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THE DISTRIBUTION OF THE GROWTH DIVIDENDS

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ABSTRACT/RÉSUMÉ

The distribution of the growth dividends

Widespread increases in inequality over the past three decades have raised the question of the distribution of the growth dividends. This paper finds that there is no single answer to this question. The mechanisms that link growth and income inequality are found to differ depending on the *sources* of growth and on whether one considers income inequality *before or after* government redistribution, that is, inequality in market incomes, i.e. income derived before taxes and transfers, or inequality in disposable incomes, that is, income after taxes and transfers. Labour productivity growth is found to have contributed to rising market income inequality, while this was partly mitigated through government redistribution, on average across OECD countries over the last decades. By contrast, employment growth is found to have had an equalising impact, benefiting mostly the households in the lower part of the income distribution. These two forces tended to offset each other and resulted in a broadly distribution-neutral impact of GDP per capita growth, on average across OECD countries over the last three decades. While inequality has risen in many countries, this would tend to suggest that factors other than GDP growth itself have been driving widening income gaps between rich and poor households.

JEL codes: O15; O47; D31; H23

Keywords: growth, inequality, redistribution, general means

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L'impact distributionnel de la croissance

La hausse généralisée des inégalités au cours des trois dernières décennies a soulevé la question de la répartition des fruits de la croissance. Cette étude conclut cependant qu'il n'y a pas de réponse unique à cette question. Les mécanismes qui relient la croissance aux inégalités de revenus diffèrent selon les sources de croissance et si l'on considère l'inégalité des revenus avant ou après la redistribution du gouvernement, c'est à dire avant ou après impôts et transferts. La croissance de la productivité du travail est identifiée comme ayant contribué à l'augmentation des inégalités de revenu avant redistribution, mais ce résultat est en partie atténué par la redistribution, en moyenne dans les pays de l'OCDE et au cours des dernières décennies. En revanche, la croissance de l'emploi a un effet égalitaire en bénéficiant principalement aux ménages dans la partie inférieure de la distribution des revenus. Ces deux forces ont tendance à se compenser, aboutissant à un impact globalement neutre de la croissance du PIB par habitant sur les inégalités. Alors que l'inégalité a augmenté dans de nombreux pays, cela suggère que des facteurs autres que la croissance du PIB ont pu creuser les inégalités.

Codes JEL: O15; O47; D31; H23

Mots clés: croissance, inégalité, redistribution, moyennes généralisées

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THE DISTRIBUTION OF THE GROWTH DIVIDENDS

Mikkel Hermansen, Nicolas Ruiz and Orsetta Causa[1]

1. Introduction and main findings

1. Widespread increases in inequality over the past three decades have raised the question of the distribution of the growth dividends, that is, whether growth has a natural tendency to widen income inequality. This paper revisits this question on the basis of a panel of OECD countries. In doing so, it sets an empirical framework for the analysis of the links between structural policies and household income distribution (Causa et al., 2016). Assessing the extent to which economic growth tends to be income equalising, neutral or disequalising, features prominently in the policy debate and the academic literature (Dollar and Kraay, 2002; Dollar et al., 2015; Brueckner et al., 2015). However, measurement difficulties, methodological factors and reverse causality issues tend to plague the interpretation of the growth-inequality nexus (Forbes, 2000; Banerjee and Duflo, 2003; Brueckner et al., 2015).

2. The current work extends previous contributions and brings new elements to the discussion in several ways:

- It recognises upfront that growth can affect different parts of the income distribution differently, reflecting different mechanisms.[2] It thus goes beyond the usual practice of aggregating income inequality into a single indicator such as the Gini coefficient, but instead relies on the use of a more granular approach to income distribution. This is achieved by the use of general means, which allows capturing differential income developments at different parts of the income distribution.

- The paper relies on a comprehensive and highly harmonised dataset on income distribution for a panel of OECD countries over the period going from the mid-80s to around 2012; this minimises the risk of estimation bias associated with measurement errors (Forbes, 2000).

- Potential endogeneity issues due to reverse causality between growth, household income and inequality are addressed through the use of dynamic panel data estimation techniques. Note that in this regard, the potential feedback from inequality to growth is not embedded in the empirical framework and therefore not addressed in this paper.[3]

- The analysis considers the impact of growth on both pre and post-tax and transfer income distributions, as inequality developments may be different if measured on income derived from

1. The authors are members of the Economics Department of the OECD. They would like to thank Economics Department colleagues Alain de Serres, Dennis Dlugosch, Christian Kastrop, Catherine L. Mann, Jean-Luc Schneider, Jan Strasky and colleagues from the Directorate for Employment, Labour and Social Affairs and the Statistics Directorate for useful comments and suggestions. They also thank Caroline Abettan for editorial assistance.

2. See Voitchovsky (2005) for a similar discussion.

3 . See OECD (2015b) for a characterisation of such feedback effects.

market activities, e.g. wages, self-employed and capital income, or measured after redistribution through taxes and transfers, i.e. on disposable income.[4]

- Last but not least, the approach allows for analysing the differential impact of two proximate sources of GDP growth – labour productivity and labour resource utilisation – on income inequality.

3. The main findings of this paper are:

- There is no evidence that GDP growth triggered rising inequality in household disposable incomes, once controlling for other factors and on average across OECD countries over the period under consideration.

- The breakdown of growth into its main sources, i.e. productivity and labour utilisation, sheds light on the mechanisms of the growth and inequality nexus:

  – The evidence suggests that productivity growth is not by itself inclusive: aggregate labour productivity gains boost market incomes only for households from the lower-middle class and above. However, this disequalising effect is partly cushioned by redistribution.

  – Labour utilisation growth is by contrast inclusive: higher aggregate employment translates into higher market and disposable incomes for middle class and poor households.

4. The rest of the paper is organised as follows. Section 2 details the data on income distribution and the measures of inequality used. Section 3 shows the development of growth and inequality in OECD countries over the last decades. Section 4 presents the empirical approach and the econometric methods, while the detailed results are presented in section 5. Section 6 provides various robustness analyses. The last section concludes.

2. Data and inequality measurement[5]

Data sources

5. Mismeasurement and poor comparability of inequality statistics, across countries and over time, have been a serious concern for assessing the link between inequality and growth. In order to reduce measurement error, the data used in this paper come from the OECD Income Distribution Database, a secondary dataset developed to monitor all OECD countries' income distribution outcomes. The dataset covers the period going from the mid-80s to 2012.[6] It gathers a number of standardised indicators under the form of semi-aggregated tabulations (e.g. mean income by deciles applied in this study) based on national sources, deemed to be most representative for most countries. The method of data collection aims to maximise international comparability as well as inter-temporal consistency of the data (which is achieved

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4. Taxes and transfers have a direct impact on the distribution of the growth dividends. Such policies, among others, are included in the empirical analysis in the companion to this paper (Causa et al. 2016). See also Causa et al. (2015).

5. This section focuses primarily on the micro sources used and the measures of inequality adopted, given the fact that the macro variables and concepts used are deemed to be more standard. Sources for the macro economic variables are the National Accounts and the OECD Economic Outlook Database.

6. See Gasparini and Tornarolli (2015) for a review of the database.

through a common set of protocols and statistical conventions based on internationally agreed statistical standards). As a result, compared to similar initiatives in this field,[7] the usual risks associated with second-hand datasets are limited, or at least the statistical errors introduced are kept low (Atkinson and Brandolini, 2001). However, one disadvantage of this approach is that as a result of the process, the data available for analysis are no longer the original micro dataset but the income deciles generated from the microdata.

6. The OECD Income Distribution Database covers different income sources: wage and salary income, self-employment income, capital income, property income and private pensions, the sum of which equals *market income*, i.e. income derived by households from market activities. Social security transfers from public sources can also be added and taxes and social security contributions subtracted, yielding household *disposable income*, which is generally considered the best proxy of households' economic resources (OECD, 2015a).[8] While measures based on disposable incomes generally cover the whole population, market income-based measures typically cover the working-age population because wage and salaries make up the bulk of market income. The distinction between market income and disposable income is fundamental for shedding light on the channels through which growth benefits household incomes, going from market-driven mechanisms to redistribution via taxes and transfers.

7. Despite the relatively high quality of the data and the degree of details available for the definition of income, two caveats need being borne in mind. The first is that, as most country sources rely on household surveys, the data used here may underestimate top incomes (Ruiz and Woloszko, 2015). An associated risk is to partially miss the link between growth and inequality, should the fruits of growth happen to be disproportionately captured by the very top of the distribution, as has been the case in the United States during the 1980s as well as in the aftermath of the recent economic crisis (Piketty and Saez, 2013).

8. A second limitation comes from the unbalanced nature of the panel data. While the OECD Income Distribution Database reports information starting in 1974, in practice there are only a few observations for the 1970s and early 1980s (see Table 1). The database provides information for 16 countries for years around the mid-1980s, for 12 countries around 1990, 19 around the mid-1990s, to stabilise at almost all 34 OECD countries since 2005. There are also substantial differences in the coverage by country; while there are more than 25 observations for Canada and Finland, the number of observations for most countries ranges between 5 and 10, in particular due to the use of EU-SILC surveys for European countries, which started in 2004.

7. See Deininger and Squire (1998) for an overview.

8. Ideally, household income should include in kind public transfers (such as in the area of education and health). Unfortunately, these data are only available over many time periods through the national accounts for aggregate household income, hence preventing from assessing income distribution. See OECD (2008; 2011) for analyses on the distributional impact of in kind public transfers.

Table 1. Construction of a panel of countries from the OECD Income Distribution Database

year	AUS	AUT	BEL	CAN	CHE	CHL	CZE	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC	HUN	IRL	ISL	ISR	ITA	JPN	KOR	LUX	MEX	NLD	NOR	NZL	POL	PRT	SVK	SVN	SWE	TUR	USA
1985				X					X																		X							
1986								IP				X													IP									
1987				X					IP																		IP							
1988								IP				X													IP									
1989				X					IP																		IP							
1990								X				X													X									
1991				X					IP											X							IP					X		
1992								IP				X													IP									
1993				X					IP											IP							IP					IP		
1994								IP				X													IP									
1995				X					X						IP	X			X	X	X					X	X					X		X
1996	IP							IP				X	X												IP									
1997				X					IP						IP	IP			IP	IP	IP					IP	IP					IP		IP
1998	IP							IP				X	IP												IP									
1999				X					IP					X	X	IP			IP	IP	IP					IP	IP					IP		IP
2000	X							X				X	X											X	X									
2001				X					IP					X	IP	IP			IP	IP	IP					IP	IP					IP		IP
2002	IP							IP				X	IP											IP	IP									
2003				X					IP					X	IP	IP			IP	IP	X					IP	X					IP		IP
2004	X	X	X				X	X		X	X	X	IP				X	X					X	X	IP				X	X	X			
2005				X					X					X	X	X			X	IP	IP					IP	IP	X				IP	IP	X
2006	IP	X	X				X	IP		X	X	X	IP				X	X				X	X	IP	X				X	X	X			
2007				X		IP			X					X	IP	X			IP	IP	IP					IP	IP	X				IP	X	IP
2008	X	X	X				X	X		X	X	X	X				X	X				X	X	X	X				X	X	X			
2009				X	X	X			X					X	X	X			X	X	X					X	X	X				X	X	X
2010	X	X	X				X	X		X	X	X	X				X	X				X	X	X	X				X	X	X			
2011				X	X	X			X							IP			X	X						X	X	X				X	X	X
2012	X	X	X				X			X	X	X					X	X				X	X	X	X				X	X	X			

Note: A shaded cell represents a country-year observation available in the OECD Income Distribution Database (version of September 2015, terms of reference for wave 6). X denotes a spell length of two years and IP denotes spells obtained by linear interpolation. The total number of observations in the panel is 259, of which 90 are interpolated.
Source: OECD Income distribution Database.

9. In order to make the most of the data available, while not reducing unduly the length of the time horizon, the current analysis covers the period going from the mid-1980s up to 2012, as roughly one third of OECD countries have information available since the mid-1980s. In addition, some countries (such as Denmark and New Zealand) only display data at five-year intervals up to the mid-2000s. This issue is addressed by linear interpolation techniques, which appears as a reasonable option given that external data sources allow for concluding that inequality in these countries has been broadly stable over the periods for which interpolations are performed.[9]

10. The empirical analysis relies on 2-year spell observations in an attempt to reduce the influence of short-run fluctuations and limit the reliance on interpolated values. For instance, only observations from 2004, 2006, 2008, 2010 and 2012 are available (and therefore included) for Austria and Belgium. While a spell of 5 years has been applied in previous comparable studies (see Forbes, 2000; Brueckner et al., 2015), this is not doable in the current work: a spell of 3 years or more would result in a too short panel given the data at hand and the estimation strategy applied (see below). Overall, the database covers 259 observations out of the 476 possible 2-years spells (Table 1).

Assessing income inequality using general means

Using general means to uncover the granularity of income distribution

11. Income distributions are generally characterised using income standards, i.e. functions that gauge the distribution by a single income level indicating the general affluence of the distribution or some part of it (Foster and Szekely, 2008). The mean and the median are examples of income standards that are widely used as stylised measures of a country's overall level of material conditions. More narrowly, the mean income of some specific part of the population such as the bottom 40% or 20%, called partial means, are also used, in particular for the measurement of poverty.

12. The analytical framework of this paper aims to uncover the granularity of the income distribution, moving progressively from the bottom to the top, by the use of general means as income standards. Unlike partial means, general means take into account the *entire* income distribution, but emphasise lower or higher incomes depending on the value taken by a specific parameter α, often referred to as the order of the general mean. Taking the entire income distribution into account avoids the need to set arbitrary thresholds that give full weight to some parts of the distribution and no weight to the remaining parts, as is the case in poverty measurement for example. General means adopt a more flexible stance by putting different weights on different parts of the income distribution. Such flexibility allows for explicitly considering a continuum of social preferences, depending on e.g. the differential weight attributed to the living conditions of the poor relative to those of the middle class.

13. For an income distribution $x=(x_1,\ldots,x_N)$, the general mean of order α, $\mu(x, \alpha)$, is defined as:

$$\mu(x,\alpha) = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^{\alpha}\right)^{\frac{1}{\alpha}} \quad if\ \alpha \neq 0$$

$$= \prod_{i=1}^{N} x_i^{\frac{1}{N}} \quad if\ \alpha = 0$$

9. See Gasparini and Tornarolli (2015) for other customisation techniques.

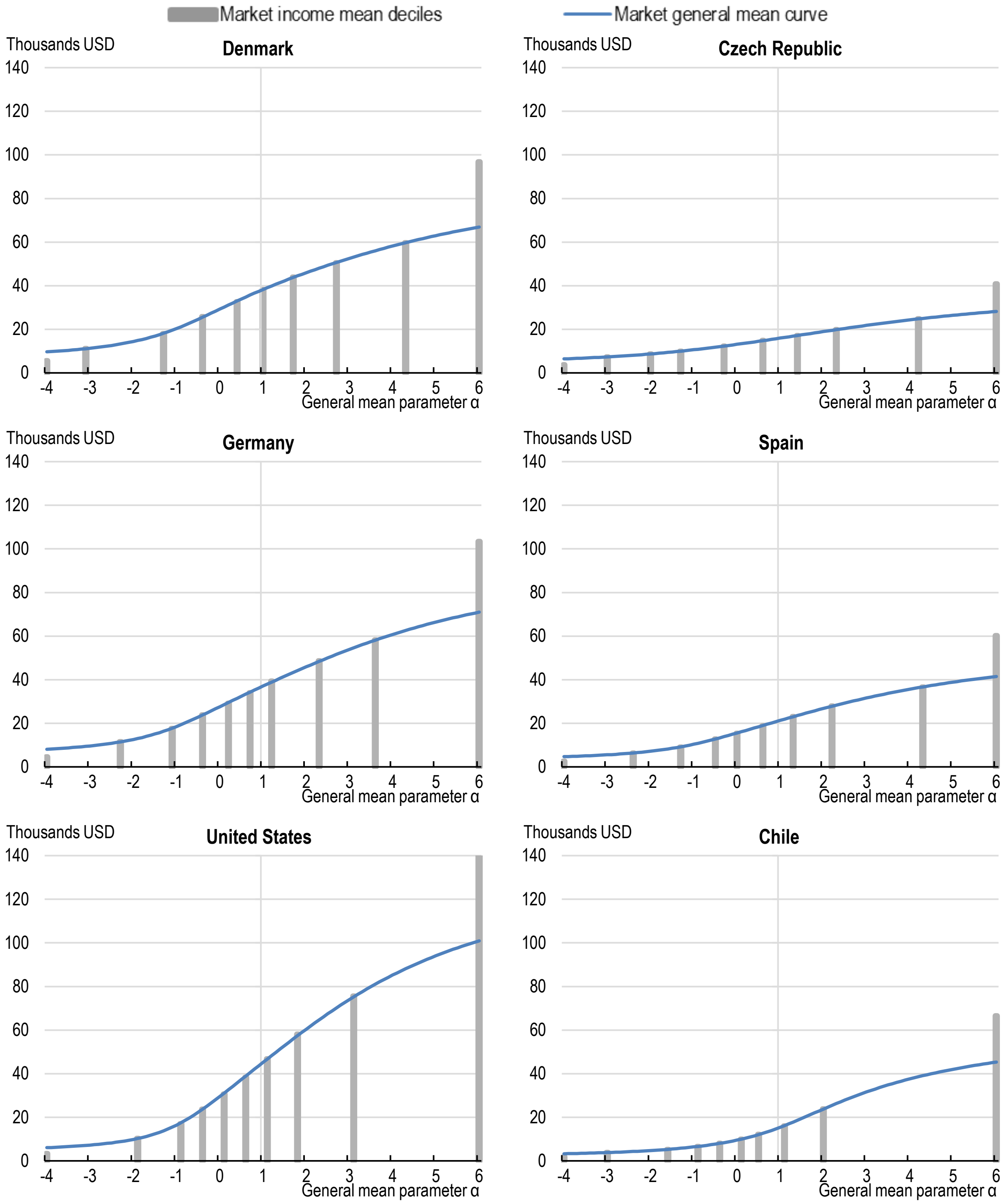
14. A useful property of the general means is their monotonicity with respect to the parameter α, i.e. α'> α implies μ(x,α')> μ(x,α). General means increase as α rises and decrease as α declines: a lower α gives more emphasis to lower values in an income distribution while conversely a higher α gives more emphasis to higher values in an income distribution. The arithmetic mean thus becomes a special case (α=1) of the general mean, which forms a natural benchmark. Thus, variations in the parameter α allow for computing income levels focusing on any segment of the income distribution, from the bottom to the top. In fact, the more α approaches -∞, the more μ(x,α) converges towards the lowest income in the distribution. This case echoes the Rawlsian perspective, as the income distribution is summarised by the affluence of its poorest member. Conversely, when α approaches +∞, μ(x,α) converges towards the income of its richest member.

