slightly lower at the very top. The elephant curve is in fact even more pronounced in this alternative method. This variation is largely due to "Other Asia", which accounts for the largest share of world national income for which we do not have DINA estimates. In the "dynamic calibration" methodology, bottom groups in Other Asia grow relatively more than middle and top income groups of Other Asia, as compared hence moderately increasing growth rates at the bottom of the global growth curve and slightly reducing them at the middle of the global distribution. Overall impacts on the results are however limited given that this region represents a relatively low share of world national income (about 16.5%, see Figure 2).

Figure 9 – Global inequality dynamics, 1980-2016

(dynamic calibration)

Figure 10 – Share of growth captured by income group, 1980-2016

(dynamic calibration)

Figure 11 – Top 10% income shares in world regions, 1980-2016

(dynamic calibration)

Figure 12 – Top 10% share of global income, 1980-2016

(dynamic calibration)

4 Projections

Which of the two forces governing global inequality (between-country and witin-country inequality) is likely to dominate in the future? No one can answer this question with certainty, but simple modelling exercises can help answer it. On the basis of 1980-2016 global and national income inequality dynamics, we project the evolution of global inequality between 2016 and 2050.

Projections are carried in two steps. First, we predict income inequality at the subregional level based on assumptions about the growth rate of national income based, the growth rate of adult population and the share of growth captured by income group. We then merge all subregional distributions (as in scenario 4) for each year between 2016 and 2050 to get global inequality estimates for this period.

i. Income and population growth projections

National incomes

The evolution of national incomes in countries around the world are based on OECD forecasts[131]. The OECD provides predictions about Gross Domestic Product annual growth rates up to 2050 for most countries around the world. We use these growth rates to carry forward the total national income of each country, and we then aggregate the resulting projections into the subregions defined above.

For countries included in our analysis but not included in OECD forecasts, we apply the same national income growth rate, calculated so that the total growth rate of the world's national income between 2016 and 2050 matches OECD's forecasts about

[131] OECD (2017), GDP long-term forecast (indicator). doi: 10.1787/d927bc18-en.

global GDP growth. After aggregating countries into subregions, we noted that some subregions in the emerging world had surprisingly low growth rates implied by OECD world forecasts. We chose to be more optimistic about growth rates in the emerging world than the OECD:

Africa is assumed to growth at an average annual growth rate of 3%.

Other South America is assumed to growth at an average annual growth rate of 2.5%.

Other Asia is assumed to growth at an average annual growth rate of 2.5%.

We view this relative optimism as a conservative assumption: the higher the growth rates in the emerging world, the faster the reduction of global inequality, via the between-country equality channel. We stress that results of global inequality projections are remarkably robust to these alternative growth rates scenarios, as long as growth rates are held at “reasonable” levels (between 2% and 7%). This result reinforces our main conclusion: it is within-country inequality, more than between-country convergence, that is likely to govern global income inequality dynamics in the coming decades.

Adult populations

Projections about adult population growth are from the United Nations’ World Population Prospects. The UN provides annual growth rates forecasts up to 2050 for nearly all countries around the world. We therefore apply the same procedure as for national incomes, carrying forward adult populations based on their predicted annual growth rates.

ii. Definition of three within country inequality scenarii

Now that we have predicted the evolution of average national income per adult in all subregions between 2016 and 2050, we have to make assumptions about how growth is distributed among the adult population of each aggregate. As explained in 3.1, the evolution of the average income per adult of each income group (percentile) between two dates is given by:

$$ainc_p^{t+1} - ainc_p^t = \frac{sharegrowth_p}{size_p} \times (avg^{t+1} - avg^t)$$

Where $sharegrowth_p$, $size_p$ and avg^{t+1} are respectively the share of growth captured by percentile p, the population size of percentile p (1% for the Top 1%, for instance), and the average national income per adult at date $t+1$. In order to predict global inequality, we thus have to predict the evolution of inequality within countries by making assumptions about the share of growth captured by income group. In the World Inequality Report 2018, we assess three scenarios:

Business-as-usual scenario: assumes that inequality will grow at the same speed as it did between 1980 and 2016 in the corresponding subregion. In China, for instance, the Top 1% captured 15% of income growth between 1980 and 2016. Based on the above formula, equipped with average growth projections from the OECD, and assuming that the Top 1% continues to capture 15% of national income growth for every year between 2016 and 2050, we can therefore predict the average income of the Top 1% in China every year up to 2050.

US 1980-2016 scenario: assumes that in all subregions, inequality will grow at the same speed as it did in the US between 1980 and 2016. The Top 1%, for instance, captured about 35% of growth over the period in the US, so we can predict the evolution of inequality in other subregions by assuming that the Top 1% will capture 35% of growth every year between 2016 and 2050 and by computing the corresponding average income based on the above formula.

Europe 1980-2016 scenario: assumes that in all subregions, inequality will grow at the same speed as it did in Europe as a whole between 1980 and 2016. The Top 1%, for instance, captured about 18% of growth over the period in Europe, so we can predict the evolution of inequality in other subregions by assuming that the Top 1% will capture 18% of growth every year between 2016 and 2050 and by computing the corresponding average income based on the above formula.

After having predicted national incomes, adult populations and inequality trajectories within subregions between 2016 and 2050, we finally estimate the evolution of global inequality by merging all subregions for each scenario and for each year in the period. This gives us an estimation of the different possible trajectories of global income inequality in the next three decades.

5 Discussion

Despite the limited available data on global inequality, we have attempted to estimate the main features of global inequality dynamics in the last 40 years by making assumptions about inequality trajectories within broad geographical areas, and on the basis of Distributional National Accounts already covering a large share of global income. Interestingly, and partly because existing inequality data from WID.world already covers about three quarters of world income and two thirds of world population, our results are relatively robust to alternative specifications for missing countries.

We have proceeded in a transparent manner, providing detailed codes and sources on WID.world, so as to contribute to increase the level of transparency of existing global inequality statistics.

As more reliable estimates will become available for a growing number of "missing" countries, especially in South-East Asia, Africa, Eastern Europe and Latin America, we will be able to get a more precise picture of global inequality. In the future, we also hope to gradually improve our projections of global inequality by testing more scenarios and formulating plausible assumptions about growth dynamics in the long run.

Table 1 – Share of world population and total national income (€ PPP 2016) covered by global inequality scenarios

Scenario	Countries / Regions covered	Population covered (% of world)	National income covered (% of world)
1	Western Europe, USA	14%	33%
2	China, Western Europe, India, USA	53%	60%
3	Brazil, China, Western Europe, India, Middle-East, USA, Russia	65%	73%
4	Africa, Asia, Europe, Middle-East, USA-Canada, Russia, Latin America	100%	100%
5	Africa, Asia, Brazil, Europe, Middle-East, USA-Canada, Russia	94%	95%

Table 2 – Composition of world subregions

Subregion	Number of countries	List of countries
Brazil	1	Brazil
China	1	China
Eastern Europe	23	Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Czechoslovakia, Estonia, Hungary, Kosovo, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Serbia, Slovakia, Slovenia, USSR, Yugoslavia
France	1	France
Germany	2	German Democratic Republic, Germany
India	1	India
Middle-East and Northern Africa	22	Algeria, Armenia, Azerbaijan, Bahrain, Egypt, Georgia, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Syrian Arab Republic, Tunisia, Turkey, United Arab Emirates, Yemen

Oceania	23	American Samoa, Australia, Cook Islands, Fiji, French Polynesia, Guam, Kiribati, Marshall Islands, Micronesia, Nauru, New Caledonia, New Zealand, Niue, Northern Mariana Islands, Palau, Papua New Guinea, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna
Other Asia	31	Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, Hong Kong, Indonesia, Iran, Japan, Kazakhstan, Korea, Kyrgyzstan, Lao PDR, Macao, Malaysia, Maldives, Mongolia, Myanmar, Nepal, North Korea, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan, Tajikistan, Thailand, Timor-Leste, Turkmenistan, Uzbekistan, Viet Nam
Other Latin America	44	Anguilla, Antigua and Barbuda, Argentina, Aruba, Bahamas, Barbados, Belize, Bolivia, Cayman Islands, Chile, Colombia, Costa Rica, Cuba, Curacao, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Islands, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Montserrat, Netherlands Antilles, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Sint Maarten (Dutch part), Suriname, Trinidad and Tobago, Turks and Caicos Islands, Uruguay, Venezuela, Virgin Islands, British, Virgin Islands, US
Other North America	4	Bermuda, Canada, Greenland, Saint Pierre and Miquelon
Russia	2	Russian Federation, Ukraine
Sub-Saharian Africa	52	Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo, Cote d'Ivoire, DR Congo, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Saint Helena, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Tanzania, Togo, Uganda, Western Sahara, Zambia, Zanzibar, Zimbabwe

USA	1	USA
United Kingdom	1	United Kingdom
Western Europe	25	Andorra, Austria, Belgium, Channel Islands, Denmark, Faroe Islands, Finland, Gibraltar, Greece, Holy See, Iceland, Ireland, Isle of Man, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Sweden, Switzerland

Table 3 – Income growth and inequality in world regions

	Total cumulated per adult real growth							
Income group (distribution of per-adult pre-tax national income)	**Afric a**	**Asia**	**Wester n Europe**	**Ex USSR**	**Middle -East**	**North America**	**Lati n America**	**Worl d**
Full population	20 %	199 %	40 %	16 %	89 %	71 %	2 %	59 %
Bottom 50%	44 %	169 %	26 %	-36 %	127 %	8 %	10 %	94 %
Middle 40%	20 %	171 %	34 %	-9 %	107 %	50 %	-4 %	41 %
Top 10%	16 %	240 %	58 %	151 %	77 %	135 %	4 %	69 %
incl. Top 1%	*30 %*	*363 %*	*72 %*	*579 %*	*62 %*	*224 %*	*13 %*	*101 %*
incl. Top 0.1%	*58 %*	*643 %*	*76 %*	*2200 %*	*56 %*	*347 %*	*33 %*	*133 %*
incl. Top 0.01%	*117 %*	*977 %*	*87 %*	*7105 %*	*60 %*	*488 %*	*59 %*	*184 %*
incl. Top 0.001%	*226 %*	*1326 %*	*120 %*	*21820 %*	*70 %*	*684 %*	*91 %*	*234 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