15. Any general mean of order α satisfies axiomatic properties which are all standard in the theory of inequality measurement (Foster and Szekely, 2008). General means of orders strictly lower than 1 (α<1) satisfy a central concept in economics and in particular in inequality theory, the so-called Pigou-Dalton principle of transfers (Foster et al., 2013). This principle states that if a distribution x' is obtained from the distribution x by a *regressive* transfer (i.e. from a poor individual to a richer one), then μ(x',α)< μ(x,α). Conversely, if a distribution x' is obtained from the distribution x by a *progressive* transfer (i.e. from a richer individual to a poorer one) then μ(x',α)> μ(x,α). Most inequality indices, like the Gini coefficient, are based upon and are consistent with this principle. As a result, the qualitative inequality assessment derived from general means is consistent with that derived from standard indexes of inequality such as the Gini coefficient (Foster et al., 2013).

16. The general means approach can be used for characterising income distributions within a country as well as across countries. Ideally, general mean curves should be computed using microdata (either survey- or register-based). This is not an option for the purpose of this paper because wide and comparable household income data from the OECD Income Distribution database are only available by decile (mean income by each decile). However, in practice general mean curves computed from decile data points approximate microdata-based general mean curves sufficiently well, as long as the parameter α does not take too high or too low values. In practice, a window for α from -4 to 6 can be applied (see Appendix 1 for a comparison using actual microdata).

17. Using real household income data from the OECD Income Distribution Database, Figures 1.a and 1.b display general means curves for the year 2011/12 respectively on market income and disposable income, for selected countries. Each panel presents the value of general means associated with a continuum of α. For example, for both market and disposable income all general means emphasising the bottom (α<1) are similar in Germany and the United States, whereas all general means emphasising the top (α>1) are higher in the United States. As a result, the difference in inequality (as well as in average income) between Germany and the United States comes almost entirely from differences in the upper part of the distribution. Thus, general means make it possible to assess the "location" of inequality, i.e. to identify the portions of the income distribution that drive inequality.

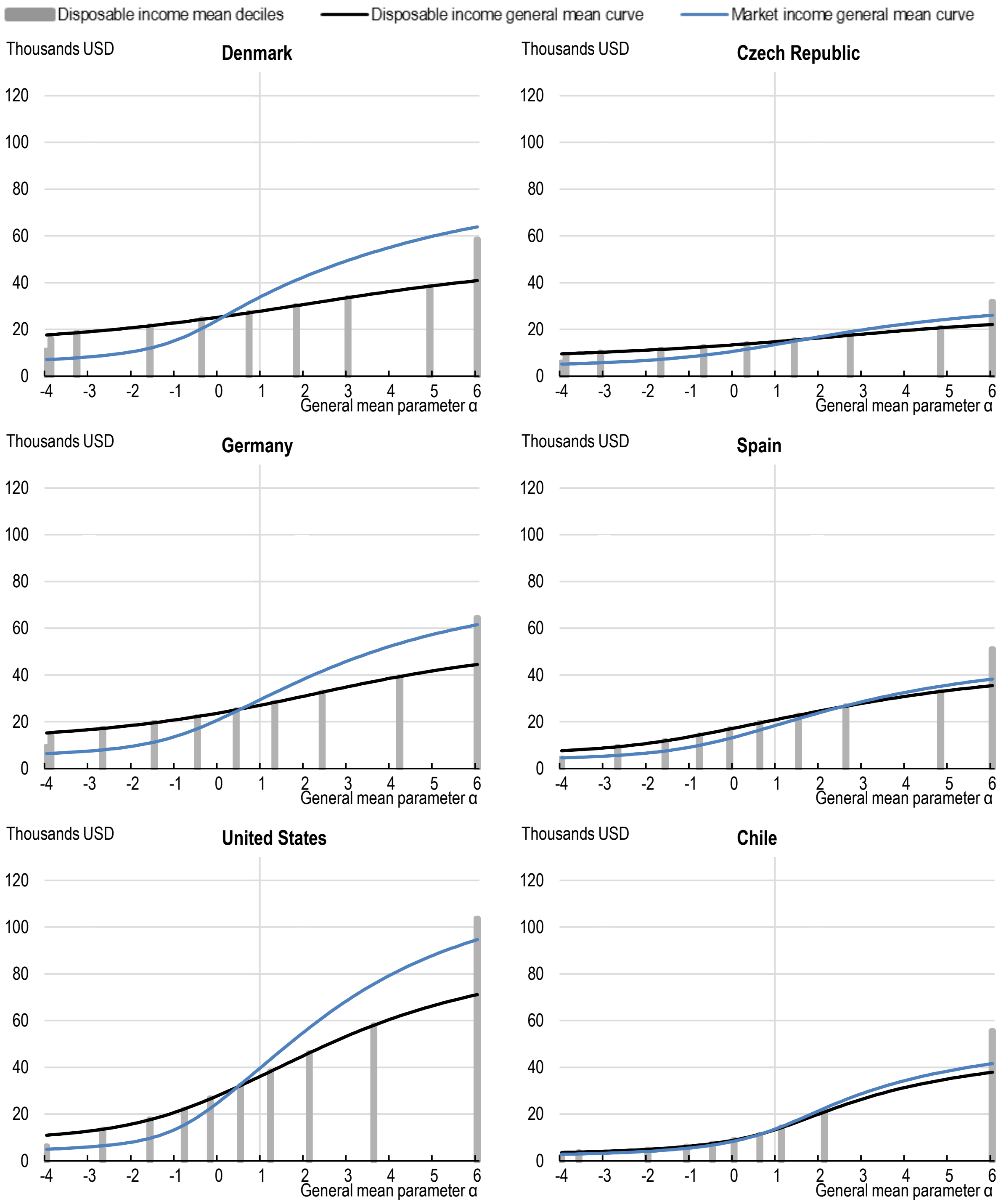
Figure 1.a. General means curves for market income: selected OECD



Note: Household market incomes across the distribution are measured by the full range of income standards, i.e. from top to bottom-sensitive income standards (see text for details), for the working-age population (age 18-65). Data refer to 2011 for Denmark, Germany and Chile; 2012 for Czech Republic, Spain and United States. Market incomes are expressed in USD, constant prices and constant PPPs (OECD base year 2010) with Purchasing Power Parities for private consumption of households. Grey bars represent the mean income for each decile as reported in the OECD Income Distribution Database.

Source: OECD Income distribution Database.

Figure 1.b General means curves for disposable income: selected OECD countries



Note: Household incomes across the distribution are measured by the full range of income standards, i.e. from top to bottom-sensitive income standards (see text for details). Both series cover the full population. Data refer to 2011 for Denmark, Germany and Chile; 2012 for Czech Republic, Spain and United States. Household incomes are expressed in USD, constant prices and constant PPPs (OECD base year 2010) with Purchasing Power Parities for private consumption of households. Grey bars represent the mean income for each decile as reported in the OECD Income Distribution Database.

Source: OECD Income distribution Database.

18. The value of the general mean parameter α and the corresponding emphasis on different parts of the household disposable income distribution is illustrated in Figure 2. The implied weight allocated to a given decile is computed as the elasticity of the general mean with respect to average income of the decile (see Dollar et al., 2015 for a similar approach).[10] Intuitively, the weight measures how sensitive the general mean is to a relative income change in a particular decile, the idea being that the more sensitive the general mean is, the more important the income group is being weighted (or "valued").[11] This shows for instance that across OECD countries, when α = -4, the weight of the first decile is around 0.8, that of the second decile is around 0.1 and that of the fifth (and above) decile is almost 0. At the other extreme, when α = 6, the weight of the last decile is around 0.9 while that that of the fifth (and below) decile is almost 0. In this paper, the case of α = -4 is therefore referred to as the case where the emphasis of the general mean is on incomes among the poor, while the case α = 6 is referred to as the case where the emphasis of the general mean is on incomes among the rich. The intermediate cases of α = -1 (corresponding to weighting relatively more the bottom 3 deciles) and α = 3 (corresponding to weighting relatively more the top 3 deciles) are referred to as the cases where the emphasis is on incomes among the lower-middle class and the upper-middle class, respectively.[12]

19. Distributional weights implied by general means for different αs depend on the shape of the income distribution and therefore differ across countries, as can be seen from the minimum and maximum weights reported in Figure 2. The Figure shows that such implicit weights are very similar across OECD countries, despite the large cross-country differences in income distributions; however some difference in implied weights is observed for extreme α values between advanced and emerging OECD economies as those countries exhibit large income dispersion relative to the average OECD country. Overall the analysis allows for concluding that relying a common same set of benchmark cases (αs) for the purpose of cross-country empirical work is an acceptable practice, but also suggests some caution in interpreting the results for countries such as Chile, Mexico and Turkey.

20. General means also allow for illustrating the impact of redistribution through taxes and transfers. This can be achieved by comparing market and disposable income-based general means (Figure 1.b). For instance, in Denmark, Germany and the United States, redistribution reduces disposable income compared to market income in the upper part of the distribution, while increasing it in the lower part. By contrast, in Chile, Czech Republic and Spain, taxes and transfers tend to leave virtually unchanged disposable income compared to market income in the lower-half of the distribution while slightly reducing it in the upper-half. Such visual comparisons of household income differences across the distribution before and after taxes and transfers can complement more formal analysis of redistribution such as computing relative differences in income inequality measures before and after taxes and transfers (see e.g. OECD, 2011).

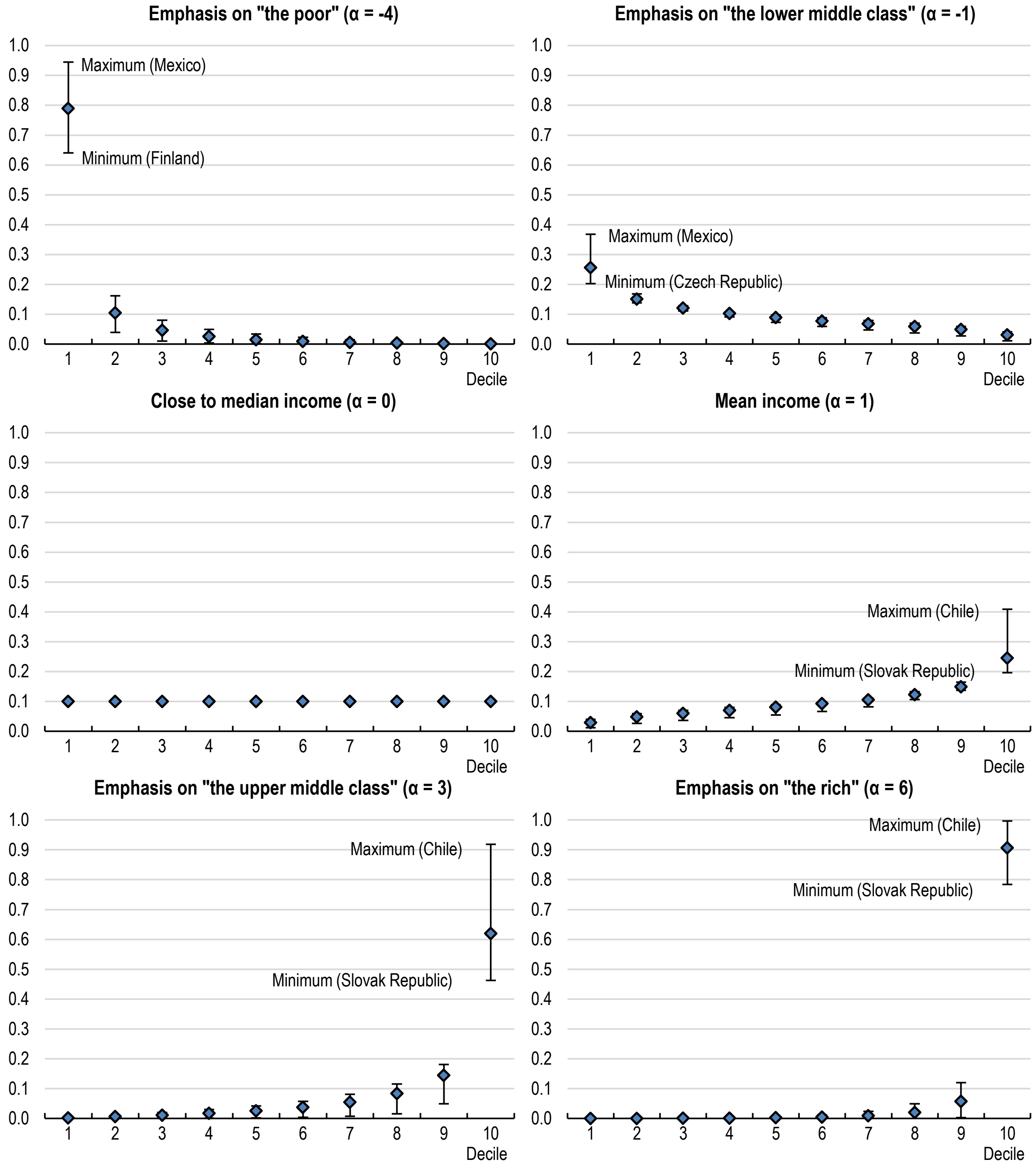
10 . The implied weight is defined as: $\omega_i = \frac{\partial \mu(x,\alpha)}{\partial x_i}\frac{x_i}{\mu(x,\alpha)} = \frac{x_i^\alpha}{\sum_{i=1}^N x_i^\alpha} \in [0,1]$.

11 . The general mean can also be interpreted as a social welfare function, whereby the weights become welfare weights assigned to individuals based on their incomes (see Dollar et al., 2015). In this paper, the general mean is merely applied as a flexible tool to summarise an income distribution.

12 . It may be surprising that the case of equal weights across the distribution is α=0 (and not α=1), which empirically produces a general mean close to the median income. The reason is that weights have been defined in a relative sense, i.e. in terms of elasticities. The arithmetic mean (α=1) emphasises higher incomes relatively more in this respect because higher incomes contribute relatively more to mean income than lower incomes. Another way to think of this is the problem of measuring the income of a "typical" individual. As stressed by the Stiglitz-Sen-Fitoussi report, the median is a better measure than the mean in this respect.

Figure 2. Distributional weights implied by general means: household disposable income deciles

Average across OECD countries, latest available year



Note: The diamond shows the average weight for each decile across OECD countries for a given general mean parameter α. The bars indicate the minimum and maximum weight among OECD countries. The weight is computed as the elasticity of the general mean with respect to average income of each decile (see text and Dollar et al., 2015).

Source: OECD Income Distribution Database.

21. Finally, the granular general mean-based approach can be used to analyse income developments at any point of the distribution. Growth in the general mean of order α, $g(x_{t+1},x_t, \alpha)$, is given by:

$$g(x_{t+1}, x_t, \alpha) = \frac{\mu(x_{t+1}, \alpha) - \mu(x_t, \alpha)}{\mu(x_t, \alpha)}$$

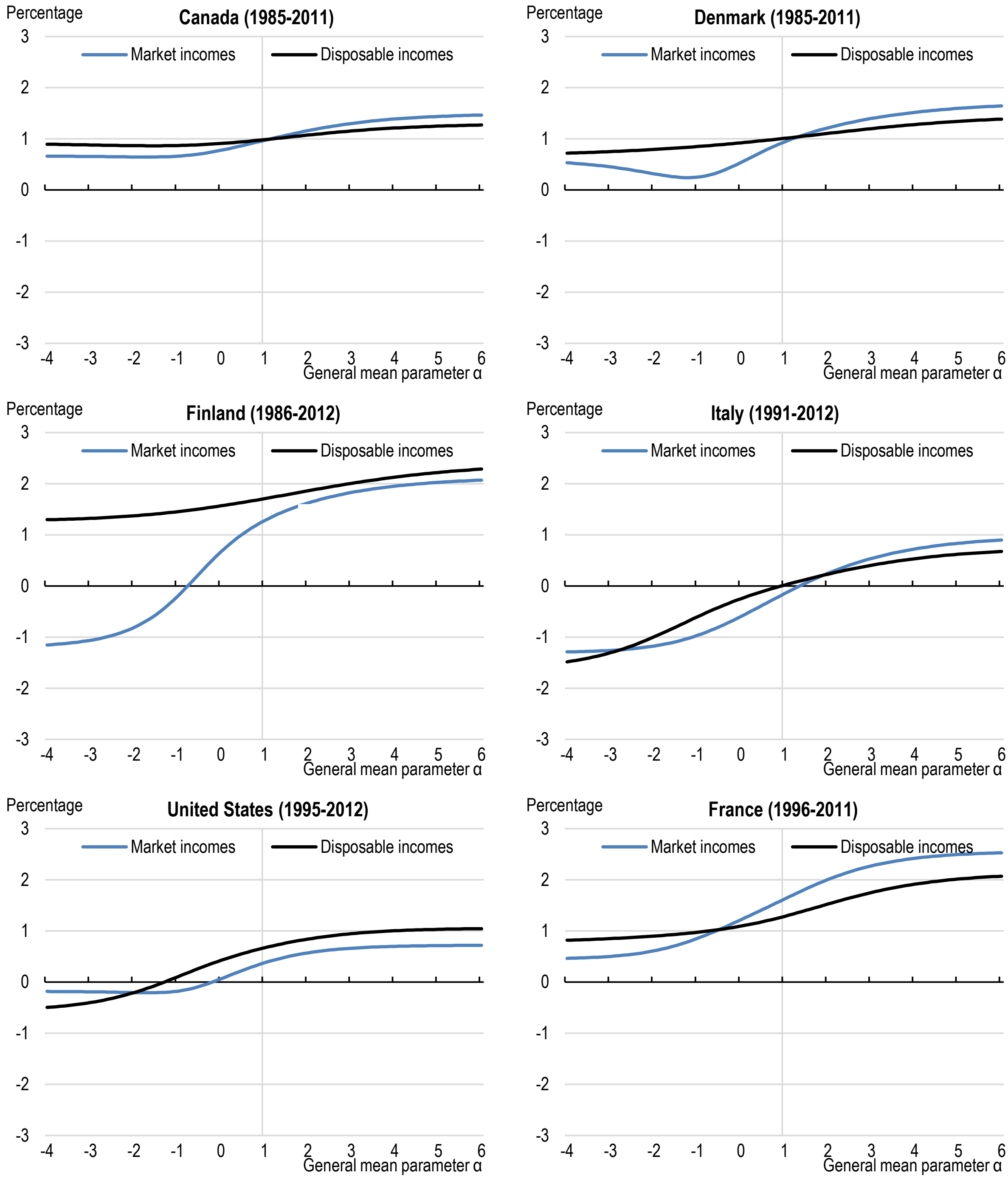
22. Figures 3.a and 3.b show general means-based growth curves on the basis of real household market and disposable income data for selected OECD countries over the period covered by the analysis. The vertical axis represents $g(x_{t+1},x_t, \alpha)$ and the horizontal axis the values of α. When α=1, the curve's height measures growth in average income. For α>1, faster growth in the general mean than in average income points to an *increase* in inequality. Conversely, for α<1, faster growth in the general mean than in average income points to a *decrease* in inequality. More generally, an S-profile indicates an increase in inequality (e.g. Italy, the United States and France) and an inverted S-profile a decrease (e.g. Czech Republic, Turkey and Poland). The relative flatness of the curve provides a qualitative assessment of the magnitude of associated changes in inequality along with their underlying sources. For instance, not only inequality in disposable income increased more strongly in Italy than in Canada, but it happens that the poor in Italy lost ground even in absolute terms while in Canada all incomes have grown, albeit in an unequal way.

23. As an extension, general means growth curves allow for assessing the impact of taxes and transfers on income distribution developments. For instance in Canada, Denmark and Finland, the rise in market income inequality has been almost completely offset by redistribution: growth in real disposable income has been very similar across the distribution while that of real market income has been stronger in the upper compared to the lower half of the income distribution. Finally, this granular approach allows for uncovering the very specific and differentiated impact of redistribution on specific income groups. Such is the case in the United Kingdom, where mean disposable income of the middle class grew faster than mean market income while such incomes grew at the same rate at the low and the high end of the distribution. This indicates that redistribution has tended to benefit the middle class. General means growth curves can thus provide a nuanced and extensive analysis of income distribution developments.

24. To summarise, using general means as income standards delivers, within a single analytical framework, a comprehensive assessment of countries' income distributions. It can be used all at once to track changes in income levels for different income groups as well as to see whether the resulting changes in inequality have been widespread or concentrated in narrower segments of the distribution. It is thus particularly well-suited for policy analysis and for tracking the incidence of growth on inequality: the possibility to diagnose, on the basis of a simple measure, whether inequality increases occurred across the whole distribution of income or within a narrower part of the distribution allows for a finer understanding of distributional developments – and, as a result, for a better fine tuning and design of appropriate policy responses.[13]

13. As a result of these properties, this approach has been recently fully extended as a general tool being now systematically used by the World Bank for tracking inequality and poverty (Foster et al., 2013).

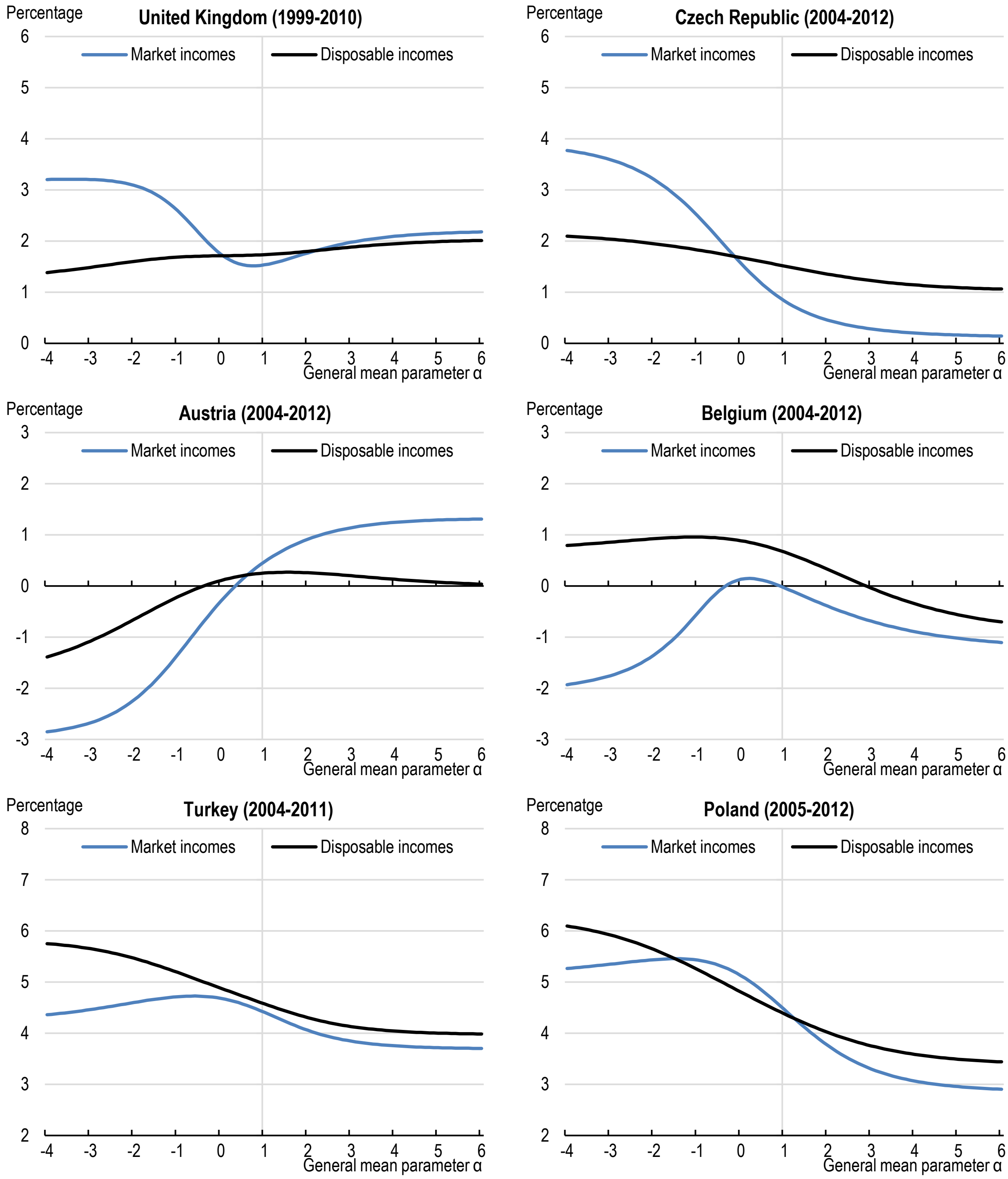
Figure 3.a. General means-based growth curves for selected OECD countries



Note: Household incomes across the distribution are measured by the full range of income standards, i.e. from top to bottom-sensitive income standards (see text for details).The data show average annual growth rates and refer to the period between the first and the last observations included in the analysis. Both series cover the full population. Income data are expressed in USD, constant prices and constant PPPs (OECD base year 2010) with Purchasing Power Parities for private consumption of households.

Source: OECD Income Distribution Database.

Figure 3.b. General means-based growth curves for selected OECD countries



Note: Household incomes across the distribution are measured by the full range of income standards, i.e. from top to bottom-sensitive income standards (see text for details).The data show average annual growth rates and refer to the period between the first and the last observations included in the analysis. Both series cover the full population. Income data are expressed in USD, constant prices and constant PPPs (OECD base year 2010) with Purchasing Power Parities for private consumption of households.

Source: OECD Income Distribution Database.

Using general means as inputs to inequality measurement

25. General means applied to household income data are distribution-sensitive income measures. They are not designed to “quantify” inequality, as done by single indices of income spread, like the Gini coefficient. As explained above, because general means are consistent with the Pigou-Dalton principle of transfers, convergence (divergence) in incomes between e.g. households in the top and the bottom of the distribution allows for diagnosing a decrease (increase) in inequality, but not for measuring the magnitude of that decrease (increase): inequality changes can be inferred by performing pairwise comparisons of income measures at several points of the distribution, but it is not possible to deliver the magnitude of such changes. Having said that however, general means can be used in a straightforward way to build synthetic measures of inequality of a general form, i.e. Atkinson inequality measures (Atkinson, 1970).

26. Atkinson inequality measures are constructed by comparing a general mean of order $\alpha<1$ to the arithmetic mean ($\alpha=1$). As α decreases below 1, preferences become more egalitarian, placing relatively more weight on the poor and less weight on the rich than mean income (see Figure 2). In the context of Atkinson measures, α is referred to as the inequality aversion parameter.[14] The lower is the value of α, the higher is a society’s aversion to inequality. For $\alpha<1$, the Atkinson inequality measure is given by:

$$\mathrm{A}(\mathrm{x},\alpha)=\frac{\mu(x,1)-\mu(x,\alpha)}{\mu(x,1)}=1-\frac{\mu(x,\alpha)}{\mu(x,1)}$$

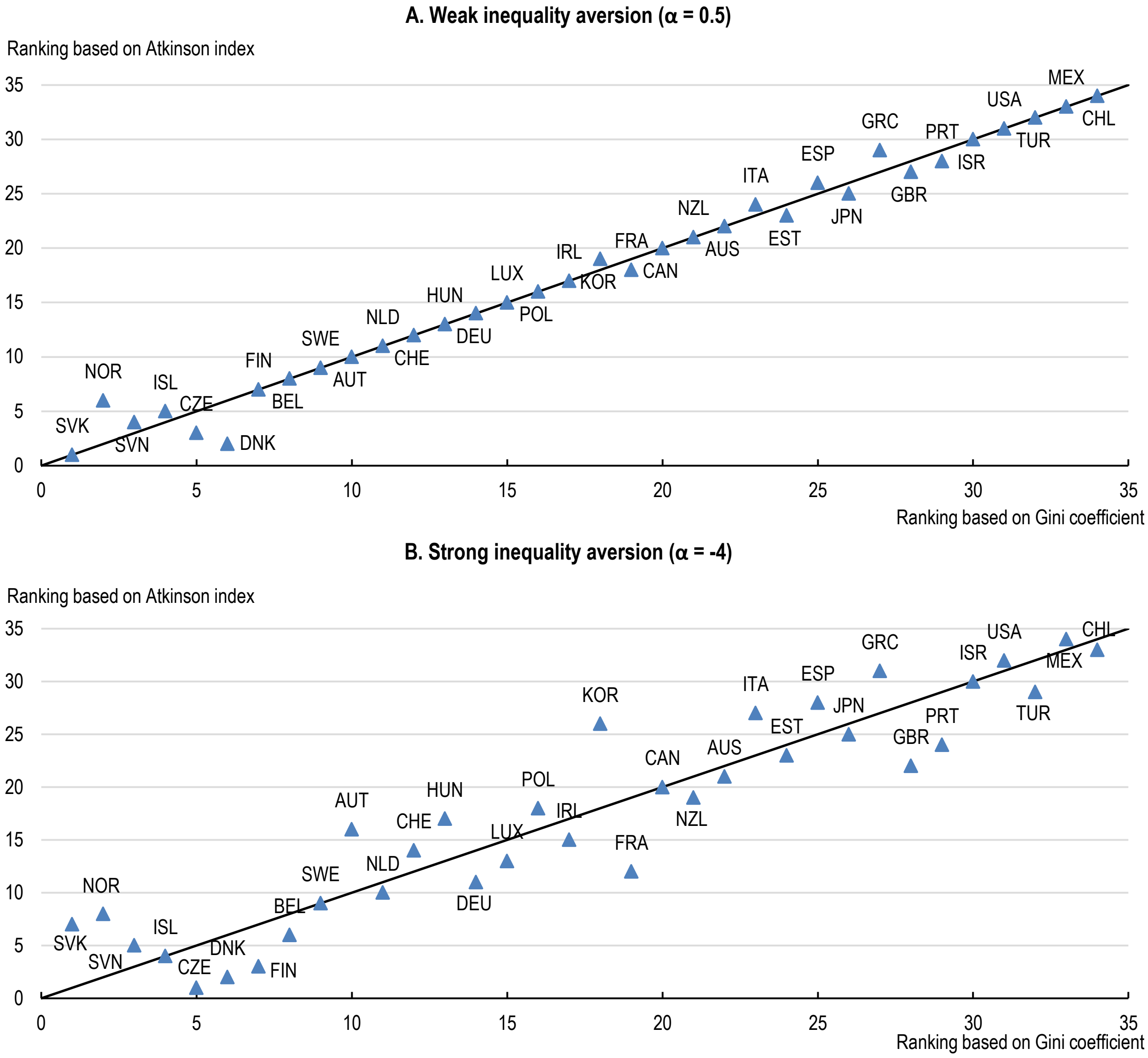
By construction $A(x,\alpha)$ varies between 0 and 1, and inequality increases as it moves from 0 to 1: the minimum level of inequality is obtained when the sum of all incomes is equally distributed in the society. In this framework, the arithmetic mean represents a neutral situation in a society when the aggregate income is distributed equally; the shortfall between the general mean and the arithmetic mean represents the loss of income induced by an unequal distribution of income. For a given distribution of income, the lower the value of α, the higher the level of inequality aversion and the higher the resulting level of inequality according to the Atkinson measure. If a society becomes more averse to inequality, the parameter α used to compute the general mean decreases, and the Atkinson inequality index increases.

27. Any synthetic index of inequality embodies to some extent different underlying social valuations of inequality: while the Gini focuses more on the middle class, alternative indexes such as the Theil measure are relatively more sensitive to the upper part of the income distribution. A main advantage of the Atkinson inequality index is to allow for a flexible and transparent social valuation through the selection of the parameter α, which explicitly reflects different views about the weights to be applied to different parts of the income distribution.[15] As a result, estimating Atkinson measures over a range of values for α allows for characterising the profile of inequality and accommodating different social preferences in the area of inequality. The Gini coefficient can be considered as a special case of this broader analytical framework. In fact, by setting a relatively weak inequality version with $\alpha=0.5$, it turns out that the particular Atkinson measure approximates the Gini coefficient, at least in terms of countries’ ranking (Figure 4, Panel A). By contrast, by setting a stronger inequality aversion with e.g. $\alpha=-4$, differences in countries relative positions occur compared to the Gini coefficient (Figure 4, Panel B).

14. Note that the Atkinson inequality index can also be specified by $\alpha=1-\varepsilon$, with higher values of ε representing higher aversion to inequality.

15 . The generalised Gini coefficient (S-Gini) also allows for an “inequality aversion” parameter, see Donaldson and Weymark (1980; 1983).

Figure 4. The impact of stronger inequality aversion in assessing cross-country inequality rankings



Note: Rankings based on household disposable income. See text for definition of the Atkinson index. Data refer to 2009 for Japan; 2010 for the United Kingdom; 2011 for Canada, Chile, Denmark, France, Germany, Israel, New Zealand, Norway, Sweden, Switzerland, and Turkey; and 2012 for the rest.

Source: OECD Income Distribution Database.

3. Developments in growth and income inequality across OECD countries

28. GDP per capita and average real household disposable incomes have tended to grow in parallel, on average across OECD countries over the last two decades (Figure 5).[16,17] However, incomes have grown

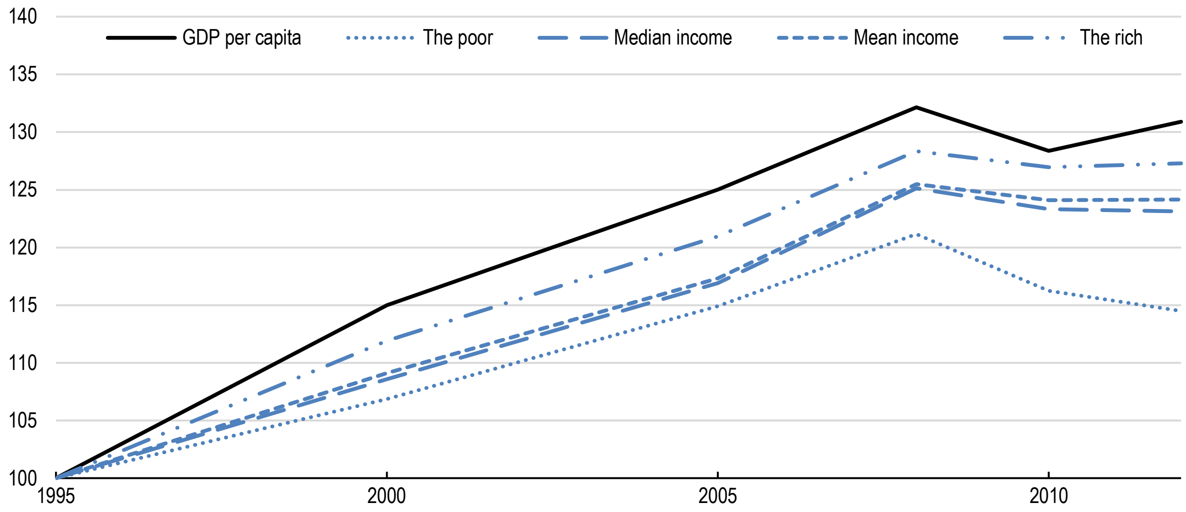
16 . For this illustration 1995 is chosen as the starting year instead of mid-1980s so that the average can be based on a larger set of countries.