Table 4 – Share of growth captured by income group in world regions

Income group (distribution of per-adult pre-tax national income)	Africa	Asia	Western Europe	Ex USSR	Middle-East	North America	Latin America	World
Full population	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Bottom 50%	22 %	12 %	14 %	-71 %	11 %	2 %	64 %	13 %
Middle 40%	34 %	38 %	38 %	-28 %	33 %	33 %	-76 %	30 %
Top 10%	44 %	50 %	48 %	200 %	56 %	65 %	112 %	57 %
incl. Top 1%	*27.65 %*	*19.19 %*	*18.26 %*	*125.81 %*	*21.55 %*	*33.69 %*	*181.87 %*	*27.71 %*
incl. Top 0.1%	*9.94 %*	*9.06 %*	*6.98 %*	*75.03 %*	*7.31 %*	*17.45 %*	*202.62 %*	*13.65 %*
incl. Top 0.01%	*2.36 %*	*4.68 %*	*2.98 %*	*37.62 %*	*3.33 %*	*8.71 %*	*156.64 %*	*7.23 %*
incl. Top 0.001%	*0.49 %*	*2.17 %*	*1.39 %*	*18.34 %*	*1.73 %*	*4 %*	*104.06 %*	*3.64 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

Table 5– Total cumulated real growth per adult in world regions (dynamic calibration)

	Total cumulated real growth per adult							
Income group (distribution of per-adult pre-tax national income)	Africa	Asia	Western Europe	Ex USSR	Middle-East	North America	Latin America	World
Full population	20 %	199 %	40 %	16 %	89 %	71 %	2 %	59 %
Bottom 50%	44 %	213 %	27 %	-36 %	127 %	10 %	10 %	115 %
Middle 40%	20 %	182 %	34 %	-9 %	107 %	51 %	-4 %	43 %
Top 10%	16 %	213 %	56 %	151 %	77 %	134 %	4 %	64 %
incl. Top 1%	*30 %*	*308 %*	*70 %*	*579 %*	*62 %*	*221 %*	*14 %*	*94 %*
incl. Top 0.1%	*58 %*	*534 %*	*73 %*	*2200 %*	*56 %*	*341 %*	*35 %*	*123 %*
incl. Top 0.01%	*117 %*	*798 %*	*84 %*	*7105 %*	*60 %*	*479 %*	*62 %*	*169 %*
incl. Top 0.001%	*226 %*	*1072 %*	*109 %*	*21820 %*	*70 %*	*666 %*	*96 %*	*210 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

Table 6– Share of growth captured by income group in world regions (dynamic calibration)

Income group (distribution of per-adult pre-tax national income)	**Africa**	**Asia**	**Western Europe**	**Ex USSR**	**Middle-East**	**North America**	**Latin America**	**World**
Full population	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
Bottom 50%	22 %	14 %	15 %	-71 %	11 %	3 %	64 %	15 %
Middle 40%	34 %	41 %	38 %	-28 %	33 %	33 %	-79 %	31 %
Top 10%	44 %	45 %	47 %	200 %	56 %	64 %	115 %	53 %
incl. Top 1%	*27.65 %*	*16.26 %*	*17.66 %*	*125.81 %*	*21.55 %*	*33.17 %*	*188.27 %*	*25.77 %*
incl. Top 0.1%	*9.94 %*	*7.53 %*	*6.72 %*	*75.03 %*	*7.31 %*	*17.14 %*	*210.4 %*	*12.63 %*
incl. Top 0.01%	*2.36 %*	*3.82 %*	*2.85 %*	*37.62 %*	*3.33 %*	*8.55 %*	*162.83 %*	*6.66 %*
incl. Top 0.001%	*0.49 %*	*1.75 %*	*1.27 %*	*18.34 %*	*1.73 %*	*3.9 %*	*109.64 %*	*3.27 %*

Distribution of pre-tax income among adults. Estimates combine survey, fiscal and national accounts data. All data from WID.world

Figure 1 – Share of world population by region in 2016

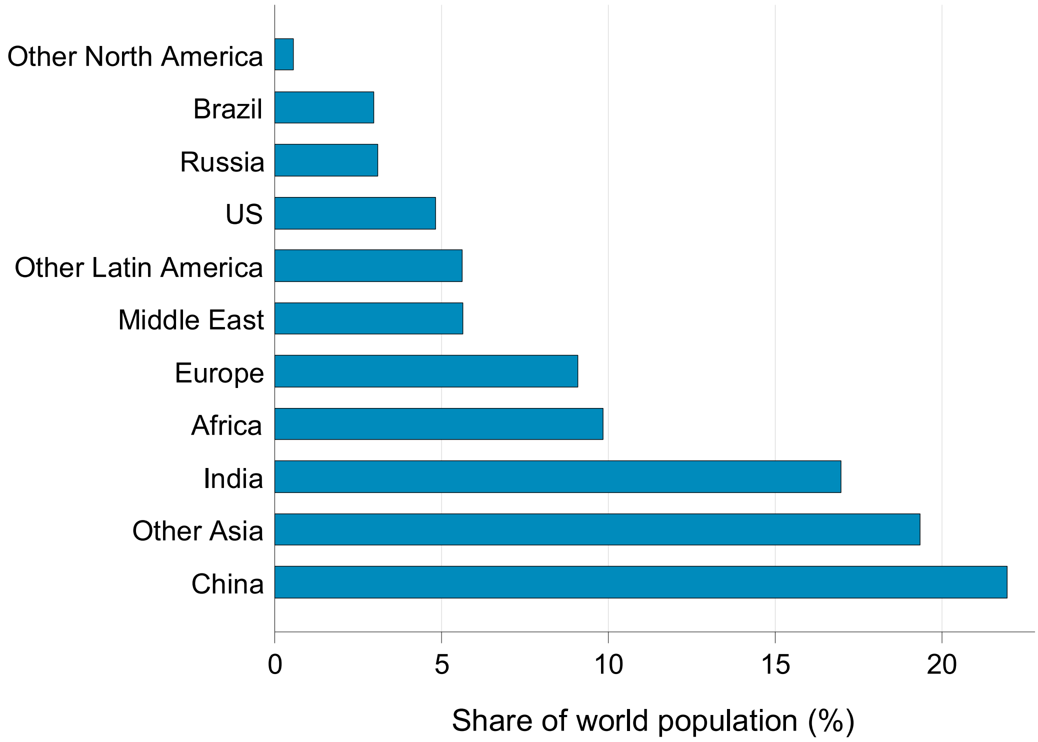


Figure 2 – Share of world national income by region in 2016

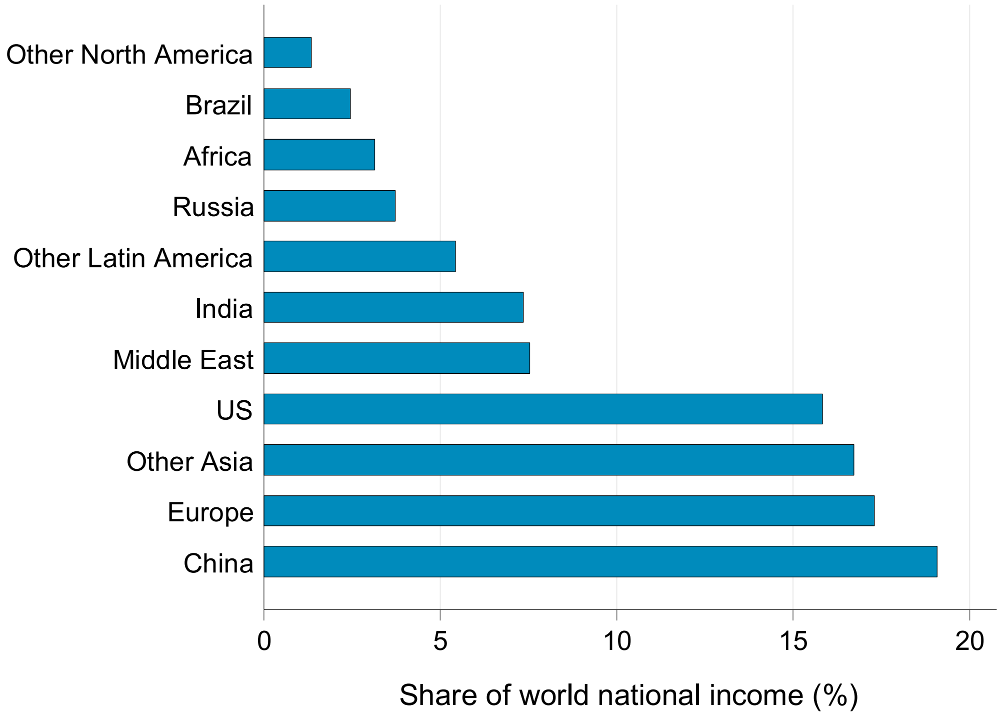


Figure 3 – Global inequality dynamics in four world aggregates, 1980-2016

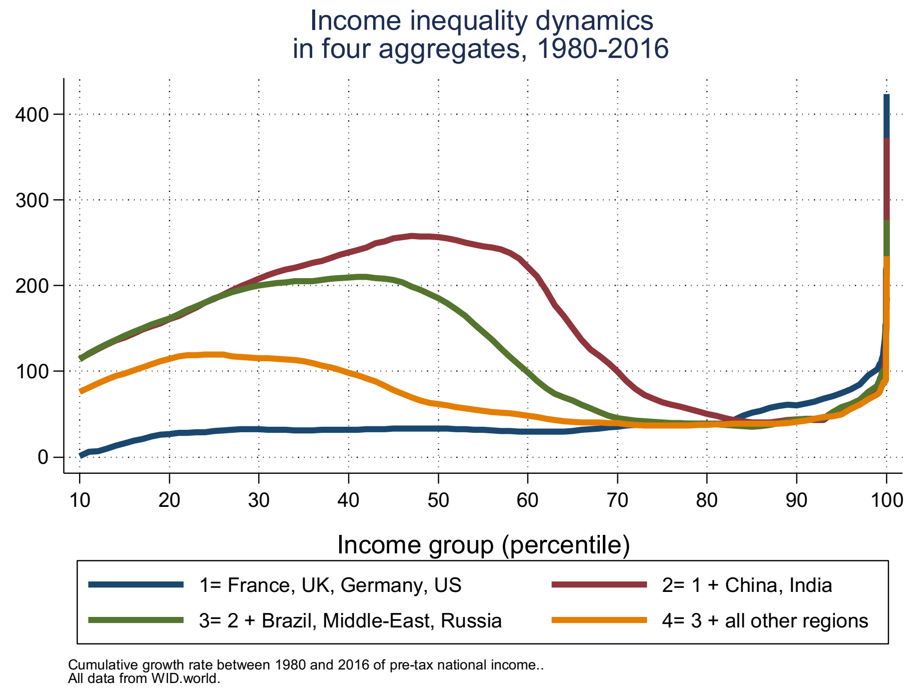


Figure 4 – Cumulative share of growth captured by income group in four world aggregates, 1980-2016

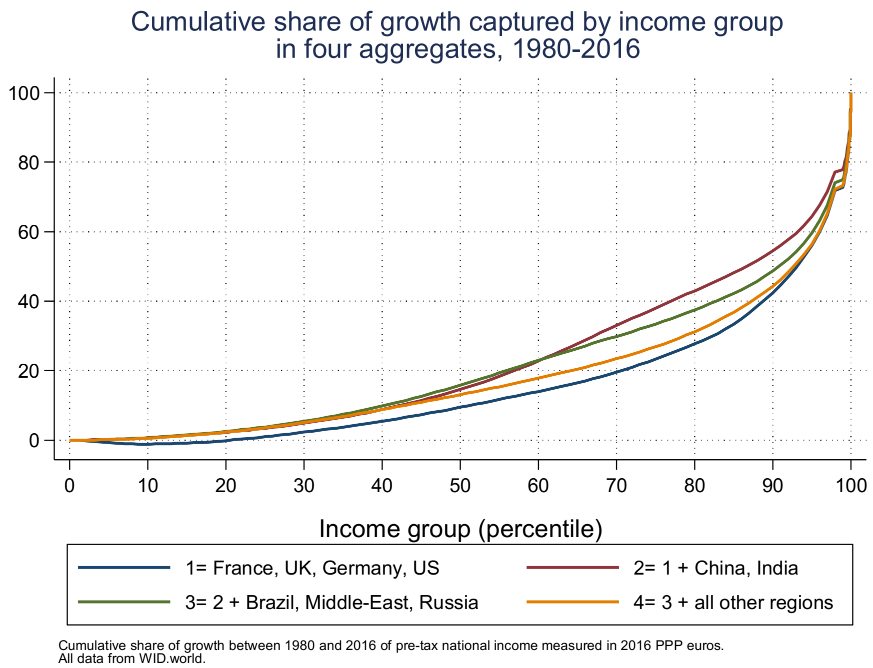


Figure 5 – Top 10% share of global income

in four world aggregates, 1980-2016

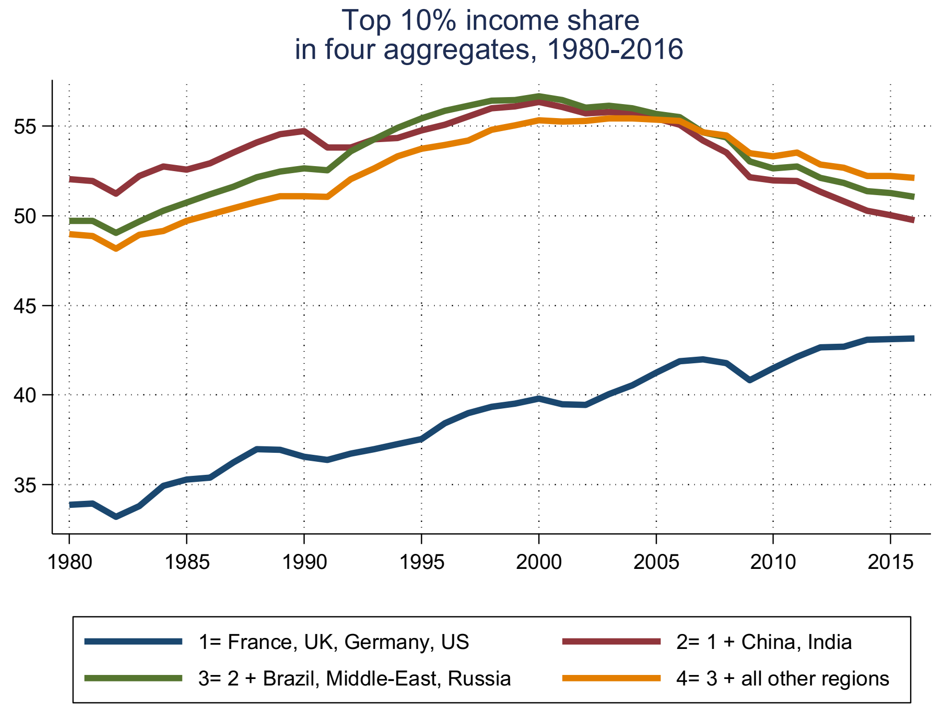


Figure 6 – Top 1% share of global income
in four world aggregates, 1980-2016

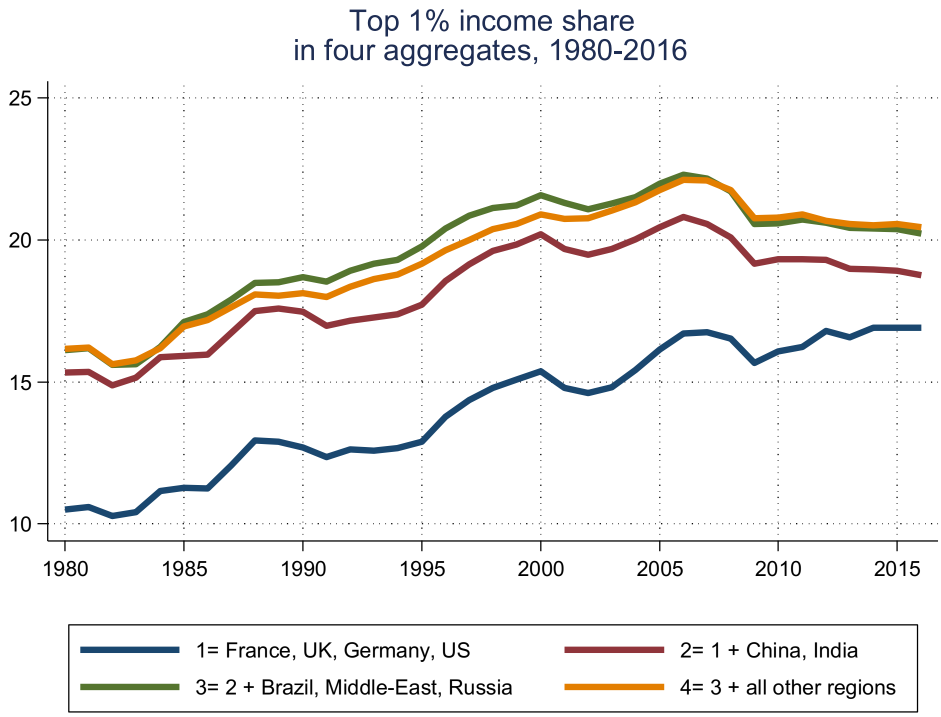


Figure 7 – Bottom 50% share of global income in four world aggregates, 1980-2016

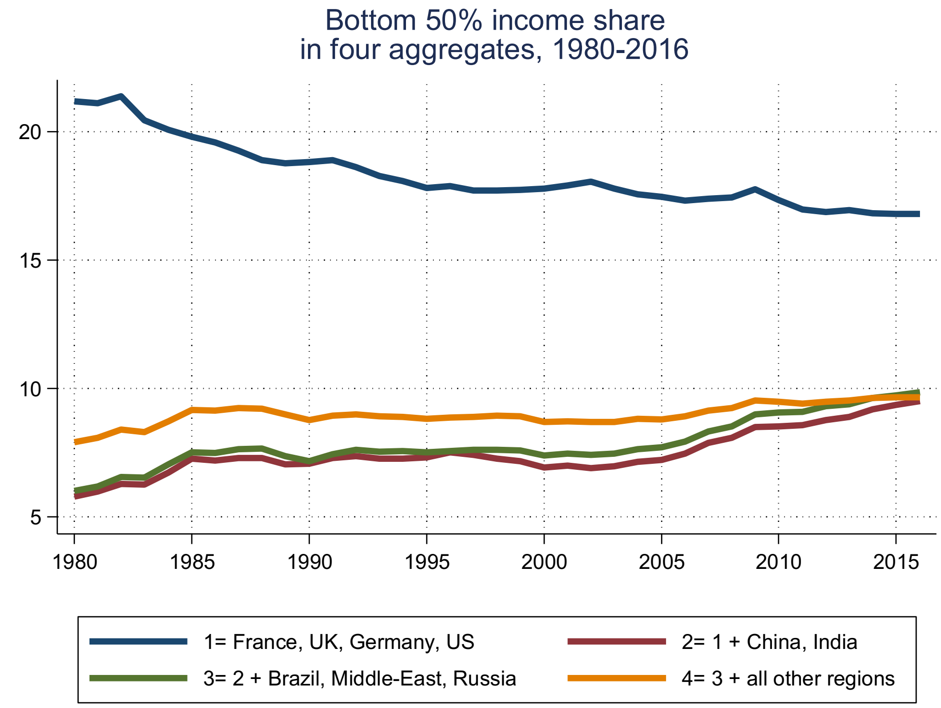


Figure 8 – Middle 40% share of global income

in four world aggregates, 1980-2016

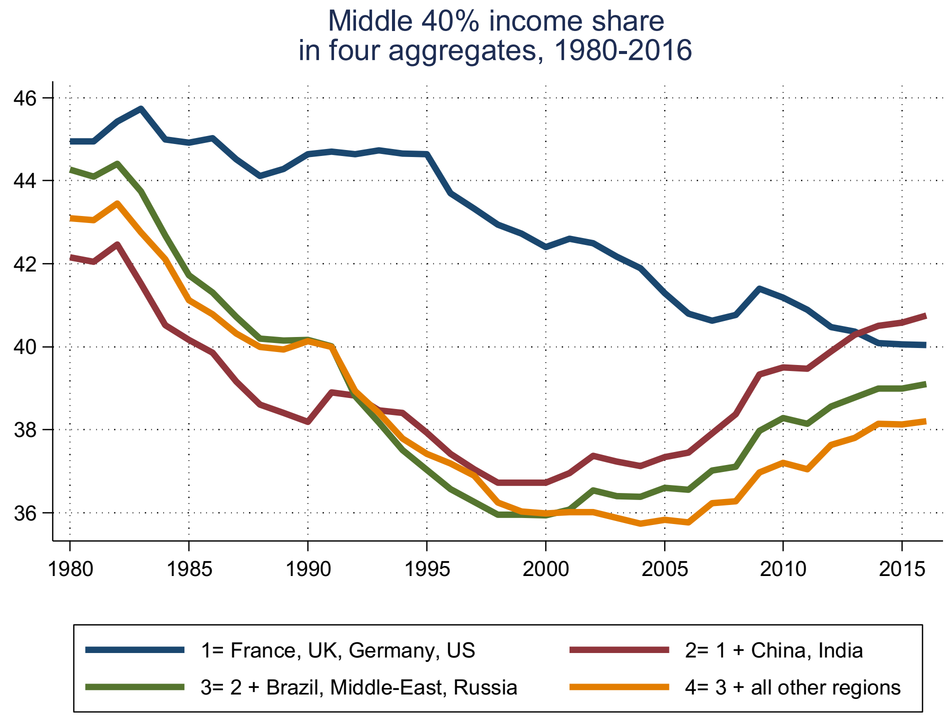
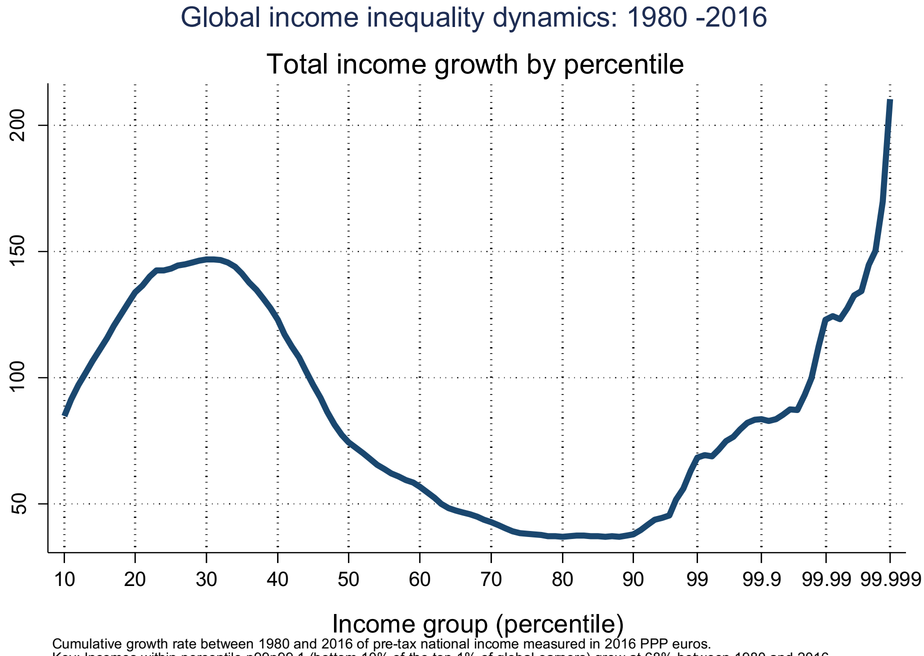


Figure 9 – Global inequality dynamics, 1980-2016

(dynamic calibration)



Cumulative growth rate between 1980 and 2016 of pre-tax national income measured in 2016 PPP euros.