17 . GDP is deflated with the GDP deflator while household disposable incomes across the distribution are deflated with consumer price deflators, as standard in the literature. While differential developments

relatively more among rich households than among poor households and OECD countries have experienced rising income inequality, as has been widely documented (OECD, 2015b).[18]

Figure 5. Developments in GDP per capita and in household disposable incomes across the distribution

Average across 19 OECD countries, 1995 = 100



Note: Countries included are Australia, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Israel, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Sweden, Turkey, United Kingdom and United States. GDP per capita and household disposable incomes are measured in constant prices by applying the GDP deflator and the consumer price index, respectively. Income groups are measured by different orders of the general mean: the poor (α=-4), median income (α=0), and the rich (α=6).Some data points have been interpolated or use the value from the closest available year, see text and Table 1.

Source: OECD National Accounts; OECD Income Distribution Database.

29. While the OECD average indicates a general and widening gap between incomes of the poorer and richer households in many countries, this masks substantial differences in countries' experiences. Appendix A2 presents growth and distributional developments for all OECD countries, going back to mid-1980s for countries for which data are available. These figures convey a message of cross-country heterogeneity. Poor households have been almost disconnected from the growth process in Sweden and even experienced real income losses in the United States; these countries have experienced marked rises in income inequality, but starting from very different initial levels of inequality. In Australia and Hungary the rise in income inequality has been comparatively milder over the whole period, as household disposable incomes of poor and rich income groups have been growing about the same pace between 1995 and 2005, deviating only over the most recent period. Other countries have experienced reductions in income inequality over the same period, especially emerging economies like Mexico and Turkey, albeit here again, developments were heterogeneous at a more granular level. Within advanced countries, inequality declined in countries such as Belgium and the Czech Republic, while it remained broadly stable in the Netherlands

between GDP and consumer prices may drive the wedge between GDP and household incomes, this has no distributional impact since a single consumer price index is used to deflate household incomes across the distribution. See Causa et al. (2014) for a comparison between trends in GDP and in average household income in current as opposed to constant prices.

18 . In terms of the Gini coefficient, the average change in inequality across OECD countries, for which data are available, amounts to 0.9 percentage points from the mid-1990s to 2012 and 3 percentage points from mid-1980s to 2012 (OECD, 2015b).

and Austria; although for some European countries OECD data are available only starting from the mid-2000s which implies some caution since distributional developments are observed within a crisis period.

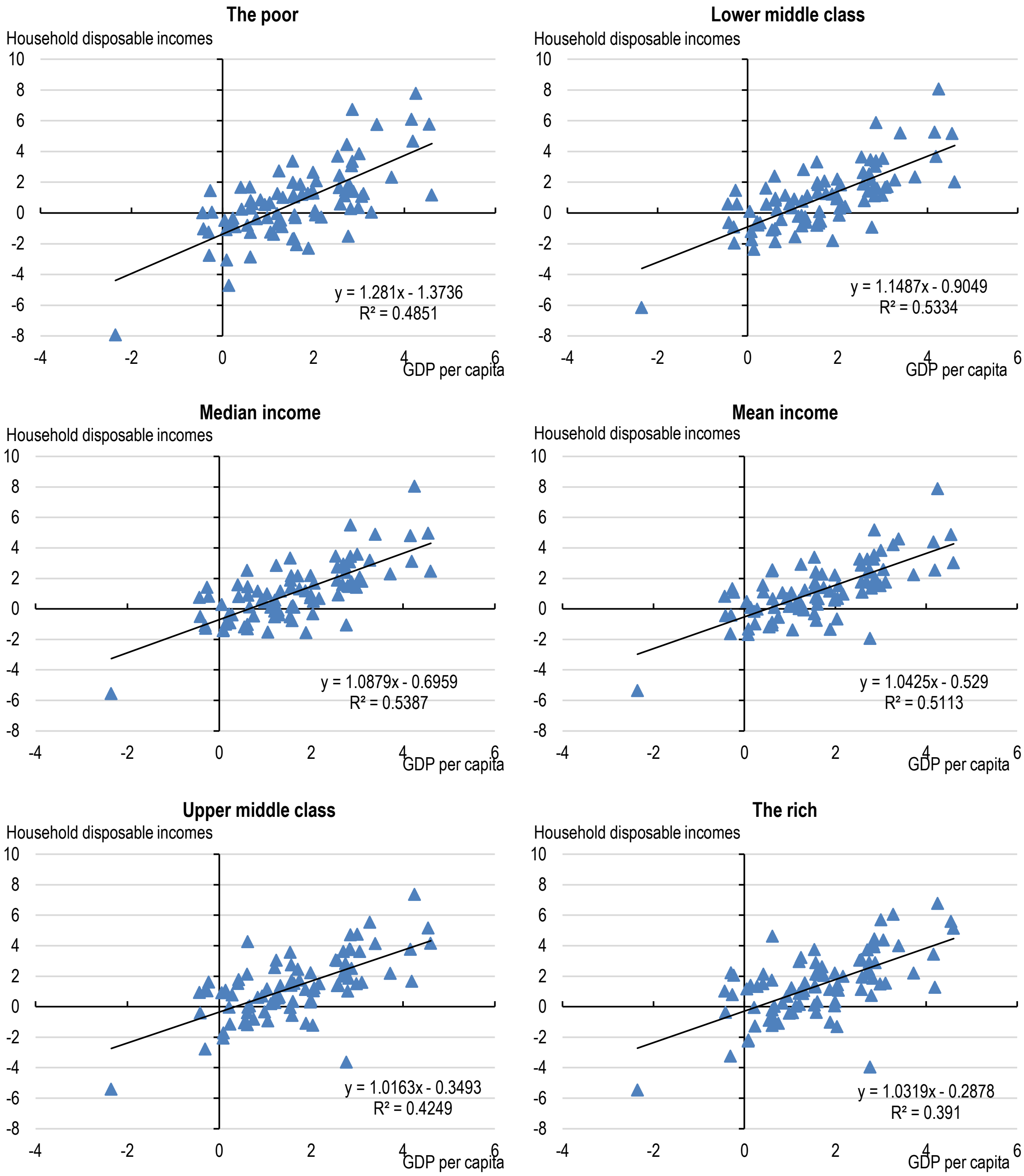
30. Upward trends in GDP per capita and in income inequality need not imply a causal relationship from growth to inequality. As an illustrative step, Figure 6 shows simple correlations between growth in GDP per capita and growth in household disposable incomes across the distribution. This is done on the basis of spells of minimum 5 years, which is the standard approach in the literature.[19] As can be seen from simple linear regression lines, growth in GDP and in household disposable incomes are positively correlated for all income groups with a slope not significantly different from 1. However, the slightly higher slopes for the lowest income groups suggest a higher sensitivity to fluctuations in GDP (see discussion in Section 5).

31. Simple bivariate correlations between raw series of GDP per capita and household disposable incomes across the distribution are by no means to be interpreted causally, but do not seem to strongly support the idea that growth has been disequalising, on average across OECD countries over the last three decades. The apparent contradiction between this pattern and that of parallel rises in GDP and in income inequality (Figure 5) is explained by differences across income groups in the intercepts of the regression lines of GDP on household disposable incomes. Such intercept is estimated to increase with household income levels, from -1.4 for poor households to -0.3 for rich households, in line with widening income gaps between rich and poor households. This would tend to suggest that factors other than GDP growth itself have been driving widening income gaps between rich and poor households, on average across OECD countries over the period under consideration. For this paper, the question is whether growth in itself is a driver of inequality, which requires moving from simple correlations to more rigorous econometric analysis.

19 . This results in 84 spells in total for all available countries based on the OECD Income Distribution database. The unbalanced data implies an average spell length of 6.8 years and the maximum spell length is 12 years.

Figure 6. Correlation between growth in GDP per capita and in household disposable across the distribution

Average annual growth rate for spells of minimum 5 years, OECD countries from mid-1980 to 2012



Note: The sample comprises all available non-overlapping spells of minimum 5 years for OECD countries (sample size = 84, average spell length = 6.8 years) and does not include imputed values. GDP per capita and household disposable incomes are measured in constant prices by applying the GDP deflator and the consumer price index, respectively. Household disposable incomes across the distribution are measured by different orders of the general mean: the poor (α=-4), the lower middle-class (α=-1), the upper middle-class (α=3), and the rich (α=6). The line and associated equation shows the fit from a simple linear regression.

Source: OECD National Accounts; OECD Income Distribution Database.

4. Econometric framework

The model

32. While the fundamental determinants of GDP, i.e. human and physical capital, labour-augmenting efficiency and population growth, are well established in growth theory and the production function framework, there exists no such framework in the case of household incomes with an explicit consideration of its distribution. However, one would a priori assume that household disposable income is affected by GDP and hence indirectly by its drivers. As a result, the household income specification is based on the assumption that in the long run the level of household income across the distribution is mainly driven by the level of GDP per capita, which "transmits" to households. The baseline specification includes a number of control variables, such as the lagged level of household income (to account for convergence), GDP growth (to account for short-run business cycle fluctuations), the GDP balance of net exports (to account for persistent gaps between household incomes and domestic output),[20] as well as country-fixed effects and time controls.[21]

33. Against this background, the model takes the following form:

$$\Delta \ln \mu_\alpha(x_{it}) = \beta_{0,\alpha} - \beta_{1,\alpha} \ln \mu_\alpha(x_{it-1}) + \beta_{2,\alpha} \Delta \ln GDP_{it} + \beta_{3,\alpha} \ln GDP_{it-1} + \beta_{4,\alpha} NX_{it} + \gamma_t + \eta_i + \varepsilon_{it} \qquad [1]$$

where period t and t-1 correspond to observations 2 years apart (Table 1), $\Delta \ln \mu_\alpha(x_{it})$ is growth in real household income between time period t and t-1 for country i, i.e. in the general mean for the part of the distribution captured by the parameter α, $\Delta \ln GDP_{it}$ is the growth in GDP per capita, NX_{it} is net exports-to-GDP, γ_t denotes time controls, and η_i denotes country fixed effects.[22]

34. The main effect of interest is the implied long-run elasticity of household income with respect to GDP per capita, given by $\varepsilon_{\mu_\alpha,GDP} = \beta_{3,\alpha}/\beta_{1,\alpha}$. This can be seen by rewriting the model to include an explicit error-correction term:

$$\Delta \ln \mu_\alpha(x_{it}) = \beta_{2,\alpha} \Delta \ln GDP_{it} - \beta_{1,\alpha} \left[\ln \mu_\alpha(x_{it-1}) - \frac{\beta_{3,\alpha}}{\beta_{1,\alpha}} \ln GDP_{it-1} - \frac{\beta_{4,\alpha}}{\beta_{1,\alpha}} NX_{it} - \frac{1}{\beta_{1,\alpha}} \gamma_t - \frac{1}{\beta_{1,\alpha}} \eta_i \right] \qquad [2]$$

35. The square bracket in [2] contains the implied equilibrium relationship between household income and its determinants. The idea is that in the long run, income generated from domestic production should fully accrue to the domestic household sector under the form of market (capital and labour) income

20. The underlying rationale is that mean household income elasticity to domestic production is more likely to deviate from 1 in economies facing persistent external imbalances insofar as they reflect a gap between household incomes and their level of consumption. In addition, previous works has shown that the difference between growth in real GDP and in real mean household income is, to a large extent, driven by differences in growth of output prices relative to consumer prices (Causa et al. 2014; 2015). In turn, the evidence would suggest that this is, to a good extent, driven by terms-of-trade effects. The results are qualitative unchanged if net exports are excluded or replaced by alternative controls, like terms of trade (see Section 6).

21. See Causa et al. (2015) for a similar specification where the income equation is complemented with an augmented-Solow growth equation for GDP per capita for simultaneous estimation.

22. Time controls consist in a linear time trend in order to enforce the mean stationarity condition in the context of System GMM (see below), and a dummy for the crisis period (2009-2010). The choice of time controls can be a delicate matter to assess the incidence of GDP growth across the distribution (Causa et al., 2015).

and redistribution (taxes net of transfers) income (see OECD, 2016, Chapter 3, for a comprehensive assessment). For most OECD countries, the net exports balance is close to zero on average over the sample.[23] Thus, absent measurement and methodological considerations, the elasticity of disposable household income with respect to GDP, $\varepsilon_{\mu_\alpha,GDP}$, should be close to one for the mean of the distribution (i.e. for α=1). The empirical model predicts that if household income and GDP per capita (or net exports) are out of equilibrium in period t-1, household income will grow faster or slower than GDP per capita in period t. This process will continue until equilibrium is restored, with the speed of adjustment determined by the convergence parameter $\beta_{1,\alpha}$.

36. In order to shed some light on the role of taxes and transfers with respect to the distributional implications of growth, the model is estimated both for household market income and for household disposable income.[24] The incidence of growth on inequality is identified through repeated estimation of the model for different values of α (in practice from -4 to 6) so as to span the income distribution from the poor to the rich.[25] As outlined in Section 2, low (high) values of α puts relatively more emphasis on the bottom (top) of the income distribution. By nature, the repeated procedure generates a very large number of estimations that cannot reasonably be reported in full. As a result, the estimates are reported graphically.[26] For the sake of completeness, Appendix 2 provides detailed estimation results for four benchmark cases: the bottom part of the distribution (α=-4), income close to the median (α=0), mean income (α=1), and the upper part of the distribution (α=6).

Estimation strategy

37. Due to the presence of the lagged income standard term $\mu_\alpha(x_{it-1})$ to account for convergence, standard econometric techniques applied in this setting generally deliver biased estimates (see Blundell and Bond, 2000). In addition, having GDP as an explanatory variable is likely to generate endogeneity from two compounding factors: reverse causality from income to GDP, and household income persistence. Dynamic panel data econometric techniques have to be applied in order to address these issues. To understand why, it is useful to first rewrite equation [1] into its dynamic form in levels:

$$\ln\mu_\alpha(x_{it}) = \beta_{0,\alpha} + (1-\beta_{1,\alpha})\ln\mu_\alpha(x_{it-1}) + \beta_{2,\alpha}\ln GDP_{it} + (\beta_{3,\alpha}-\beta_{2,\alpha})\ln GDP_{it-1} + \beta_{4,\alpha}NX_{it} + \gamma_t + \eta_i + \varepsilon_{it} \quad [3]$$

Pooled Ordinary Least squares (OLS) and the standard panel data (Within) estimator yield biased estimates of equation [3]: the OLS estimate of the convergence parameter will be biased upward due to the omission of the unobserved country fixed effects, as $\ln\mu_\alpha(x_{it-1})$ in [3] becomes positively correlated with the error term. And while the Within estimator removes the omitted variable by differencing, it introduces a negative correlation between the lagged income standard and the error term, resulting in downward bias in the speed of adjustment $(1-\beta_{1,\alpha})$ (Nickell, 1981). However, both of these estimators are useful as initial benchmarking for framing the different biases that have to be dealt with, and to see if the use of more advanced techniques allows for eliminating them. In particular, OLS and Within estimators provide respectively indicative upper and lower bounds of the Generalised Method of Moments (GMM) estimator under its system form (Bond, 2002), as confirmed in Appendix 2.

23. As explained before, controlling for the net exports in this context is meant to capture eventual long-lasting deviations between GDP and household incomes, due to persistent external imbalances.

24. In the case of household disposable income the model is estimated for the entire population, while only the working-age population (individuals aged 18-65) is considered for pre-tax and transfer income (see above).

25 . This can be thought of as an approach similar to quantile regression, which is ruled out here given the semi-aggregate nature of the data.

26. For each curve presented the full set of numerical results is available upon request to the authors.

38. GMM techniques have become the standard procedure for overcoming omitted variable and endogeneity issues in dynamic panel data models.[27] The Difference GMM estimator (DIF-GMM) originally developed by Arellano and Bond (1991) eliminates the endogeneity arising from unobserved country fixed effect η_i by first-differencing equation [3]. However, the differenced equation still suffers from correlation between the differenced income standard term on the right-hand-side and the differenced error term: lagged values of the explanatory variables in levels from period t-2 and earlier periods have thus to be used as instruments to address endogeneity.[28] The DIF-GMM approach exploits the within-country variation across time and delivers consistent estimates, provided that the instruments are valid and that the error term ε_{it} is serially uncorrelated, which can be tested by specific autocorrelation tests. The validity of instruments is however a critical concern since the differencing of income standards levels may discard much of the information in the data: household income tends to change slowly over time, implying that most of the variation in the data comes from the cross-sectional dimension. As a result, the lagged levels of the explanatory variables are likely to be weak instruments for equation [3] and may cause imprecise and biased estimates (Blundell and Bond, 1998).

39. To avoid this weak instruments pitfall, the System GMM estimator (SYS-GMM) uses the set of equations in differences from DIF-GMM with an additional set of equations in levels (see Arellano and Bover, 1995; Blundell and Bond, 1998). The relevance of this approach can be seen by noting that the differenced income standard term $\Delta\ln\mu_\alpha(x_{it-1})$ is a valid instrument for $\ln\mu_\alpha(x_{it-1})$ in equation [3], provided that it is not correlated with the residual ε_{it} and with the country fixed effect η_i. This introduces additional moment conditions,[29] which can be tested by usual Sargan/Hansen tests for over-identifying restrictions or by difference-in-Sargan/Hansen tests for the comparison between DIF-GMM and SYS-GMM. Provided that the additional instruments are valid, SYS-GMM exploits both within (countries) and between (countries) variation and thus gives more precise and less biased estimates compared to DIF-GMM. Moreover, SYS-GMM has been found to have better finite sample properties, especially when the dependent variable is highly persistent, which is likely to be the case here as mentioned before (Blundell and Bond, 1998; 2000; Bond et al., 2001).

40. Turning to the practical implementation, SYS-GMM raises the question of the choice of instruments. In principle all available lags of the explanatory variables are candidates for the set of instruments. However, the number of instruments can easily become too large and results in over-fitting of the model and thus biased estimates, especially in small samples (Roodman, 2009a).[30] Moreover, GDP is also assumed endogenous in this setting, which implies an additional set of conditions analogous to those for income standards. As a result, given the model and the data, the number of potential instruments is 162

27. See Blundell and Bond (2000), Bond et al. (2001), Forbes (2000), Panizza (2002), and Voitchovsky (2005).

28. For instance, the period t-2 income standard level $\ln\mu_\alpha(x_{it-2})$ is an instrument candidate as it is correlated with the differenced income standard $\Delta\ln\mu_\alpha(x_{it-1}) = \ln\mu_\alpha(x_{it-1}) - \ln\mu_\alpha(x_{it-2})$ by construction while it is uncorrelated with the differenced error term $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i-1t}$, given the assumption in DIF-GMM that residuals are serially uncorrelated.