Key: Incomes within percentile p99p99.1 (bottom 10% of the top 1% of global earners) grew at 68% between 1980 and 2016.
The top 1% captured 26% of total growth. All data from WID.world.

Figure 10 – Share of growth captured by income group, 1980-2016

(dynamic calibration)

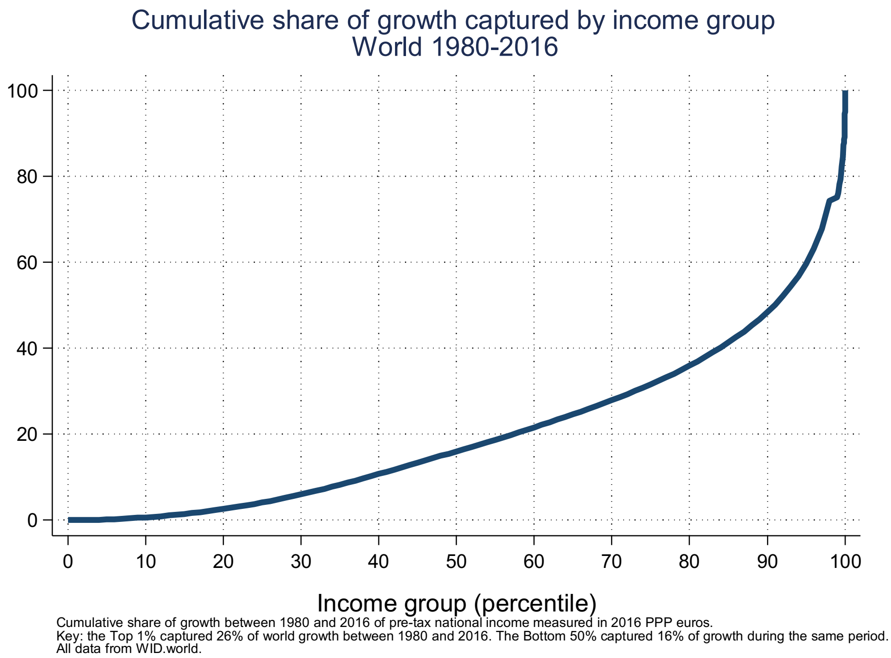


Figure 11 – Top 10% income shares in world regions, 1980-2016 (dynamic calibration)

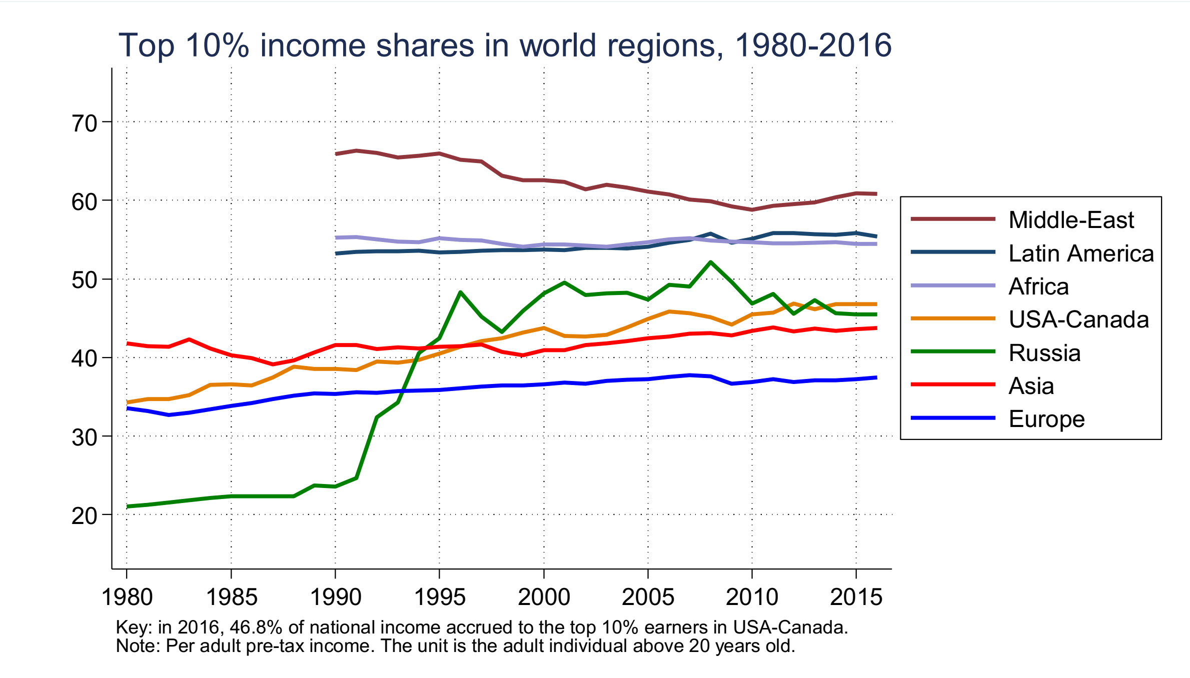
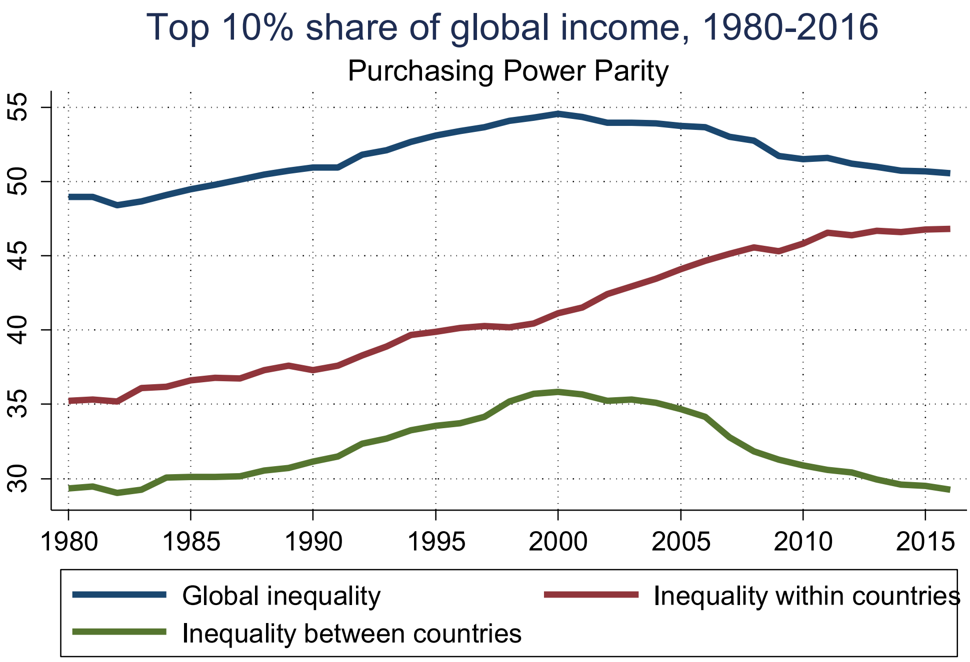


Figure 12 – Top 10% share of global income, 1980-2016 (dynamic calibration)



Key: in 2016, 50.6% of the world's income accrued to the Top 10% global earners.
Assuming perfect equality between countries, the Top 10% earners would represent 46.8% of global income.
Note: Per adult pre-tax income. The unit is the adult individual above 20 years old.

Are younger generations higher carbon emitters than their elders? Appendix

This appendix presents a technical discussion, additional figures and data tables related to Chapter 3.

Appendix 1 – Derivation of the intrinsic estimator

The Age Period Cohort model of logged CO_2 emissions can be written as follows

$$\log(CO_{2i}) = y_i^{apc} = \mu + \alpha_a + \beta_p + \gamma_c + \varepsilon_i \quad (1)$$

Where μ is the intercept or adjusted mean logged-CO_2 emissions, α_n the n-th household age effect row age effect or coefficient for the i¯th age group, β_j the j-th column period effect or the coefficient for the j-th time period; γ_k is the k-th diagonal cohort effect or the coefficient for the k-th cohort, with k=a-i+j. ε_{ij} is a random error with $E(\varepsilon_{ij}) = 0$.

The model is reparameterized in order to centre its parameters and hence treat it as a fixed effects generalized linear model:

$$\sum_i \alpha_i = \sum_j \beta_j = \sum_k \gamma_k = 0 \quad (2)$$

In conventional matrix form it can be written as:

$$Y = Xb + \varepsilon$$

Where *Y* is a vector of log-transformed CO_2 emission rates, *X* is the regression design matrix, which consists of column vectors for the vector of model parameters b, with

$$b = \left(\mu_0, \alpha_1, \dots, \alpha_{a-1}, \beta_1, \dots, \beta_{p-1}, \gamma_1, \dots, \gamma_{a+p-2}\right)^T \quad (3)$$

With αi βj γ_k the coefficients on each age/period cohort category.

As it was stated above, there is no uniquely defined vector of coefficient estimates because of the colinearity problem. The OLS estimator, $(X^TX)^{-1} X^TY$, does not exist: the structural identification problem of APC models. The Intrinsic Estimator approach tries to solve it by rewriting each of the infinite number of solution of the model as:

$$b_{est} = B + kB_0 \quad (4)$$

Where k is a scalar and B_0 is a unique eingenvector which does not depend on the observed CO_2 emissions, only on the design matrix X – it is determined by the number of age, period and cohorts categories. In the CGLIM approach, k is not constrained to 0 which implies that B_0 can play a role in the estimation of effect coefficients while it should not.

In fact, the linear dependence between age, period and cohort can be restated as:

$$XB_0 = 0 \quad (5)$$

With B_0, the normalized vector of B_1:

$$B_0 = \frac{B_1}{|B_1|} \quad (6)$$

$$B_1 = (0, A, P, C,)^T \quad (7)$$

With

$$A=\left(1-\frac{a+1}{2}, \dots, (a-1)-\frac{a+1}{2}\right),\ P=\left(\frac{a+1}{2}-1, \dots, \frac{p+1}{2}-(p-1)\right) \quad (8)$$

and

$$C=\left(1-\frac{a+p}{2}, \dots, (a+p-2)-\frac{a+p}{2}\right) \quad (9)$$

where a, p and c are the number of age period and cohort categories. B_0 is a function of the dimension of the design Matrix X (i.e. the number of age and period groups) and independent of the explained variable Y. It should not enter in the computation of effect coefficients (i.e. s must be set to 0).

$$b = b_0 + tB_0 \quad (10)$$

$$b_0 = (\mathrm{I} - B_0\, B_0^T)b \quad (11)$$

$$b_0 = P_{proj}b \quad (12)$$

B from equation (4) or b_0 from (10) is thus the *intrinsic estimator* of the model, which corresponds to the impact of age, period, and cohort on CO_2 emissions. It lies in the parameter subspace orthogonal to the nullspace.

Appendix 2a - Detailed CO_2 emissions per income decile in the USA

	1980			1985			1990			1995			2000		
	Mean	95% CI		Mean	95% CI		Mean	95% CI		Mean	95% CI		Mean	95% CI	
10% Poorest	2.92	2.39	3.45	3.83	3.30	4.36	3.98	3.22	4.74	4.24	3.29	5.20	4.27	3.68	4.86
D2	4.42	3.55	5.30	6.08	5.16	6.99	5.62	5.04	6.20	5.55	4.65	6.45	6.27	5.60	6.93
D3	4.45	3.50	5.40	7.23	6.33	8.13	7.71	6.63	8.80	6.52	5.66	7.38	7.07	6.22	7.92
D4	6.03	4.61	7.45	7.44	6.18	8.69	6.95	5.81	8.10	8.52	7.30	9.74	7.67	6.87	8.46
D5	6.01	5.22	6.81	7.58	6.72	8.45	8.12	7.01	9.23	8.10	6.79	9.42	8.34	7.45	9.22
D6	7.59	6.67	8.50	8.55	7.64	9.45	10.08	8.82	11.35	9.16	8.06	10.26	9.06	7.97	10.15
D7	7.78	6.75	8.81	9.06	8.21	9.92	9.55	8.55	10.56	9.54	8.31	10.76	9.76	8.48	11.03
D8	7.88	6.90	8.86	9.92	8.90	10.93	9.75	8.60	10.89	9.97	9.02	10.92	10.20	9.20	11.20
D9	9.87	8.79	10.95	10.85	9.70	12.01	9.12	8.16	10.08	10.44	9.29	11.60	10.49	9.47	11.51
10% Richest	12.49	10.45	14.52	12.75	11.51	14.00	12.78	11.06	14.50	12.94	11.80	14.07	12.40	10.96	13.83

Source: Author. Notes: the table presents mean values and 95% confidence interval bounds.

Appendix 2b - Detailed CO_2 emissions per income decile in France

	1980			1985			1990			1995			2000		
	Mean	95% CI		Mean	95% CI		Mean	95% CI		Mean	95% CI		Mean	95% CI	
D1	0.80	0.74	0.86	1.10	1.01	1.18	1.24	1.13	1.35	1.61	1.49	1.72	1.45	1.34	1.57
	1.24	1.18	1.31	1.51	1.41	1.60	1.80	1.68	1.92	1.90	1.79	2.01	1.98	1.84	2.11
	1.40	1.33	1.47	1.80	1.70	1.90	1.91	1.79	2.03	2.03	1.91	2.14	2.05	1.92	2.18
	1.54	1.47	1.63	2.08	1.94	2.23	1.95	1.84	2.06	2.19	2.06	2.31	2.23	2.10	2.35
	1.67	1.70	1.86	2.22	2.09	2.34	2.19	2.07	2.31	2.33	2.19	2.47	2.40	2.24	2.55
	1.92	1.83	2.02	2.31	2.20	2.42	2.42	2.27	2.57	2.45	2.31	2.58	2.75	2.57	2.93
	2.07	1.98	2.17	2.63	2.50	2.75	2.61	2.47	2.75	2.56	2.40	2.71	2.87	2.67	3.06
	2.29	2.19	2.40	2.79	2.67	2.91	2.75	2.61	2.90	2.82	2.61	3.04	2.96	2.77	3.16
	2.62	2.50	2.74	3.20	3.06	3.34	3.23	3.03	3.43	3.47	2.92	4.02	3.36	3.08	3.64
D10	3.33	3.16	3.50	4.37	4.13	4.61	4.45	4.05	4.86	4.32	3.77	4.87	4.41	3.87	4.94

Source: Author. Notes: the table presents mean values and 95% confidence interval bounds.

Appendix 3 – CO_2 emissions of expenditure groups by fuel

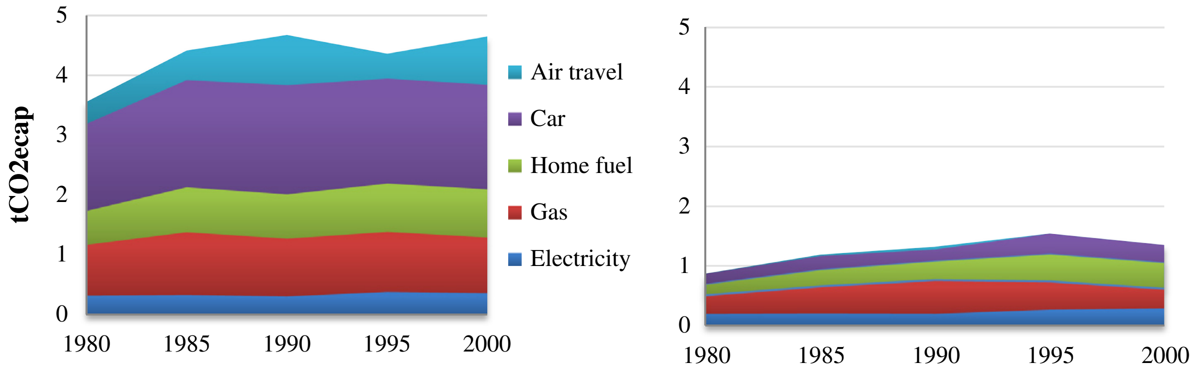
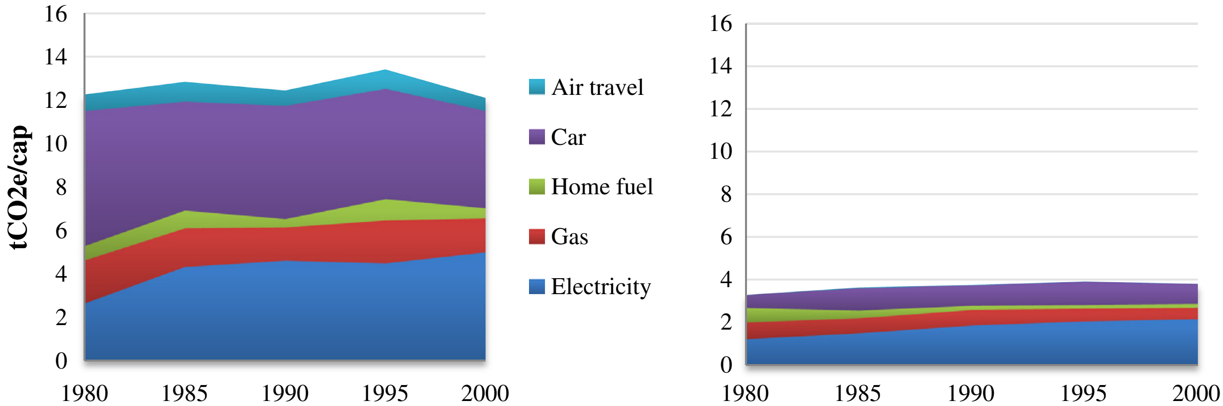


Fig. 10. Breakdown of CO_2 emissions per capita for top (left) and bottom deciles of French households.