29. Usually this is referred to as mean stationarity of the dependent and independent variables assumption, because a sufficient condition for it is constant means over time at the country level. For household income and GDP per capita, constant means over time is hardly satisfied. However, mean stationarity is not a necessary condition. Constant correlation over time between household income (GDP) and country fixed effects is also a sufficient condition (Bun and Sarafidis, 2015). This condition is much less demanding and thus assumed to be satisfied for estimation purposes. Moreover, as explained before, the inclusion of a linear time trend in the set of time controls allows additionally to enforce, albeit imperfectly, stationarity.

30. Too many instruments also weaken the Hansen and difference-in-Hansen tests for the validity of instruments (Bowsher, 2002).

in the baseline specification [3]. Given a cross-section of 34 countries and a total of 259 country-year observations, such unrestricted estimation is clearly unfeasible.

41. Two approaches to reduce the instrument count are possible. First, one can use only a limited number of lags, e.g. second and/or the third order lags of the income standard. Second, the set of instruments can be collapsed in the sense that instead of applying an instrument separately to each specific time period, the instrument is applied to all time periods at once (Roodman, 2009b). The latter approach is more restrictive in principle since it reduces the flexibility of the variance-covariance matrix but necessary in practice due to the short time dimension for a number of countries.[31]

42. The empirical work is further complicated by the need to estimate the model across the full range of income standards, as governed by the order of the general mean, α. In this paper, the set of instruments is restricted to be the same across the distribution. An alternative approach could be to select different instruments for different portions of the income distribution. However, with no prior knowledge and underlying structural model, the selection of different instruments would be very arbitrary in practice: one particular choice of instruments may yield a well-specified model at the mean, but a mis-specified model at the bottom of the distribution. The risk is then that growth incidence estimates across the distribution end up being influenced by the use of different instruments. For the equations in differences, the set of instruments contains the third lag of the income standard term $\ln\mu_{\alpha}(x_{it-3})$, a collapsed set of the second and third lag of GDP ($\ln GDP_{it-2}$, $\ln GDP_{it-3}$), and the change in net exports ΔNX_{it} (which is assumed exogenous and thus instruments itself). For the level equations, the instrument set becomes $\Delta\ln\mu_{\alpha}(x_{it-2})$, the collapsed set of $\Delta\ln GDP_{it-1}$, NX_{it} and the time controls. Finally, all reported standard errors are clustered at the country level, robust to heteroscedasticity and arbitrary patterns of autocorrelation within countries.

43. Standard SYS-GMM specification tests are satisfied for the vast majority of estimated models for both the market and disposable income (Appendix 2). The choice of the instrument sets is validated according to the Hansen test of overidentifying restrictions and the difference-in-Hansen test for the level equation restrictions.[32] Second-order autocorrelation in the error terms cannot be ruled out for some of the estimated models (such as market-income based equations for the upper part of the distribution).[33] This is why only the third lag of the dependent income variable is included among the instruments (see above) since the second lag is not a valid instrument given the presence of second-order autocorrelation.[34] Still, specification tests should be taken with great caution because those tests rely on asymptotic properties while in practice the sample size is small, especially in the cross-section dimension.

31. Reducing the instrument count (by limiting lags and collapsing the instruments) has also been found to strengthen the identification of the parameters of interest in recent comprehensive work on the issue of weak instruments in the context of cross-country growth regressions (Kraay, 2015).

32. The Sargan test can also be used to test overidentifying restrictions, but it assumes independently and identically distributed error terms across countries, which is unlikely to be satisfied. Both tests are reported in Appendix 2.

33. Autocorrelation tests are applied to error terms from the differenced equations. Under the identifying assumptions, these differenced error terms should display first-order autocorrelation. This is indeed confirmed by the first-order autocorrelation tests (see Appendix 2).

34. Measurement error in the income series is a potential source of autocorrelation (Bond et al., 2001).

5. Results

The distribution of the growth dividends

44. Household incomes elasticities to GDP per capita are presented in Figure 7 for market income (Panel A) and disposable income (Panel B). Taking the estimates at face value, a 1% increase in GDP per capita is found to increase household market incomes by slightly more than 1% for all income groups, from the poor to the rich.[35] These results would then suggest that across OECD countries and for the period going from the mid-80s to around 2012, growth in GDP per capita has been transmitted to household market incomes. The estimates thus fail to identify the distributional incidence of GDP growth on market incomes in the sense that no statistically significant difference between gains accruing to the rich and gains accruing to the poor can be detected,[36] although visual inspection would suggest some unequal distribution of the growth dividends. This reflects a relatively large degree of statistical uncertainty at the extremes of the distribution.

45. These findings do not allow for formally concluding that the distributional impact of GDP growth on market incomes was neutral. In particular, market-income based growth elasticities estimated for poor households may be weakly identified, reflecting two issues: i) at the bottom of the distribution, market income tends to concentrate around near-zero values, because public transfers, which are not part of market incomes, make the bulk of household economic resources,[37] and ii) market income tends to be relatively more volatile at the bottom, reflecting higher sensitivity to business-cycle fluctuations (Castañeda et al., 1998; OECD, 2015b).

46. Indeed, for all country/year observations, the distribution of market income annual growth rates is more volatile at low compared to high α values, while this difference is attenuated for disposable income (Figure 8). This reflects the cushioning role of taxes and transfers and automatic stabilisers in moderating income fluctuations of less affluent households. As a consequence, the lower concentration and volatility of disposable compared to market income for the bottom of the distribution imply that disposable income-based elasticities are likely to yield more robust results than market income-based elasticities.

47. The shift from household income before taxes and transfers (i.e. market income) to household income after taxes and transfers (i.e. disposable income) allows for more accurately capturing the distribution of the growth dividends. The results suggest that on average across countries and for the period going from the mid-80s to around 2012, GDP growth has been transmitted to household disposable incomes. For mean income, the estimated elasticity is significantly larger than one on a 10% significance level (as can be seen from the 90% confidence interval in Figure 7, Panel B), but this is no longer the case at the 5% level. This lends some support to the prior that in the long run income generated from GDP

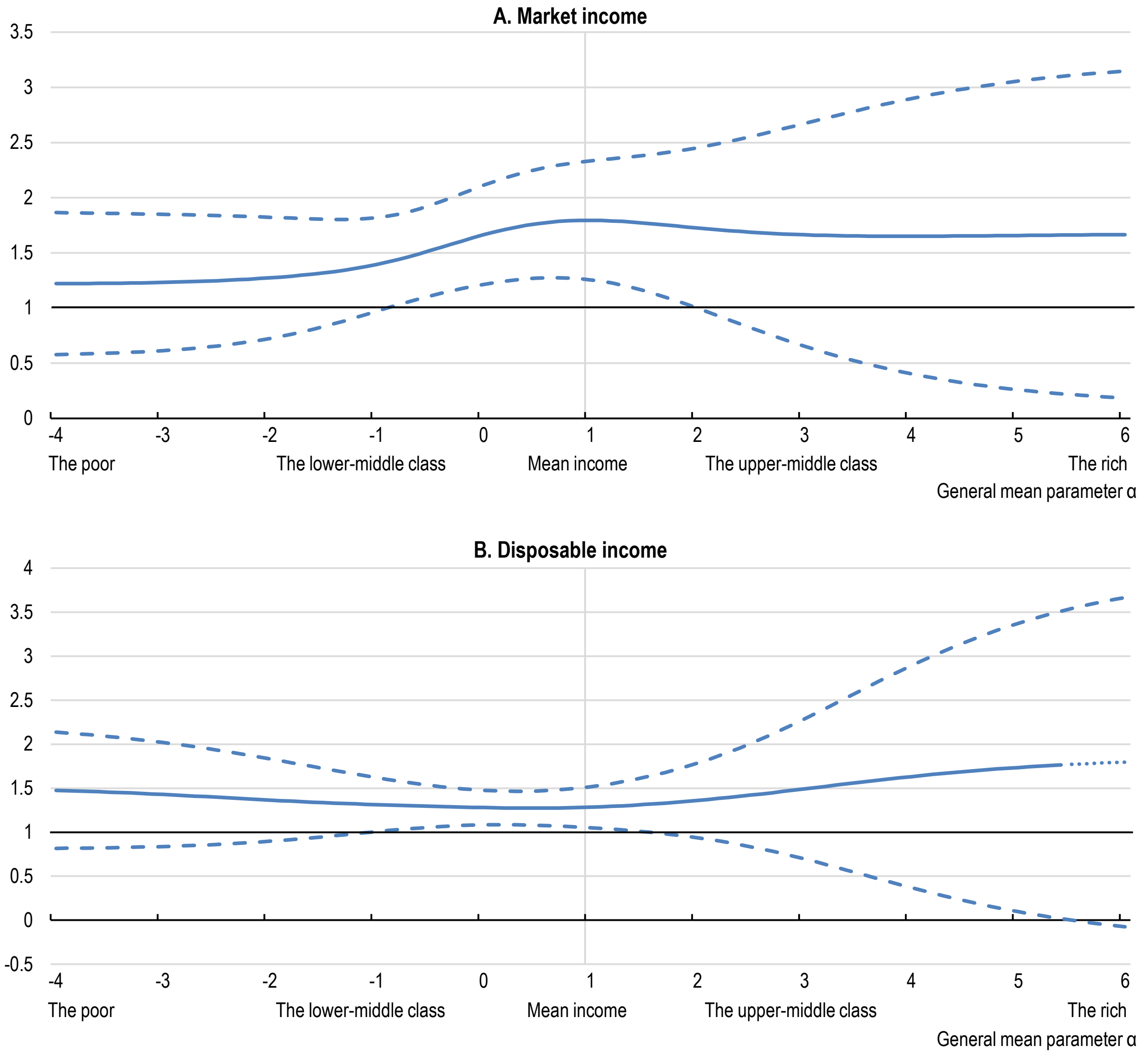
35 . The elasticity w.r.t. GDP per capita is estimated to be significantly larger than 1 around mean market income (Figure 7, Panel A). While a unit elasticity can be expected for disposable income in the long run, this need not be the case for market income. The reason is that while the value of domestic production accrues to the household sector through market incomes it is then redistributed across households through the tax and transfers system, with disposable income coming closer to the ultimate proxy for household economic resources. Moreover, in this case market incomes are measured for the working age population only (see above), while GDP per capita is measured for the whole population, which may also contribute to divergence.

36. Standard statistical tests to compare estimated elasticities from separate SYS-GMM estimations are not available.

37. But excluding children and elderly since market income estimations are restricted to the working-age population only (age 18-65).

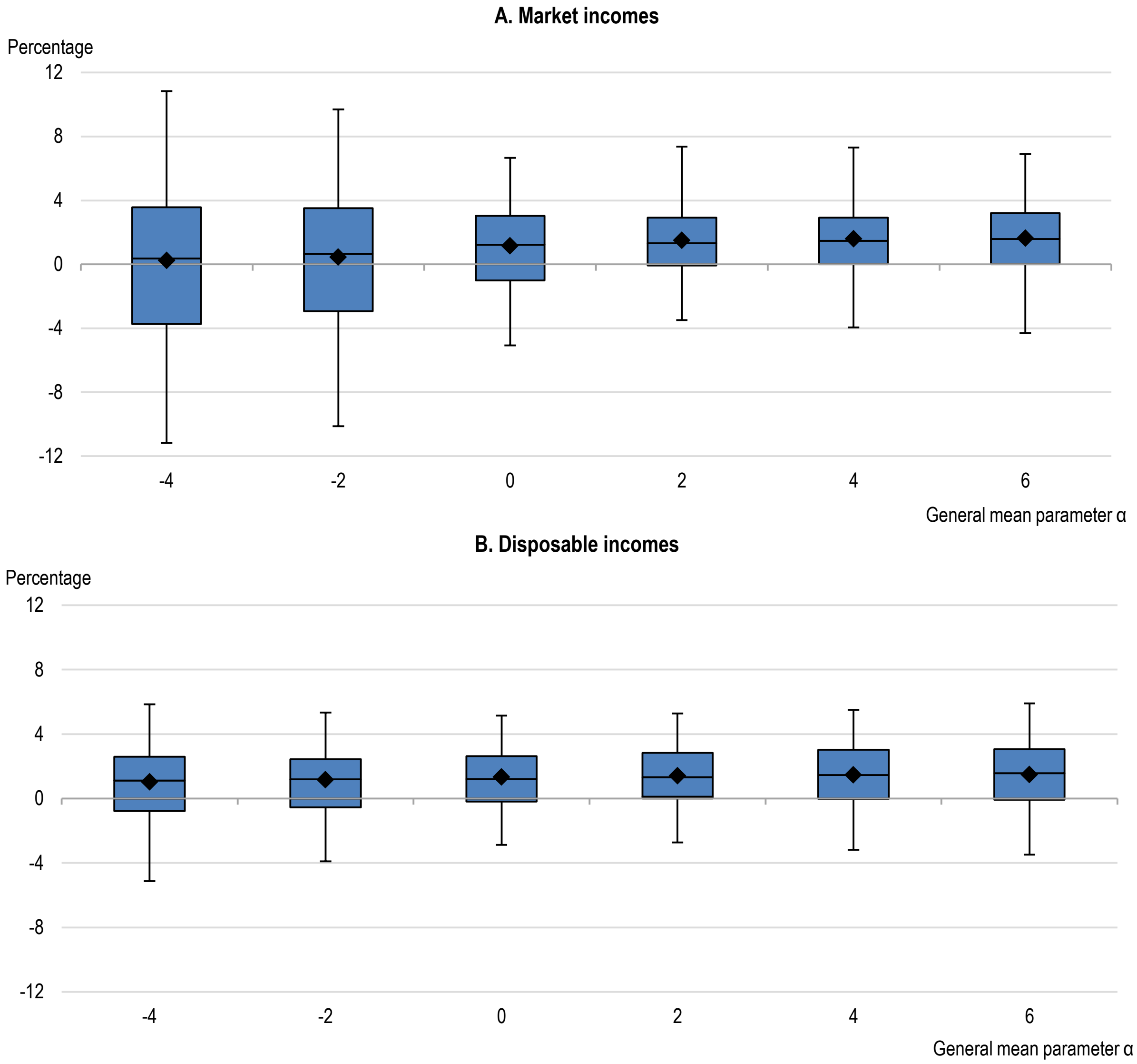
should fully accrue to the household sector. Across the distribution the estimated curve is broadly flat and close to the unitary elasticity. Thus, it cannot be rejected that GDP growth has had the same impact across the distribution of household disposable incomes. Therefore, although growth has been associated with rising income inequality in many OECD countries over the last three decades, these results offer no evidence that GDP growth triggered rising inequality.

Figure 7. Household incomes elasticity to GDP



Source: Note: Elasticity estimated by System GMM with GDP per capita as covariate. See text for details. Dashed lines represent the 90% confidence interval bands calculated by the delta method.

Figure 8. Variability of annual income growth rates across the distribution



Note: The figure shows a box plot for annualised growth rates across all country/year observations included in the empirical analysis by selected bottom to top-sensitive income standards. Each box represents the interval of growth rates ranging between 25% and 75% of all country/year observations, and the line representing the median. Associated whiskers display the 5% and 95% percentiles, and the diamonds represent the mean growth rate for each income standard.