Appendix 4 - Age period cohort regression in France

logCO2cap	Coef.	Robust Std. Err.	z	P>z	[95% Conf.	Interval]
logdeptotuc	0.6778	0.0123	55.2400	0.0000	0.6538	0.7019
Nbpers	-0.2057	0.0061	-33.9000	0.0000	-0.2176	-0.1938
Rooms	0.0582	0.0120	4.8500	0.0000	0.0347	0.0817
Partimmo	-0.3252	0.0495	-6.5600	0.0000	-0.4223	-0.2280
_Itypelog_2	-0.0966	0.0285	-3.3900	0.0010	-0.1524	-0.0407
_Itypelog_3	-0.2615	0.0159	-16.4500	0.0000	-0.2927	-0.2304
_Irg_2	0.0419	0.0152	2.7600	0.0060	0.0122	0.0717
_Irg_3	0.0239	0.0127	1.8800	0.0610	-0.0011	0.0489
_Irg_4	0.0380	0.0186	2.0500	0.0410	0.0016	0.0744
_Icommune_1	0.0058	0.0145	0.4000	0.6880	-0.0226	0.0343
_Icommune_2	0.0797	0.0131	6.0900	0.0000	0.0540	0.1053
_Icommune_3	0.0099	0.0203	0.4900	0.6270	-0.0299	0.0496
_Idate_2	0.1713	0.0127	13.5100	0.0000	0.1465	0.1962
_Idate_3	0.0451	0.0125	3.6100	0.0000	0.0206	0.0697
_Idate_4	-0.1037	0.0156	-6.6500	0.0000	-0.1342	-0.0731
_Idiplome_1	0.0784	0.0192	4.0900	0.0000	0.0408	0.1160
_Idiplome_2	0.0622	0.0252	2.4700	0.0140	0.0128	0.1115
_Idiplome_3	-0.0200	0.0254	-0.7900	0.4300	-0.0697	0.0297
_cons	0.3415	0.1175	2.9100	0.0040	0.1112	0.5717
coh_1910	-0.1578	0.0337	-4.6900	0.0000	-0.2237	-0.0918
coh_1915	-0.0853	0.0259	-3.2900	0.0010	-0.1361	-0.0344
coh_1920	0.0005	0.0259	0.0200	0.9860	-0.0504	0.0513
coh_1925	0.0081	0.0183	0.4400	0.6590	-0.0277	0.0439
coh_1930	0.0507	0.0180	2.8100	0.0050	0.0154	0.0860
coh_1935	0.1272	0.0169	7.5400	0.0000	0.0941	0.1602
coh_1940	0.1248	0.0161	7.7500	0.0000	0.0933	0.1564
coh_1945	0.1204	0.0154	7.8300	0.0000	0.0902	0.1505
coh_1950	0.0601	0.0133	4.5200	0.0000	0.0341	0.0862
coh_1955	-0.0018	0.0121	-0.1500	0.8820	-0.0256	0.0220
coh_1960	-0.0327	0.0143	-2.2900	0.0220	-0.0606	-0.0047
coh_1965	-0.0625	0.0174	-3.6000	0.0000	-0.0966	-0.0285
coh_1970	-0.1517	0.0231	-6.5800	0.0000	-0.1969	-0.1065
age_0025	0.0942	0.0150	6.3000	0.0000	0.0649	0.1235
age_0030	0.0192	0.0119	1.6100	0.1060	-0.0041	0.0425
age_0035	-0.0389	0.0117	-3.3300	0.0010	-0.0619	-0.0160
age_0040	-0.0276	0.0125	-2.2000	0.0280	-0.0522	-0.0030
age_0045	-0.0615	0.0136	-4.5200	0.0000	-0.0881	-0.0348
age_0050	-0.0470	0.0152	-3.0900	0.0020	-0.0768	-0.0172
age_0055	-0.0120	0.0160	-0.7500	0.4530	-0.0435	0.0194
age_0060	-0.0027	0.0172	-0.1500	0.8770	-0.0363	0.0310

age_0065	0.0101	0.0184	0.5500	0.5830	-0.0260	0.0462
age_0070	0.0298	0.0192	1.5500	0.1200	-0.0078	0.0674
age_0075	0.0364	0.0235	1.5500	0.1220	-0.0097	0.0826
per_1980	0.2827	0.0141	19.9900	0.0000	0.2550	0.3104
per_1985	0.0034	0.0117	0.2900	0.7690	-0.0195	0.0264
per_1990	-0.2632	0.0152	-17.3700	0.0000	-0.2929	-0.2335
per_1995	-0.6146	0.0147	-41.9400	0.0000	-0.6434	-0.5859
per_2000	0.5917	0.0143	41.4400	0.0000	0.5637	0.6197
Rescacoh	1.5945	0.0535	29.8200	0.0000	1.4897	1.6993
Rescaage	0.6838	0.0308	22.1800	0.0000	0.6233	0.7442

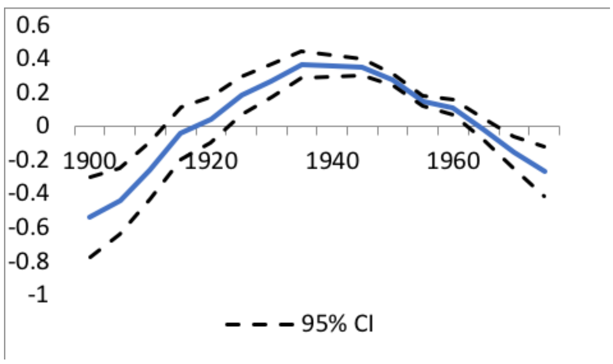
Source: Author. Results from the APCD regression including controls described in Appendix 5.

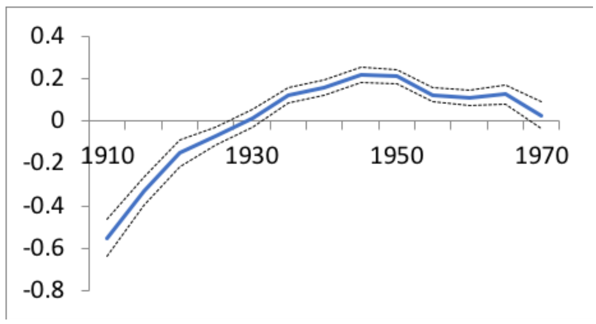
Appendix 5 - Categorical variables for France

0.educatio	School drop out
1.educatio	Baccalauréat
2.educatio	Bachelor
3. education	Master and Doctorate
1.urban	Urban
2.urban	Rural
1.region	North, North east and Bassin Parisien
2.region	Center, Rhones Alpes, Bourgogne
3.region	West coast
4.region	South coast
1.date	Built before 1948
2. date	Built from 48 to 70
3. date	Built from 70 to 80
4.date	Built from 80 to 2000
1.typelog	Single household
2.typelog	Small flat (2 to 9 dwellings)
3.typelog	Large flat (+9 dwellings)

Note: categorical variables are very similar in the American database, with 52 state controls instead of 4 regions.

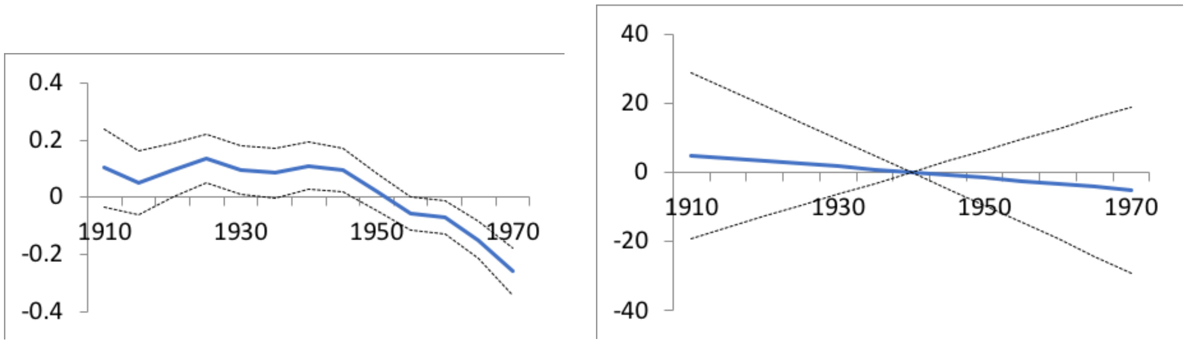
Appendix 6a - APC-IE cohort estimates (left) and CGLIM cohort estimates (right) for France





The figure plots γ_c coefficients of model (4) for France, obtained with the intrinsic estimator or the CGLIM estimator. The thin lines plot 95% confidence intervals. The constraint imposed on the CGLIM is to set all period effects to zero.

Appendix 6b - APC-IE cohort estimates (left) and CGLIM cohort estimates (right) for the USA



The figure plots γ_c coefficients of model (4) for the USA, obtained with the intrinsic estimator or the CGLIM estimator. The thin lines plot 95% confidence intervals.The constraint imposed on the CGLIM is to set all period effects to zero.

Carbon and inequality: from Kyoto to Paris Appendix A

This appendix presents Environmental Input Output framework used to construct consumption-based CO2e in the chapter entitled *"Carbon and inequality: from Kyoto to Paris"*.

Environmental Input-Output methodology

Several studies have performed environment input output analyses combined with consumer budget surveys (See Herendeen and Tanaka, 1976; Peters et al. (2006); Weber and Matthews (2008); Papathanasopolou and Jackson (2009); Pourouchottamin et al. (2013)). The approaches followed in the above-mentioned articles vary slighty from one study to the other (due to assumptions made, specific research question or because of data availability) but the general framework, i.e. extending the Leontief approach extended to the environment and to consumer expenditures, is the same. We give a brief overview of this framework below.

1 Leontief's equation for one region

The standard method to represent total consumption in an economy is based on Leontief's Input-Output framework (Leontief, 1941) , which enables a systematic representation of production in an economy as a function of other sectors' inputs, final demand, imports and exports.

Considering a region r with i economic sectors, producing goods and services $(i=1,\ldots,n)$ with production x_i per sector i , satifying a final demand y_i from sector i and an intermediary consumption (x_{ij}) from other sectors j ($j=1,\ldots,n$) it is possible to write total production as the sum of intermediate consumption and final demand:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \quad (1)$$

It is then possible to write, in Matrix form:

$$x = Ax + y \qquad (2)$$

With x =(x_i) the (n × 1) vector of total production in region r , with x_i the production of sector i ; y =(y_i) the (n × 1) vector of final consumption, with y i final demand for sector i , including imports, public administration and net fixed-capital investments; A=[a_{ij}] , the (n × n) matrix of Input-Ouput coefficients in the economy (also called Input-Output table or table of technical coefficients), with $a_{ij} = x_{ij}/x_j$, i.e. each element of the A matrix represents the quantity of input from sector i required to produce one unit of sector j . Solving (1) for x , we obtain “Leontief's equation”:

$$x = (I - A)^{-1} y \qquad (3)$$

With $(I\text{-}A)^{-1}$ the so-called “Leontief inverse”: each of its elements informs on the “supply chain” of the economy, i.e. the amount of total production in each sector required to sustain one unit increase in final demand of a particular sector, assuming fixed production ratios (Leontief, 1941).

2 Leontief equation for m regions

This framework can be generalized to a multi-regional case, with m regions and n production sectors in each region (Miller and Blair, 1985). It is then possible to write:

$$\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} & \dots & A_{1m} \\ A_{21} & A_{22} & \dots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mm} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{pmatrix} + \begin{pmatrix} Y_{11} + \sum_{z\neq 1}^{m} Y_{1z} \\ Y_{22} + \sum_{z\neq 2}^{m} Y_{2z} \\ \vdots \\ Y_{mm} + \sum_{z\neq \mathrm{m}}^{m} Y_{mz} \end{pmatrix} \quad (4)$$

Where $X_r = (x_i^r)$, the vector of domestic production of region r for each sector i ; $A_{rr} = [a_{ij}^{rr}]$, the Input-Output Matrix for region r ; $A_{zr} = [a_{ij}^{zr}]$, the bilateral Input-Output Matrix between region r and region z , each element $a_{\mathrm{ij}}^{\mathrm{zr}}$ represents the quantity of products of sector i in region z used by sector j in region r , per unit of production; $Y_{rr} = (\mathrm{y_i^r})$, the vector of final domestic demand of region r for sector i ; $Y_{zr} = (y_i^{zr})$ the vector of final products of sector i consumed in region r and coming from region z.

In economic terms, each off-diagonal of the "meta" A matrix represents bilateral, interindustry trade. For the case of region 1, the first line represents all exports from region 1 to other regions, while the first column represents imports from other countries to region 1 .

Expressing (4) in algebraic form allows to identify all the production sectors which contribute to the fabrication of products X_r , for each region we have:

$$(X_r) =^t ({}^t(1) \times [I - A_r]^{-1} \times [diag(Y_r)]) \quad (5)$$

With $[(diag(Y_r)]$ the diagonalized Matrix of (Y_r), with $y_{ii} = y_i$ and (1) the unity vector and ^{t} denoting Matrix transpose.

3 Factoring in the environment

In his article "Environmental repercussions and the economic structure: an input-output approach", Leontief (1970) laid the foundations of "Environmental Input Output Analysis" (EIO). Once the multi-regional Input-Output framework has been derived, it is straightforward to factor in resource requirements in each sector and in each region. In order to do so, we multiply the monetary value of each step of the production function by the unit material requirement specific to this step.

The indirect material requirement of each sector is then given by:

$$(E_r) =^t ({}^t(e_i^r) \times [I - A_r]^{-1} \times [diag(Y_r)] \quad (6)$$

(e_i^r) is a column vector with each of its elements, e_i^r, equal to total energy consumption of sector i in region r divided by the monetary value of total production of sector i in region r.

4 Issues with environmental Input Output analysis

The main difficulty in performing multi-regional Input Output analysis relates to data availability and input output table harmonization. The "Global

Trade Analysis Project" (GTAP) provides, since 1993, standardized I-O tables for the world economy. In particular, GTAP provides the [A_{mm}] , [P^{Ir}] , [A^{IMr}] , (Y_r) , (Y_{mr}) matrices and vectors. Several pieces of the multi-regional I-O puzzle are however lacking: matrices [A_{mr}] and vectors (Y_{mr}) are not available in GTAP. Instead, the following datasets are available:

- Matrix [A^{IMr}] = $\sum_{m \neq r}^{R}$ [A_{mr}] representing the sum for all regions of all imports towards region r, for all sectors. A^{IMr} then gives, by sector, total imports from intermediary consumption and by sector of origin, but without informing on the origin of such imports.
- Vector Y_r^i representing the sum, by sector, and over all regions, of all direct imports to region *r*, differentiated by sector of origin.
- Matrix P^{Ir} =[p_{im}^{Ir}] representing the repartition of all direct and intermediary imports of each sector i , by region m . p_{iz}^{I} , represents the share of total imports for sector i in country r , coming from region m but irrespectively of their sector of origin.

Given such data availability, the following simplifying hypotheses are generally made in the literature:

- Knowing the share s of total imports from sector *j* of region m to region *r* (information given by P^{Ir}), it is assumed that each sector *i* of region *r* imports the same share s of its requirements from sector *j* of region *m* . This is indeed not true. A simple example (see Pourouchottamin et al., 2013) makes clear why : if a country like France imports 70% of its energy requirements from the Middle-East, this does not mean that the specific siderurgy sector imports 70% of its energy requirements from the Middle-East (in fact, energy imports to the French siderurgy sector are essentially coal, almost inexistent in the Middle-East).
- The same hypothesis is made for direct imports.

Matrices A_{mr} and Y_{mr} can be approximated by weighting the coefficients of matrix A^{IMr} and of vector Y_r^I with the respective shares of global imports by region m from matrix P^{IR} . We obtain:

$$[A_{mr}] = [P_m^{Ir}] \times [A^{IMr}] \quad (7)$$

$$(Y_{mr}) = [P_m^{Ir}] \times (Y_r^I) \quad (8)$$

With [P_m^{Ir}] =diag(p_{im}^I) , the diagonalized matrix of vector (p_{im}^I) , the column m of matrix P^{Ir} .

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Carbon and inequality: from Kyoto to Paris Appendix B

This appendix presents Supplementary Figures and Tables related to the chapter entitled *"Carbon and inequality: from Kyoto to Paris"*.

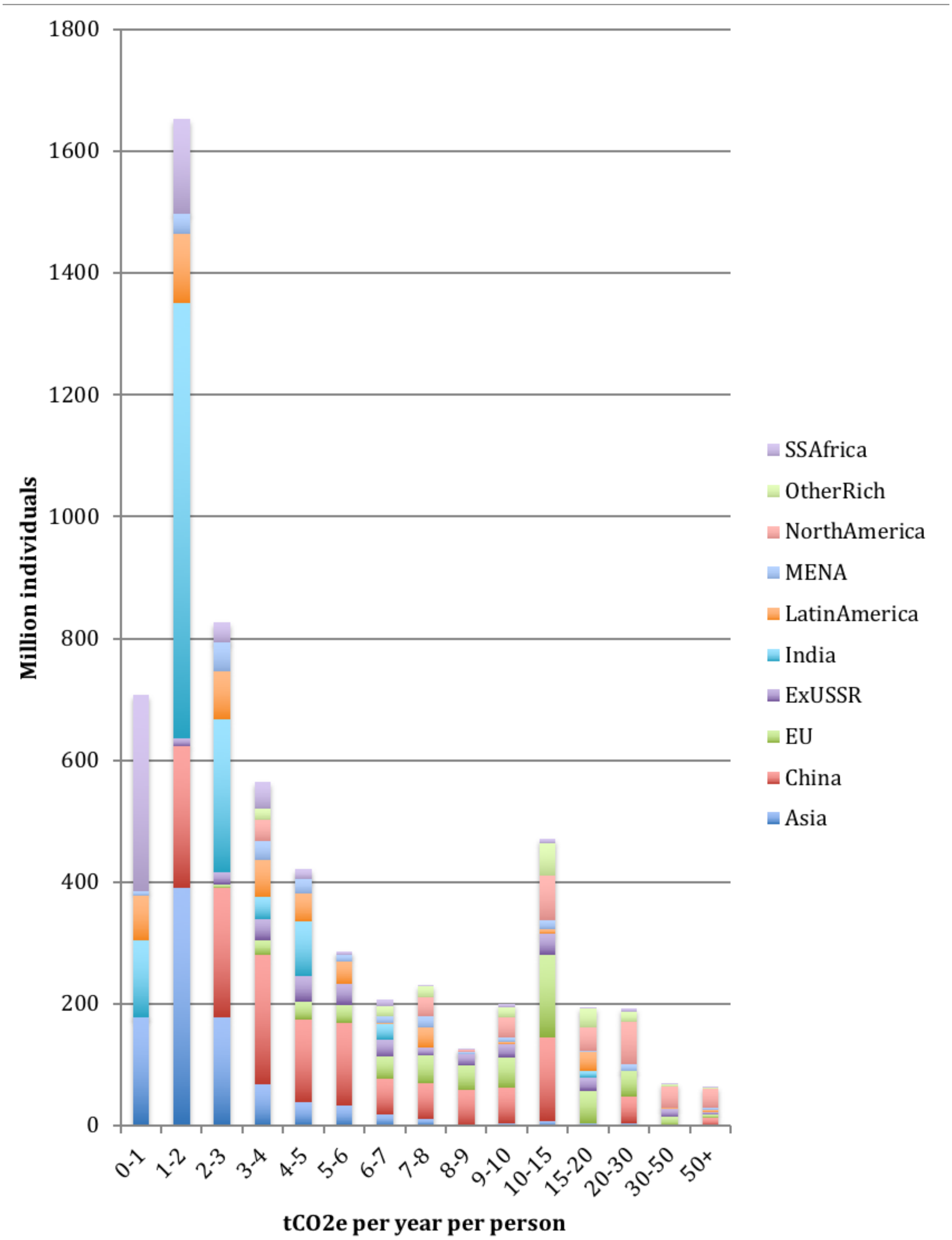
Table 1 - List of countries and available years