Decomposing the growth dividends: the role of productivity and labour utilisation

48. The impact of GDP per capita on household income can be decomposed along its two main sub-components, i.e. labour productivity (LP) and labour resource utilisation (LU):

$$\frac{\text{GDP}}{\text{P}} = \frac{\text{GDP}}{\text{E}}\frac{\text{E}}{\text{P}} = \text{LP} \cdot \text{LU} \qquad [4]$$

where P is total population and E is total employment (number of workers). The empirical model can thus be re-estimated with GDP divided into these two subcomponents. This modifies equation [3] in the following way:

$$\Delta \ln \mu_\alpha(x_{it}) = \theta_{0,\alpha} - \theta_{1,\alpha} \ln \mu_\alpha(x_{it-1}) + \theta_{2,\alpha} \Delta \ln LP_{it} + \theta_{3,\alpha} \ln LP_{it-1} + \theta_{4,\alpha} \Delta \ln LU_{it} + \theta_{5,\alpha} \ln LU_{it-1} + \theta_{6,\alpha} NX_{it} + \gamma_t + \eta_i + \varepsilon_{it} \quad [5]$$

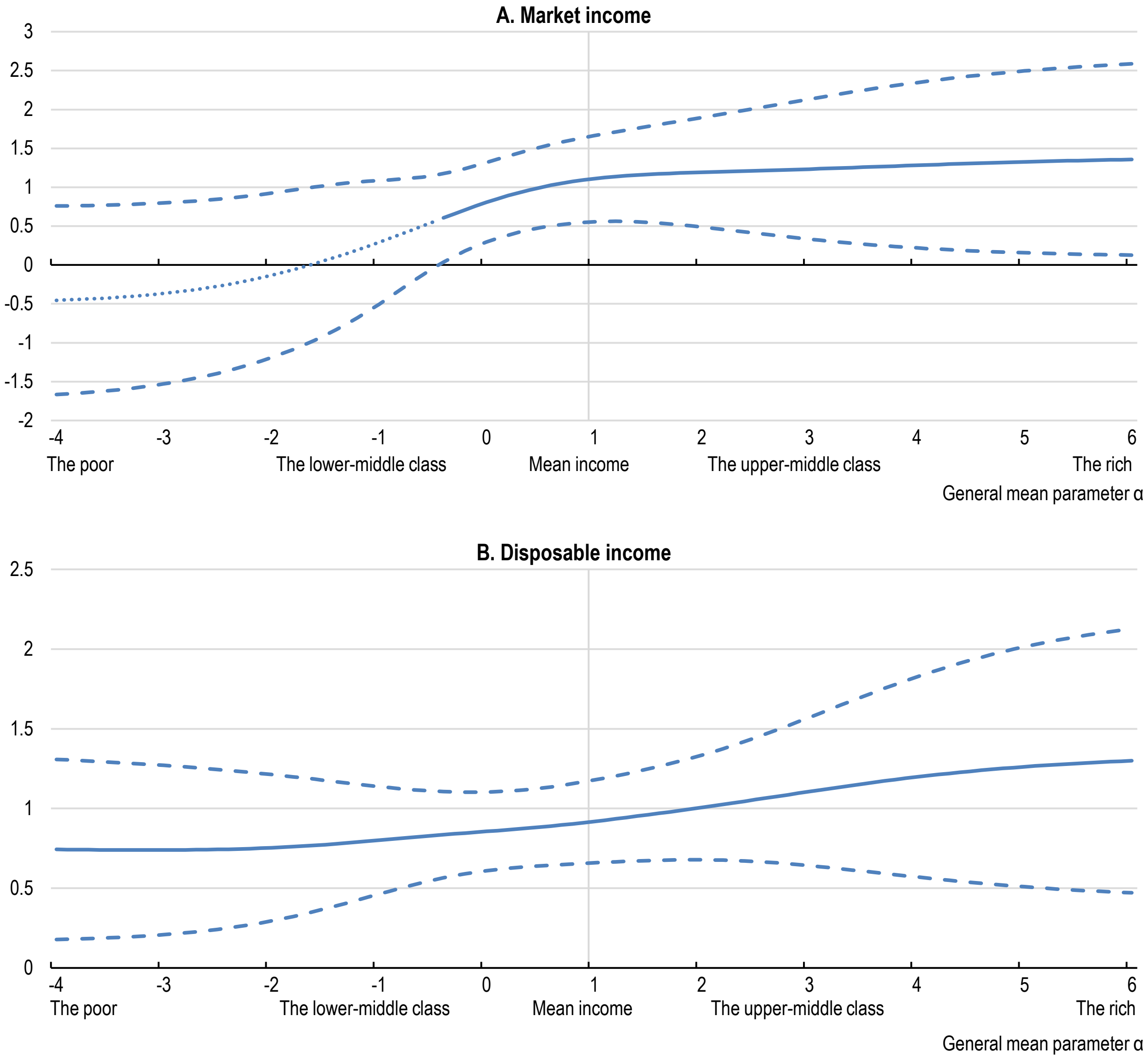
Labour productivity

49. Household incomes elasticities to labour productivity are presented in Figure 9 for market income (Panel A) and disposable income (Panel B). The estimates suggest that across OECD countries and for the period going from the mid-80s to around 2012, labour productivity gains fully benefitted household market and disposable incomes (with an elasticity of one for mean income). However, when looking at the distribution of market income, such gains only accrued to households from the middle class and above (i.e. for α>-1). Below this portion of the distribution, the empirical model does not uncover a significant relationship between productivity and household market incomes (see Appendix 2). By contrast, when looking at the distribution of disposable income, productivity gains also accrued to poor households. Associated gains are estimated to be of somewhat lower magnitude compared to those accruing to rich households, albeit confidence intervals do not allow for inferring a statistical significant difference.

50. Growth in productivity is found to be disequalising in the sense that households in the lower part of the market income distribution do not get any significant benefits from associated income dividends through market mechanisms. This implies that productivity growth has been associated with rising market income inequality, across OECD countries and over the last decades, which could reflect that poor households are often excluded from market-based activities. It could also reflect various channels such as e.g. skilled-biased technical change and "routinisation", i.e. the idea that technology substitutes more easily for labour in performing routine rather than non-routine tasks, affecting in particular households around the lower-middle class (Acemoglu and Autor, 2011). However, the latter explanation can only go so far considering that many low-skilled jobs, involving manual tasks, are often among the most difficult to replace with technology.

51. The comparison between market income-based and disposable income-based results would suggest that redistribution via taxes and transfers allowed for productivity gains to accrue to less affluent households, on average across OECD countries and for the period going from the mid-80s to around 2012: the poor and the lower-middle class were taken on board when moving from market to disposable income, which reflects income transfers from the upper part of the market income distribution. One interpretation is that productivity gains lifted market incomes among the middle class and above and part of associated gains were taxed away to redistribute income to more vulnerable households, who would have otherwise been excluded from the process. Still, even when considering post-redistribution incomes, the estimates suggest that productivity growth was slightly disequalising, as shown above.

Figure 9. Household incomes elasticity to labour productivity

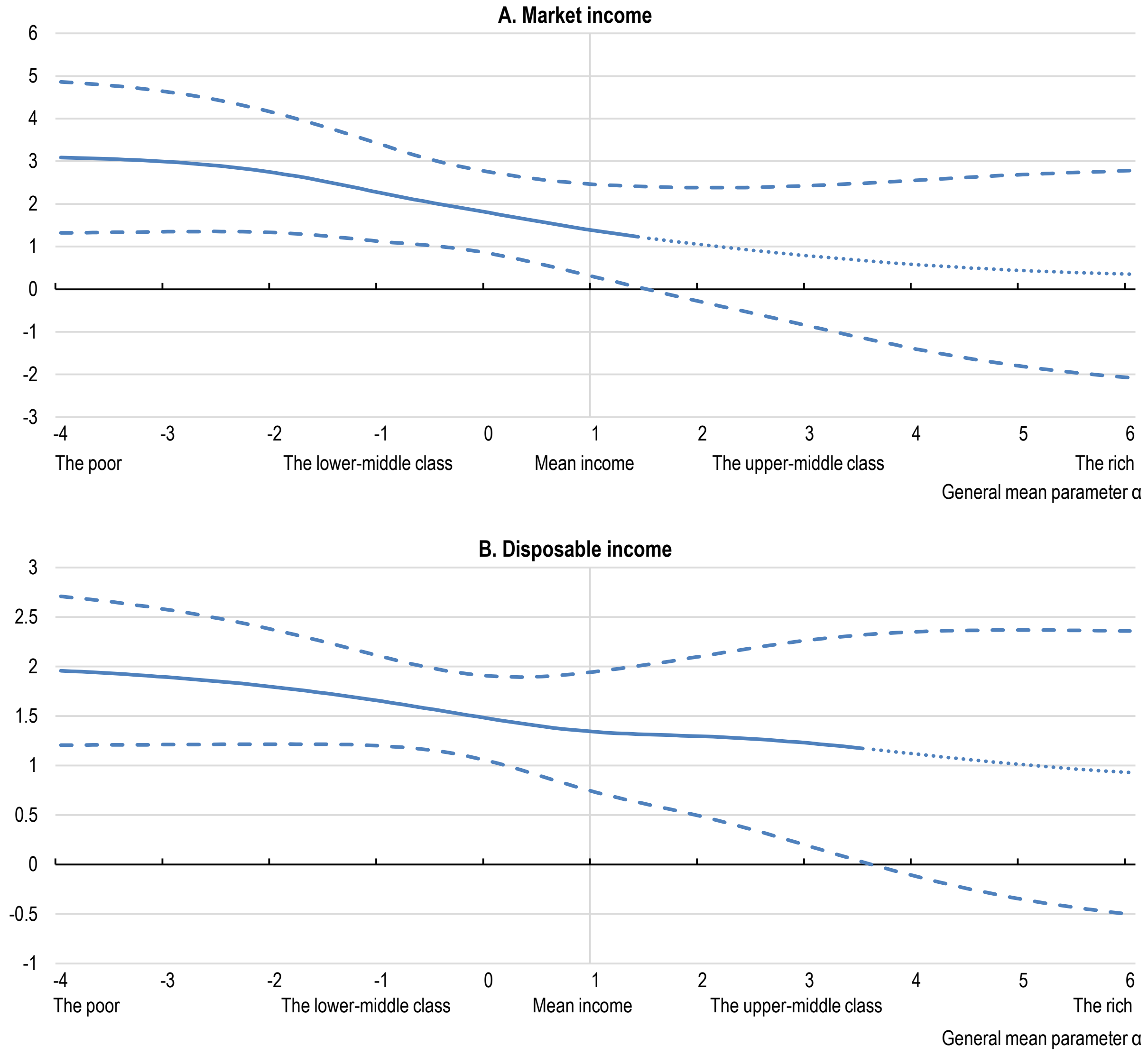


Note: Elasticity estimated by System GMM with labour productivity and labour utilisation as covariates. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

Labour utilisation

52. Household incomes elasticities to labour utilisation are presented in Figure 10 for market income (Panel A) and disposable income (Panel B). The estimates suggest that across OECD countries and for the period going from the mid-80s to around 2012, the distributional incidence of growth in labour utilisation has been opposite to that of growth in labour productivity. The dividends of labour utilisation have primarily accrued to middle class and poor households, a finding that holds across both market and disposable income-based estimates distribution; while households in the top of the distribution have been disconnected from that process. This implies that labour utilisation growth has been equalising.

Figure 10. Household incomes elasticity to labour utilisation



Note: Elasticity estimated by System GMM with labour productivity and labour utilisation as covariates. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

53. The estimates, taken at face value, deliver large effects: a rise in labour utilisation by 1% is estimated to lift market incomes at the bottom of the distribution by 3%, more than one percentage point compared to the mean of the distribution. These results imply that employment gains are key to lift the material conditions of the poorest and to reduce income inequality. The composition of growth is thus a key determinant of its incidence across the distribution.

6. Robustness analysis

54. This section presents robustness analysis applied to the GDP, and labour productivity and labour utilisation estimates. The results are briefly described here, while figures are available in Appendix 4.

Changes in the set of internal instruments

55. The first robustness test is based on the choice of SYS-GMM internal instruments (Figure A4.1 and A4.2). One specification reduces the instrument set to the lowest possible set with only one lag for income and GDP, and also discards the collapse option (see above). A second specification then increases the instrument set to the largest possible set using all available lags, which has to be collapsed to avoid an excessive number of instruments (see above). In both cases, results are qualitatively unchanged, but estimates generally become more imprecise, especially in the bottom of the income distribution. Disposable income gains from labour productivity growth are no longer significant among the poor when using only one lag in the instrument set. Disposable income gains from labour utilisation growth become significant for the rich when using all available lags in the instrument set.

Sensitivity of the net exports control

56. The second test replaces net exports by a terms-of-trade index (export prices to import prices) (Figure A4.3). Persistent divergences between real mean household income and real GDP have been found to be partly explained by differences in price developments of consumer and output prices, with terms of trade being the main driver (Causa et al., 2014; 2015). In practice, this change has a very limited impact on the results: household income elasticities to GDP become slightly lower, and the return to labour productivity for the upper-middle class and the rich decreases. Similar results are found by replacing net exports by consumer relative to the GDP deflators or not using any control at all (not reported).

Changes in the sample composition

57. The third test applies to the sample composition. The sample size, 34 OECD countries, is relatively small and thus leaves little room for proper estimation on subsamples. Therefore, only one test is performed, and it consists in the exclusion of emerging market economies with the highest levels of inequality (Chile, Mexico and Turkey) (Figure A4.4). Insofar as growth in these countries has, in contrast with the majority of advanced economies, been associated with a substantial reduction in inequality over the sample period, their exclusion may alter the results. Estimates of the impact of GDP growth on household disposable incomes become slightly higher for more affluent households, suggesting some disequalising effect. However, confidence bands do not allow for rejecting the hypothesis of equal growth incidence across the distribution, even in this restricted sample. For labour productivity and labour utilisation the distributional incidence found in the entire sample is amplified for the market income distribution, and reduced for the disposable income distribution: labour productivity becomes more (less) disequalising and labour utilisation less (more) equalising, on the basis of disposable (market) income.

Computations by deciles and quintiles

58. The last robustness test consists in replacing the general mean by mean income by quintiles and deciles as the dependent variable (Figure A4.5 and A4.6). As mentioned in the second section, such partial means have the disadvantage of relying on relatively arbitrary cut-offs. On the other hand, the household income data used in this paper are delivered in the form of mean income by deciles (Appendix 1), which leads to naturally test this approach. In practice, the estimates based on quintiles and deciles draw a qualitatively similar, albeit less smooth, picture across the distribution than using generalised means. However, uncertainty on the estimated elasticities in the bottom and the top decile is very large.

7. Conclusion

59. This paper has provided an assessment of the transmission of growth to household incomes and their distributions. Previous contributions in this area suffer from potential limitations by considering single measures of growth and inequality. The findings reported here, by decomposing further these two

dimensions, shed new light on the growth and inequality nexus. First, decomposing the sources of growth allows for disentangling the differential effects of productivity and labour utilisation on inequality. Second, applying the general means approach to income distribution uncovers that different sections of the distribution are impacted differently by growth and its components.

60. On the basis of this framework, the results suggest that growth in GDP per capita has not by itself been the driver of the well-documented rise in income inequality over the last decades: across OECD countries and for the period going from the mid-80s to around 2012, growth in GDP per capita benefitted household incomes with no significant differences across the distribution. This result is in line with previous studies using broader and more heterogeneous sets of countries (Dollar and Kraay, 2002; Dollar et al., 2015; 2016; Brueckner et al., 2015).

61. The finding that growth has been broadly distribution-neutral on average across OECD countries is identified as the outcome of two opposite forces. On the one hand, labour productivity gains have benefitted disproportionally the upper-part of the income distribution, especially on the basis of market incomes due to the cushioning effect on disposable incomes of redistribution though taxes and transfers. On the other hand, labour utilisation gains have benefited only the lower part of the income distribution. The sources of growth are thus a key determinant of its effect on income inequality: insofar as growth is ultimately driven by productivity, a contributor to increasing income inequality, ensuring that productivity gains are conducive to job creation is crucial to make growth more inclusive.

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APPENDIX 1: GENERAL MEANS BASED ON GROUPED MEAN DATA

1. In this paper, general mean curves are computed from household income distributions summarised by 10 data points, i.e. by income deciles. This is a necessary approximation to the preferred case of a general mean approach based on full micro dataset, given the constraints of the OECD income Distribution Database.

2. This appendix uses microdata from EU-SILC to study the validity of approximating general means with grouped data.[38] In particular, it attempts identifying the range of αs for which the approximation is sufficiently good. A proper answer to this question would require a rigorous analysis of asymptotic properties, which is beyond the scope of this paper. The evidence should therefore only be taken as illustrative of a particular data source and a finite number of countries.

3. The exercise proceeds in the following way:

- Six countries (Finland, France, Greece, Poland, Slovenia, and United Kingdom), representing a broad range of inequality and income levels, are selected from EU-SILC in year 2012.[39]
- Household disposable income, according to the EU-SILC definition, is applied. Incomes below one are excluded since the general mean is not well-defined in this range. Moreover, the bottom and top percentile are excluded to reduce the influence of extremely low and high incomes. As explained in Section 2, the general mean approaches the lowest (highest) income in society as α approaches $-\infty$ (∞). Hence, the general mean is sensitive to extreme values of income, and, as is standard in such cases, the sample is "trimmed". [40]
- The final sample is weighted according to the cross-sectional weights supplied by EU-SILC to ensure a valid representation of the income distribution.
- For each country, two general mean curves are computed for values of α from -10 to 12: i) a "microdata general mean curve" based on the available and weighted sample, ii) a "decile general mean curve" based on the same microdata, but using mean income by deciles computed in a first step.

4. The two general mean curves are presented in Figure A1.1. By definition the arithmetic mean (α=1) is the same whether computed from the full sample or from subgroup means. As a result, the two curves overlap for αs around 1. For lower values of α the microdata-based general mean curve falls below the decile-based general mean curve gradually as the lowest incomes in the microdata sample starts to kick in. For α=-4 the ratio between the decile curve and the microdata curve is around 1.1 for all the selected countries, except Greece with a ratio of 1.4. For α=-10 the ratio reaches 1.2-1.4 and exceeds 2 for Greece.

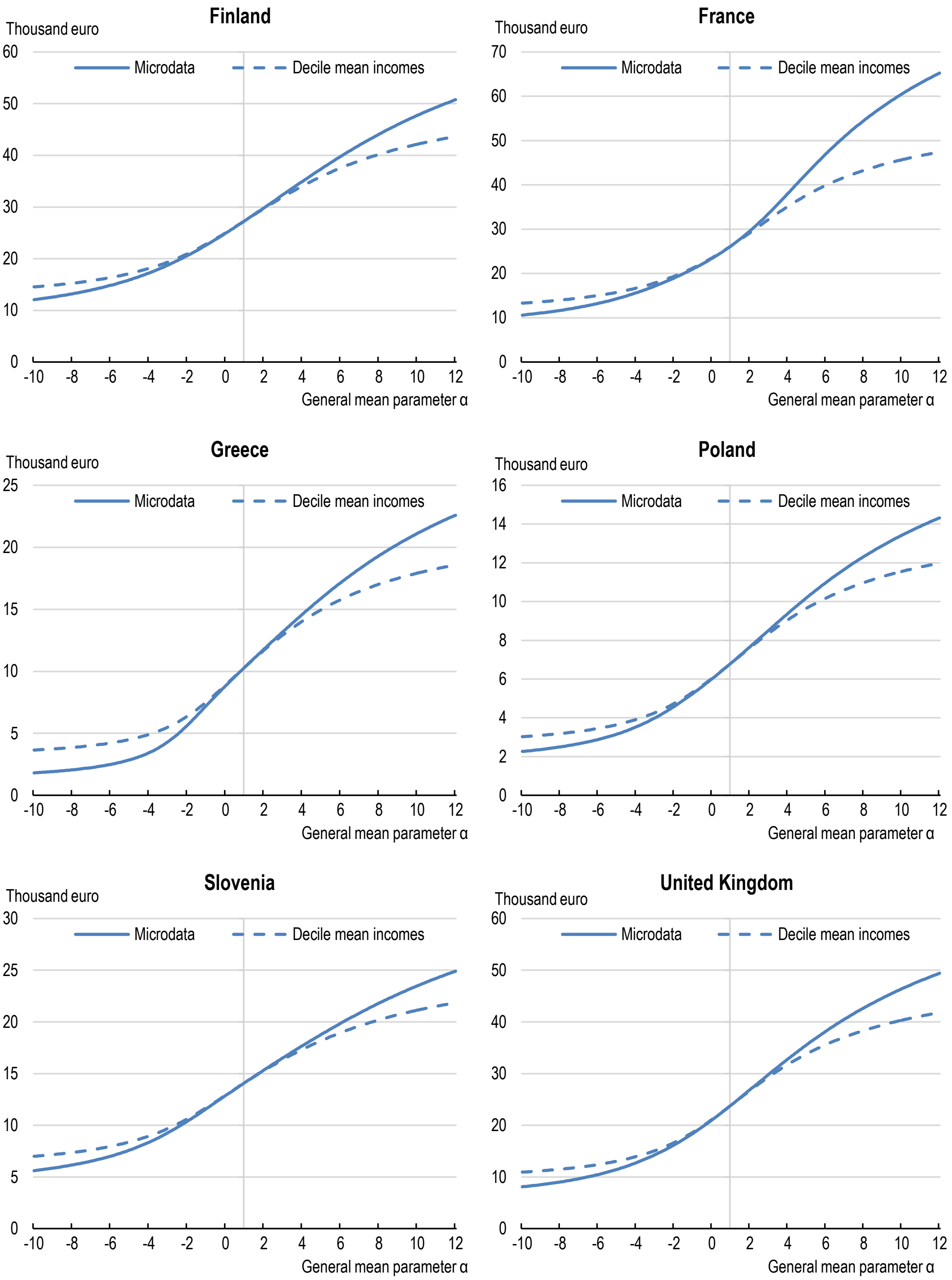
38. EU-SILC covers 23 OECD countries.