Region	Country	Y1998	Y2003	Y2008	Y2013
China	China	Yes	Yes	Yes	Yes
EU	Austria	Yes	Yes	Yes	Yes
EU	Belgium	Yes	Yes	Yes	Yes
EU	Bulgaria	Yes	Yes	Yes	Yes
EU	Czech Republic	Yes	Yes	Yes	Yes
EU	Denmark	Yes	Yes	Yes	Yes
EU	Estonia	Yes	No	Yes	Yes
EU	Finland	Yes	Yes	Yes	Yes
EU	France	Yes	Yes	Yes	Yes
EU	Germany	Yes	Yes	Yes	Yes
EU	Greece	Yes	Yes	Yes	Yes
EU	Hungary	Yes	Yes	Yes	Yes
EU	Ireland	Yes	Yes	Yes	Yes
EU	Israel	Yes	Yes	Yes	Yes
EU	Italy	Yes	Yes	Yes	Yes
EU	Latvia	Yes	Yes	Yes	Yes
EU	Luxembourg	Yes	Yes	Yes	Yes
EU	Netherlands	Yes	Yes	Yes	Yes
EU	Norway	Yes	Yes	Yes	Yes
EU	Poland	Yes	Yes	Yes	Yes
EU	Portugal	Yes	Yes	Yes	Yes
EU	Singapore	Yes	Yes	Yes	Yes
EU	Slovakia	Yes	Yes	Yes	Yes
EU	Slovenia	Yes	Yes	Yes	Yes
EU	Spain	Yes	Yes	Yes	Yes
EU	Sweden	Yes	Yes	Yes	Yes
EU	Switzerland	Yes	Yes	Yes	Yes
EU	United Kingdom	Yes	Yes	Yes	Yes
India	India	Yes	Yes	Yes	Yes
Latin America	Bolivia	Yes	Yes	Yes	Yes
Latin America	Brazil	Yes	Yes	Yes	Yes
Latin America	Colombia	Yes	Yes	Yes	Yes
Latin America	Costa Rica	Yes	Yes	Yes	Yes
Latin America	Dominican Republic	Yes	Yes	Yes	Yes
Latin America	Ecuador	Yes	Yes	Yes	Yes
Latin America	El Salvador	Yes	Yes	Yes	Yes
Latin America	Guatemala	Yes	Yes	Yes	Yes
Latin America	Honduras	Yes	Yes	Yes	Yes
Latin America	Jamaica	Yes	Yes	No	No
Latin America	Mexico	Yes	Yes	Yes	Yes
Latin America	Nicaragua	Yes	Yes	Yes	Yes
Latin America	Panama	Yes	Yes	Yes	Yes
Latin America	Paraguay	Yes	Yes	Yes	Yes
Latin America	Peru	Yes	Yes	Yes	Yes
Latin America	Uruguay	Yes	Yes	Yes	Yes
Mid.East/N.A	Egypt	Yes	Yes	Yes	Yes

Mid.East/N.A	Iran, Islamic Republic of	Yes	Yes	Yes	Yes
Mid.East/N.A	Jordan	Yes	Yes	Yes	Yes
Mid.East/N.A	Morocco	Yes	Yes	Yes	Yes
Mid.East/N.A	Saudi Arabia	Yes	Yes	Yes	Yes
Mid.East/N.A	Tunisia	Yes	Yes	No	No
North America	Canada	Yes	Yes	Yes	Yes
North America	United States of America	Yes	Yes	Yes	Yes
Other Asia	Bangladesh	Yes	Yes	Yes	Yes
Other Asia	Cambodia	Yes	Yes	Yes	Yes
Other Asia	Indonesia	Yes	Yes	Yes	Yes
Other Asia	Korea, Republic of	Yes	Yes	Yes	Yes
Other Asia	Malaysia	Yes	Yes	Yes	Yes
Other Asia	Mongolia	No	Yes	Yes	Yes
Other Asia	Nepal	Yes	Yes	Yes	Yes
Other Asia	Pakistan	Yes	Yes	Yes	Yes
Other Asia	Philippines	Yes	Yes	Yes	Yes
Other Asia	Sri Lanka	Yes	Yes	Yes	Yes
Other Asia	Thailand	Yes	Yes	Yes	Yes
Other Asia	Vietnam	Yes	Yes	Yes	Yes
OtherRich	Australia	Yes	Yes	No	No
OtherRich	Japan	Yes	Yes	Yes	Yes
OtherRich	New Zealand	Yes	No	No	No
Russia/C.Asia	Albania	Yes	Yes	Yes	Yes
Russia/C.Asia	Armenia	Yes	Yes	Yes	Yes
Russia/C.Asia	Azerbaijan	No	Yes	Yes	Yes
Russia/C.Asia	Belarus	Yes	Yes	No	No
Russia/C.Asia	Croatia	Yes	Yes	Yes	Yes
Russia/C.Asia	Georgia	Yes	Yes	Yes	Yes
Russia/C.Asia	Kazakhstan	Yes	Yes	No	No
Russia/C.Asia	Kyrgyzstan	Yes	Yes	Yes	Yes
Russia/C.Asia	Russian Federation	Yes	Yes	Yes	Yes
Russia/C.Asia	Tajikistan	Yes	Yes	Yes	Yes
Russia/C.Asia	Turkey	Yes	Yes	Yes	Yes
Russia/C.Asia	Ukraine	Yes	Yes	Yes	Yes
S.S.Africa	Angola	Yes	No	No	No
S.S.Africa	Benin	No	Yes	No	No
S.S.Africa	Burkina Faso	Yes	Yes	Yes	Yes
S.S.Africa	Burundi	Yes	No	Yes	Yes
S.S.Africa	Cameroon	Yes	Yes	Yes	Yes
S.S.Africa	Cote d'Ivoire	Yes	Yes	Yes	Yes
S.S.Africa	Ethiopia	Yes	Yes	No	No
S.S.Africa	Ghana	Yes	Yes	No	No
S.S.Africa	Guinea	No	Yes	Yes	Yes
S.S.Africa	Kenya	Yes	No	Yes	Yes
S.S.Africa	Liberia	No	No	Yes	Yes
S.S.Africa	Madagascar	Yes	Yes	Yes	Yes
S.S.Africa	Malawi	Yes	Yes	Yes	Yes
S.S.Africa	Mali	No	Yes	Yes	Yes
S.S.Africa	Mauritania	Yes	Yes	Yes	Yes
S.S.Africa	Mozambique	Yes	Yes	Yes	Yes
S.S.Africa	Namibia	No	Yes	No	No

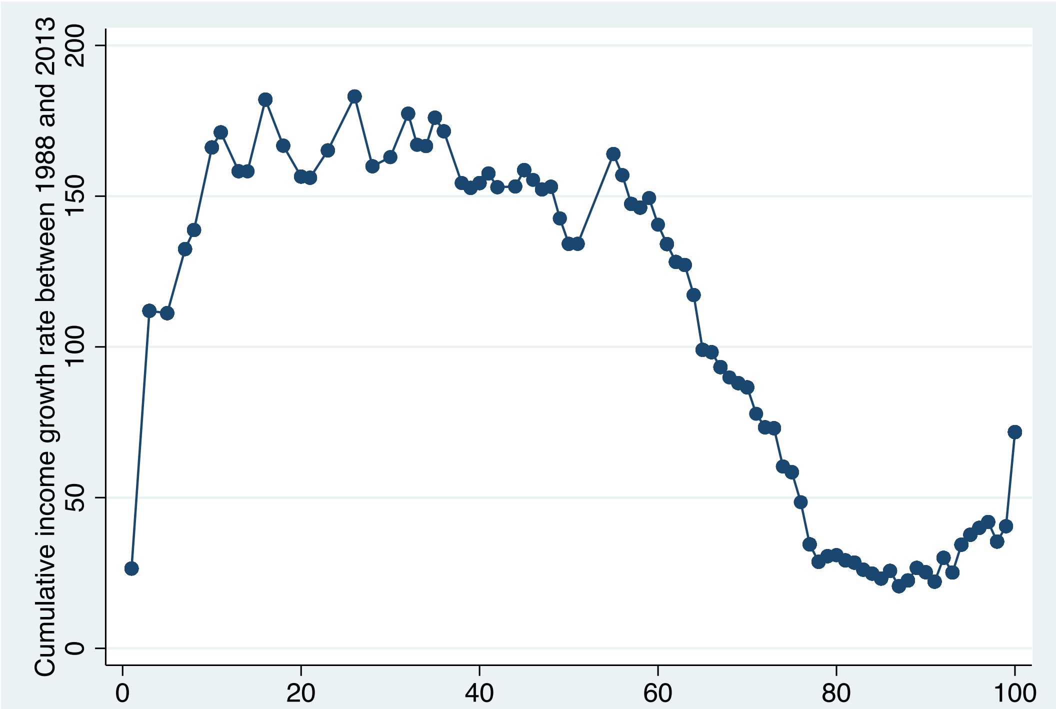
S.S.Africa	Niger	No	No	Yes	Yes
S.S.Africa	Nigeria	Yes	Yes	Yes	Yes
S.S.Africa	Rwanda	Yes	Yes	Yes	Yes
S.S.Africa	Senegal	No	Yes	No	No
S.S.Africa	Sierra Leone	No	Yes	No	No
S.S.Africa	South Africa	Yes	Yes	Yes	Yes
S.S.Africa	Sudan	No	No	Yes	Yes
S.S.Africa	Tanzania, United Republic of	No	Yes	Yes	Yes
S.S.Africa	Uganda	Yes	Yes	Yes	Yes
S.S.Africa	Zambia	Yes	Yes	Yes	Yes

Figure 1 - Global distribution of CO2e emitters



Source: authors. Key: 708 million individuals emit below 1 tonne of CO2e emissions per year. 324 million people in this category live in Sub-Saharian Africa, 125 million in India, 177 million in South Asia and 73 million in Latin America.

Figure 2 - Income growth from 1998 to 2013.



Income percentile

Source: authors. Key: the group representing the 2% lowest income earners in the world, saw its per capita income level increase by 28% between 1998 and 2013.

Table 2 - Income concentration shares over time (%)

year	top1	top5	top10	mid40	bot50	bot10
2013	17.8	38.2	52.7	36.3	11.0	1.0
2008	18.9	39.8	55.3	35.4	9.3	0.8
2003	18.7	41.0	57.1	34.7	8.1	0.7
1998	17.9	39.9	56.5	35.6	7.9	0.7
1993	16.3	38.9	56.3	36.1	7.7	0.7
1988	16.0	38.2	55.5	37.9	6.6	0.6

Source: authors. Note: these are preliminary reconstructions used to derive a global GHG distribution of emissions and could be subject to ulterior modifications.