39. Figures for all countries covered by EU-SILC are available upon request.

40. See for instance recommendations by the Luxembourg Income Study.

Figure A1.1. Comparison of general mean curves computed from microdata and decile mean incomes

EU-SILC survey data, year 2012



Note: Household disposable incomes according to the EU-SILC definition. Incomes below one are excluded since the general mean is not well-defined. For each country the bottom and top percentile has been excluded to reduce the influence of very low and high incomes (trimming). Observations are weighted by cross-sectional weights in EU-SILC. Sample sizes: Finland (21,862), France (20,642), Greece (14,942), Poland (29,581), Slovenia (22,950), United Kingdom (17,990).

Source: EU-SILC.

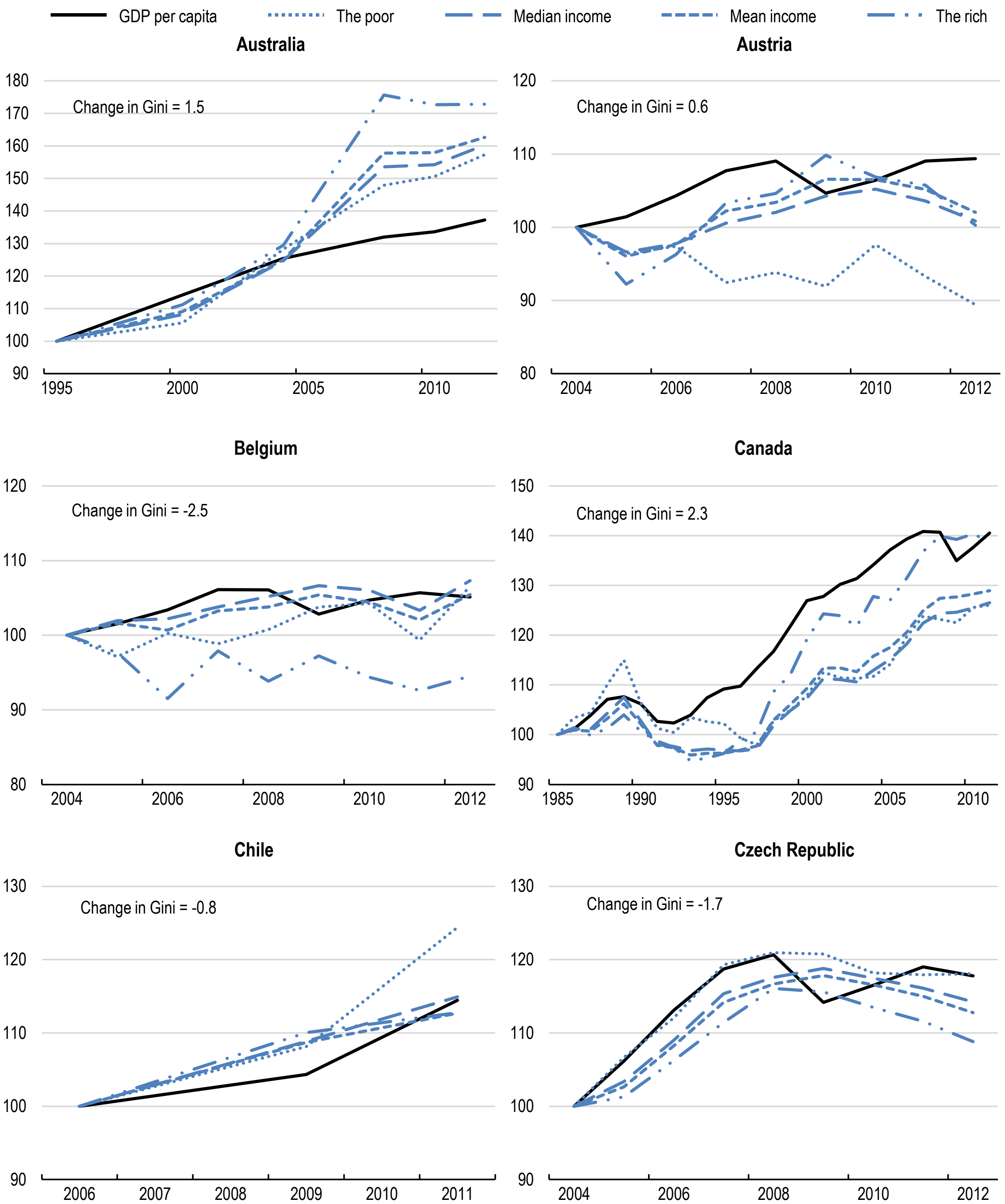
5. The opposite divergence takes place when increasing α above 1 as higher incomes are emphasised more. For α=6 the ratio between the decile curve and the microdata curve is around 0.95 for all countries, except France with a ratio of 0.85. For α=12 the ratio reaches 0.7 for France, while for the other countries it remains above 0.8.

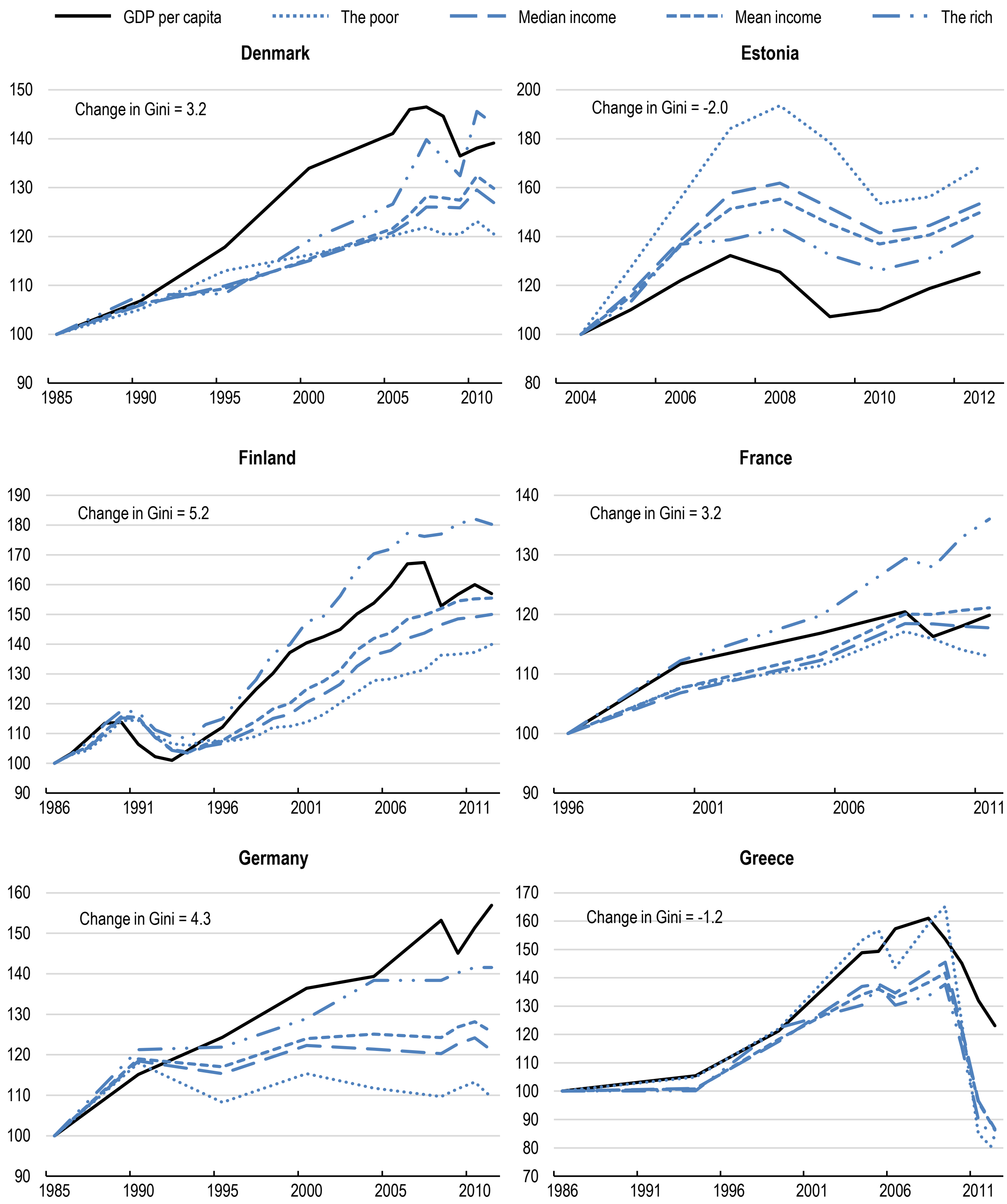
6. Although this exercise can only be taken as indicative evidence, it suggests that constructing general mean curves based on decile mean incomes is reasonable. Restricting the order of the general mean to take values from -4 to 6, as done in the paper, implies a maximum divergence of roughly 10% for most countries in EU-SILC microdata.

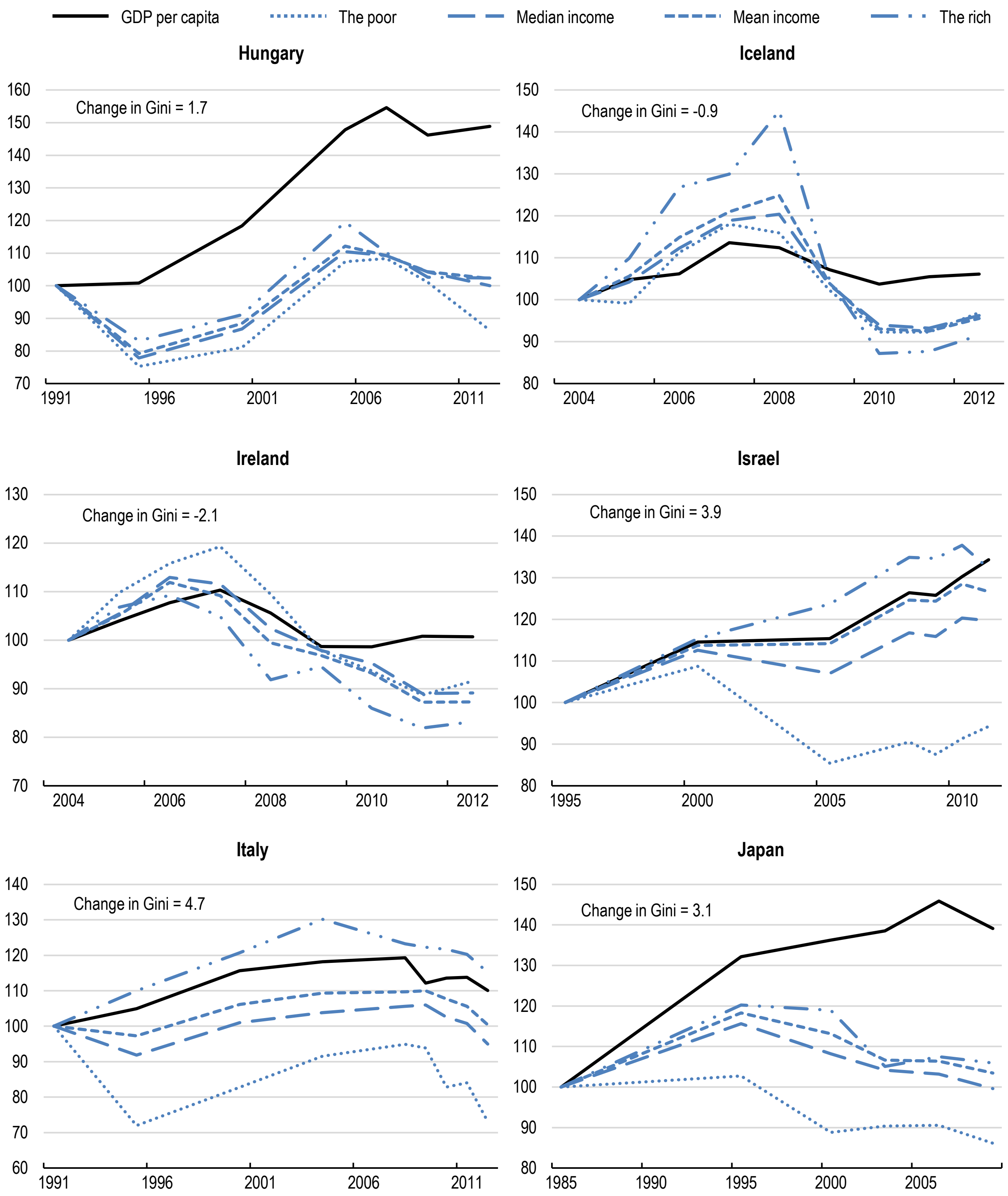
APPENDIX 2: COUNTRY PROFILES OF DEVELOPMENTS IN GROWTH AND INEQUALITY

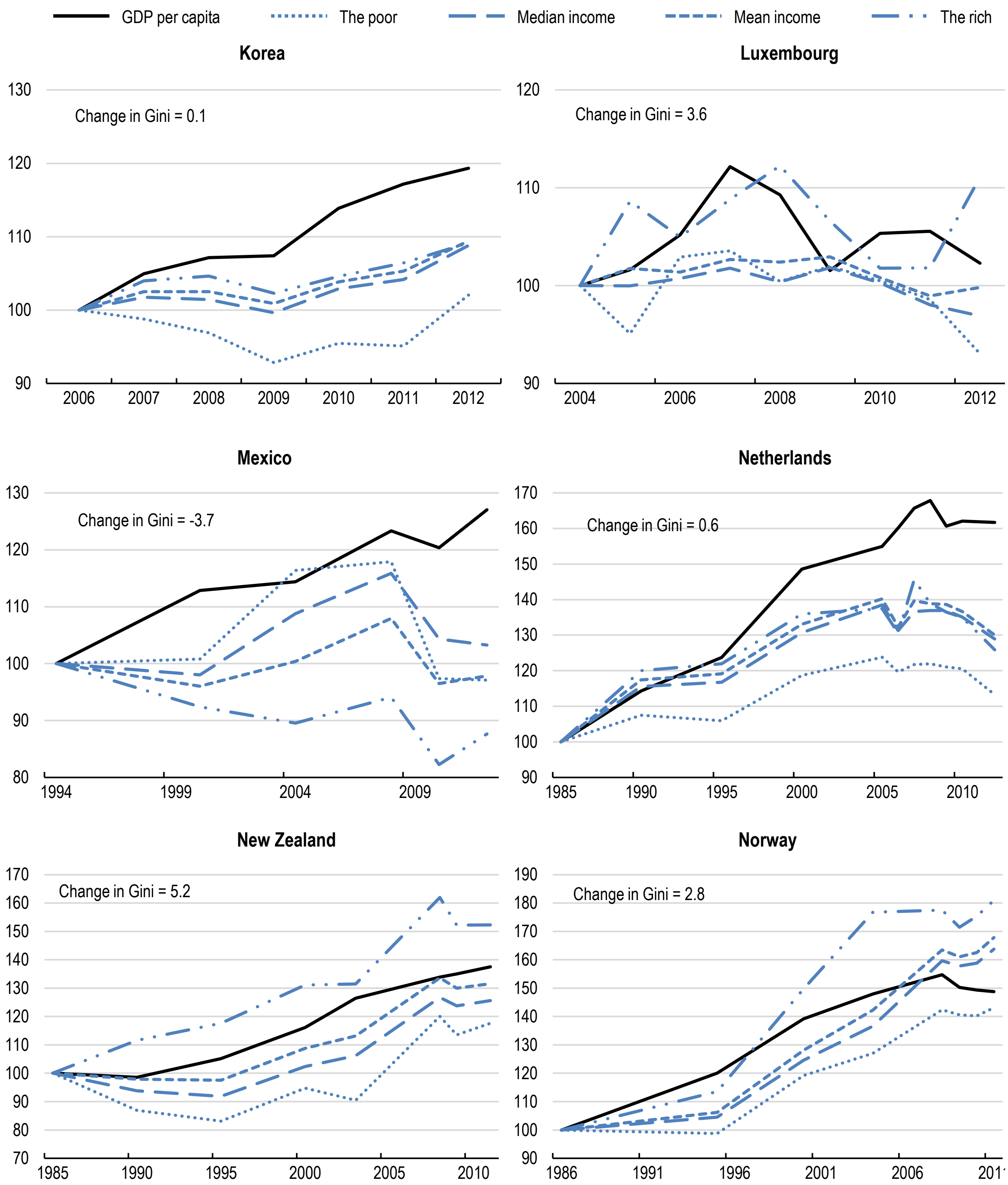
Figure A2.1. Developments in GDP per capita and in household disposable incomes across the distribution: country profiles

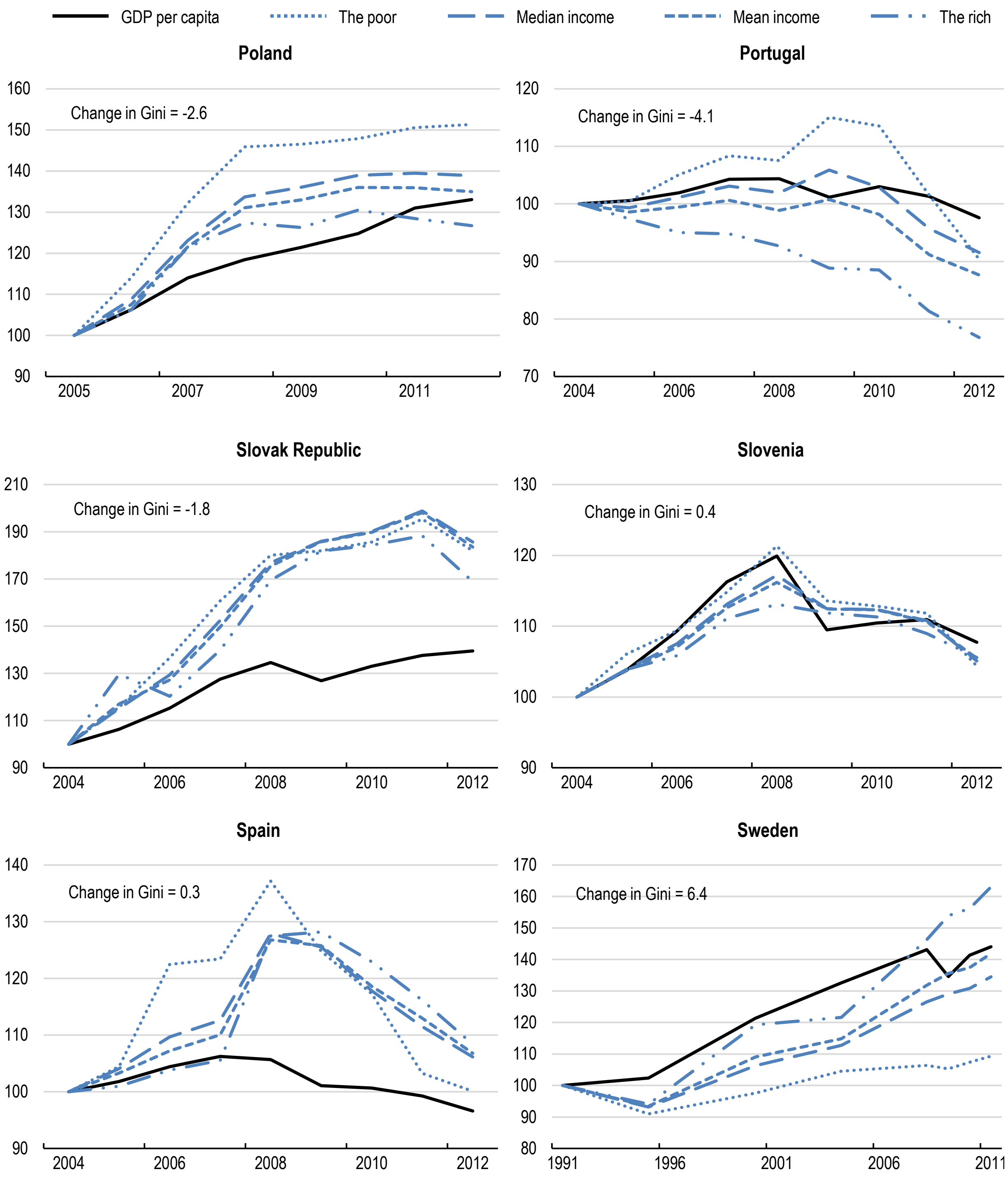
Available time period in the OECD Income Distribution Database since 1985, initial year = 100

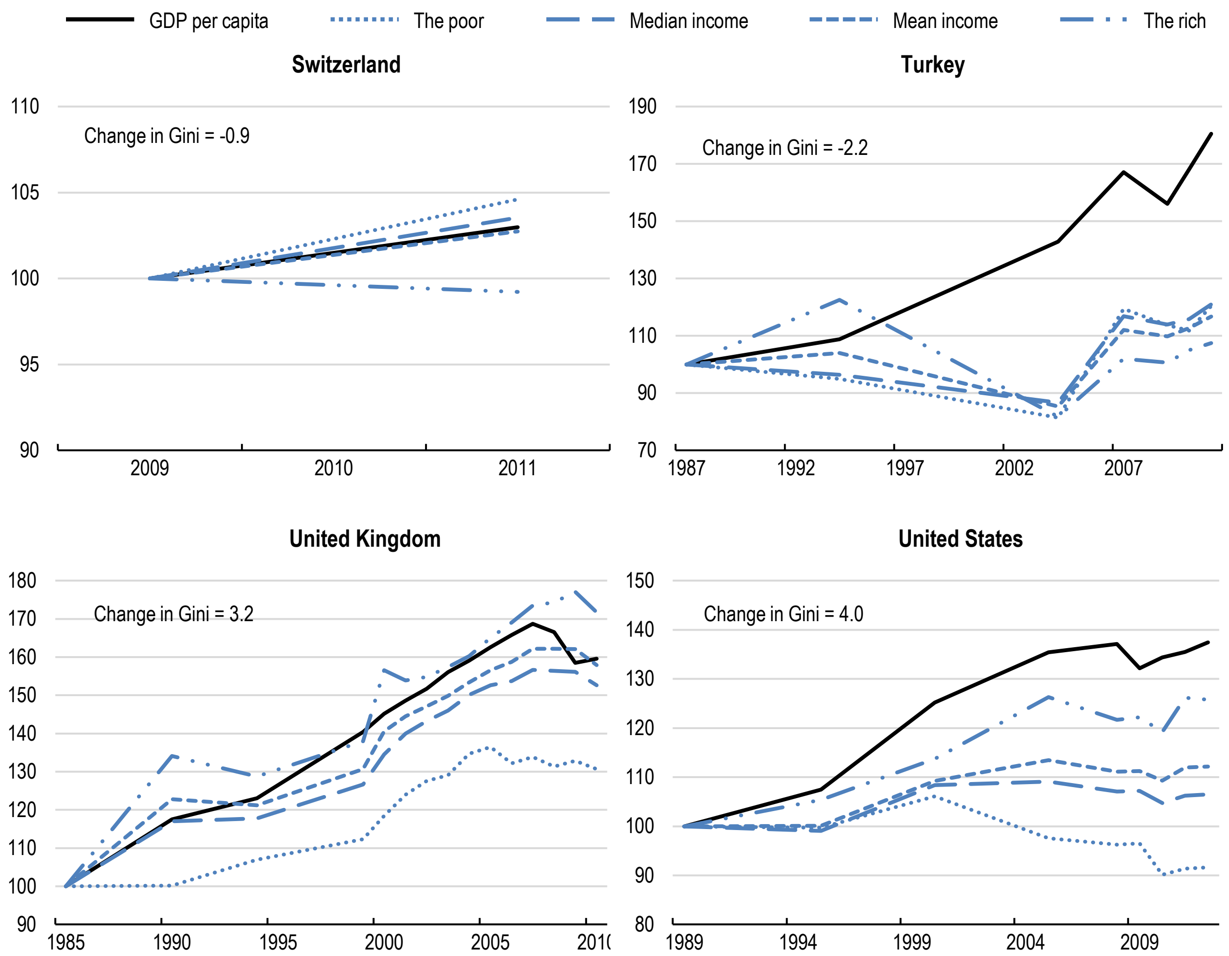



GDP per capita
The poor
Median income
Mean income
The rich
Denmark
Change in Gini = 3.2
Estonia
Change in Gini = -2.0
Finland
Change in Gini = 5.2
France
Change in Gini = 3.2
Germany
Change in Gini = 4.3
Greece
Change in Gini = -1.2


GDP per capita
The poor
Median income
Mean income
The rich
Hungary
Change in Gini = 1.7
Iceland
Change in Gini = -0.9
Ireland
Change in Gini = -2.1
Israel
Change in Gini = 3.9
Italy
Change in Gini = 4.7
Japan
Change in Gini = 3.1


GDP per capita
The poor
Median income
Mean income
The rich
Korea
Change in Gini = 0.1
Luxembourg
Change in Gini = 3.6
Mexico
Change in Gini = -3.7
Netherlands
Change in Gini = 0.6
New Zealand
Change in Gini = 5.2
Norway
Change in Gini = 2.8


GDP per capita
The poor
Median income
Mean income
The rich
Poland
Change in Gini = -2.6
160
150
140
130
120
110
100
90
2005
2007
2009
2011
Portugal
Change in Gini = -4.1
120
110
100
90
80
70
2004
2006
2008
2010
2012
Slovak Republic
Change in Gini = -1.8
210
190
170
150
130
110
90
2004
2006
2008
2010
2012
Slovenia
Change in Gini = 0.4
130
120
110
100
90
2004
2006
2008
2010
2012
Spain
Change in Gini = 0.3
140
130
120
110
100
90
2004
2006
2008
2010
2012
Sweden
Change in Gini = 6.4
170
160
150
140
130
120
110
100
90
80
1991
1996
2001
2006
2011



Note: GDP per capita and households disposable incomes are measured in constant prices by applying the GDP deflator and the consumer price index, respectively. The change in the Gini coefficient for household disposable incomes is measured from the first to the latest year as shown in the figure for each country.

Source: OECD National Accounts; OECD Income Distribution Database.

APPENDIX 3: DETAILED ESTIMATION RESULTS

Table A3.1. Household incomes elasticity to GDP

A. Market incomes elasticity for α = -4

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate		s.e.	**Within Groups** Estimate		s.e.	**DIF-GMM** Estimate		s.e.	**SYS-GMM** Estimate		s.e.
lnμ(xt-1,α)	0.95	***	*0.02*	0.65	***	*0.05*	0.26		*0.25*	0.70	***	*0.09*
lnGDPt	1.99	***	*0.20*	1.46	***	*0.22*	1.01		*0.69*	1.98	***	*0.44*
lnGDPt-1	-1.86	***	*0.20*	-0.57	**	*0.25*	0.67		*0.94*	-1.62	***	*0.44*
NXt	-0.41	***	*0.13*	-1.31	***	*0.26*	-1.63	***	*0.38*	-0.40		*0.40*
Time trend	0.01		*0.01*	-0.12	***	*0.03*	-0.25	***	*0.08*	-0.04		*0.02*
y2009-10	0.01		*0.03*	-0.01		*0.03*	-0.03		*0.04*	0.05		*0.04*
Constant	-0.96	***	*0.30*	-5.88	***	*1.58*				-1.14		*1.10*
Long-run elasticity:												
lnμ(x,α) w.r.t. GDP	2.43	***	*0.65*	2.52	***	*0.48*	2.28	***	*0.46*	1.22	***	*0.39*
Number of observations	225			225			191			225		
Number of instruments							16			29		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	0.81		0.42				-0.99		0.32	-2.51		0.01
AR(2) test [H0: no serial correlation]	-1.17		0.24				0.60		0.55	0.22		0.82
Sargan test [H0: overidentifying restrictions are jointly valid]							25.14		0.01	51.10		0.00
Hansen test [H0: overidentifying restrictions are jointly valid]							15.02		0.13	29.65		0.13
Difference-in-Hansen test [H0: level equation restrictions are valid]										7.81		0.80

B. Disposable incomes elasticity for α = -4

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate		s.e.	**Within Groups** Estimate		s.e.	**DIF-GMM** Estimate		s.e.	**SYS-GMM** Estimate		s.e.
lnμ(xt-1,α)	0.96	***	*0.02*	0.53	***	*0.05*	-0.04	***	*0.20*	0.85	***	*0.06*
lnGDPt	1.22	***	*0.11*	0.67	***	*0.11*	0.20	***	*0.29*	1.21	***	*0.29*
lnGDPt-1	-1.14	***	*0.11*	-0.14		*0.12*	0.85	***	*0.49*	-0.98	***	*0.29*
NXt	-0.25	***	*0.08*	-0.94	***	*0.12*	-0.78	***	*0.16*	-0.31		*0.19*
Time trend	0.00		*0.01*	-0.04	***	*0.01*	-0.09		*0.04*	-0.03	**	*0.01*
y2009-10	0.04	***	*0.02*	0.01		*0.01*	-0.03		*0.03*	0.05	*	*0.03*
Constant	-0.43	**	*0.18*	-0.93		*0.74*				-0.89		*0.58*
Long-run elasticity:												
lnμ(x,α) w.r.t. GDP	2.03	***	*0.52*	1.11	***	*0.16*	1.01	***	*0.18*	1.48	***	*0.40*
Number of observations	225			225			191			225		
Number of instruments							16			29		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	2.66		0.01				-0.87		0.39	-2.81		0.00
AR(2) test [H0: no serial correlation]	-1.21		0.23				0.47		0.64	-0.27		0.79
Sargan test [H0: overidentifying restrictions are jointly valid]							15.73		0.11	57.4		0.00
Hansen test [H0: overidentifying restrictions are jointly valid]							10.38		0.41	23.37		0.38
Difference-in-Hansen test [H0: level equation restrictions are valid]										12.76		0.39

C. Market incomes elasticity for α = 0

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.92 ***	*0.02*	0.49 ***	*0.05*	0.10	*0.18*	0.81 ***	*0.07*
lnGDPt	1.33 ***	*0.10*	0.99 ***	*0.10*	0.62 **	*0.28*	1.48 ***	*0.31*
lnGDPt-1	-1.19 ***	*0.10*	-0.27 **	*0.13*	0.49	*0.45*	-1.16 ***	*0.33*
NXt	-0.37 ***	*0.07*	-0.88 ***	*0.12*	-0.98 ***	*0.16*	-0.51 ***	*0.17*
Time trend	-0.01	*0.01*	-0.06 ***	*0.01*	-0.09 ***	*0.02*	-0.03 **	*0.01*
y2009-10	0.03 *	*0.01*	0.01	*0.01*	-0.01	*0.02*	0.04	*0.03*
Constant	-0.74 ***	*0.17*	-2.33 ***	*0.72*			-1.36 **	*0.54*
Long-run elasticity:								
lnμ(x,α) w.r.t. GDP	1.87 ***	*0.19*	1.42 ***	*0.14*	1.24 ***	*0.10*	1.66 ***	*0.27*
Number of observations	225		225		191		225	
Number of instruments					16		29	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	2.12	0.03			-0.89	0.37	-3.10	0.00
AR(2) test [H0: no serial correlation]	-1.36	0.17			-0.83	0.40	-1.58	0.11
Sargan test [H0: overidentifying restrictions are jointly valid]					19.22	0.04	50.2	0.00
Hansen test [H0: overidentifying restrictions are jointly valid]					13.51	0.20	21.65	0.48
Difference-in-Hansen test [H0: level equation restrictions are valid]							7.95	0.79

D. Disposable incomes elasticity for α = 0

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.88 ***	*0.02*	0.59 ***	*0.04*	0.18	*0.12*	0.74 ***	*0.06*
lnGDPt	0.95 ***	*0.08*	0.63 ***	*0.08*	0.30 *	*0.18*	0.91 ***	*0.21*
lnGDPt-1	-0.78 ***	*0.08*	-0.19 **	*0.09*	0.44 *	*0.25*	-0.58 **	*0.23*
NXt	-0.30 ***	*0.05*	-0.68 ***	*0.09*	-0.61 ***	*0.10*	-0.41 ***	*0.13*
Time trend	-0.02 ***	*0.01*	-0.02 **	*0.01*	-0.03	*0.02*	-0.03 ***	*0.01*
y2009-10	0.04 ***	*0.01*	0.02 *	*0.01*	-0.01	*0.01*	0.04 **	*0.02*
Constant	-0.57 ***	*0.12*	-0.50	*0.54*			-0.84 **	*0.32*
Long-run elasticity:								
lnμ(x,α) w.r.t. GDP	1.43 ***	*0.09*	1.08 ***	*0.13*	0.90 ***	*0.12*	1.28 ***	*0.12*
Number of observations	225		225		191		225	
Number of instruments					16		29	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	2.79	0.01			-1.42	0.15	-2.95	0.00
AR(2) test [H0: no serial correlation]	0.18	0.86			0.73	0.46	-0.49	0.62
Sargan test [H0: overidentifying restrictions are jointly valid]					9.50	0.49	42.7	0.01
Hansen test [H0: overidentifying restrictions are jointly valid]					8.92	0.54	19.40	0.62
Difference-in-Hansen test [H0: level equation restrictions are valid]							7.68	0.81

E. Market incomes elasticity for α = 1

Dependent variable:	**OLS**		**Within Groups**		**DIF-GMM**		**SYS-GMM**	
General mean lnμ(xt,α)	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
lnμ(xt-1,α)	0.91 ***	*0.02*	0.43 ***	*0.05*	-0.01	*0.24*	0.84 ***	*0.07*
lnGDPt	1.13 ***	*0.09*	0.86 ***	*0.10*	0.53 **	*0.25*	1.34 ***	*0.29*
lnGDPt-1	-0.97 ***	*0.10*	-0.19	*0.12*	0.51	*0.44*	-1.06 ***	*0.32*
NXt	-0.37 ***	*0.07*	-0.79 ***	*0.11*	-0.80 ***	*0.15*	-0.50 **	*0.19*
Time trend	-0.02 **	*0.01*	-0.04 ***	*0.01*	-0.04 **	*0.02*	-0.03 **	*0.01*
y2009-10	0.02 *	*0.01*	0.01	*0.01*	-0.01	*0.02*	0.04	*0.03*
Constant	-0.74 ***	*0.15*	-1.08	*0.69*			-1.27 *	*0.63*
Long-run elasticity:								
lnμ(x,α) w.r.t. GDP	1.81 ***	*0.16*	1.18 ***	*0.12*	1.03 ***	*0.10*	1.80 ***	*0.33*
Number of observations	225		225		191		225	
Number of instruments					16		29	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	1.38	0.17			-0.33	0.74	-3.18	0.00
AR(2) test [H0: no serial correlation]	-1.71	0.09			-2.00	0.05	-2.21	0.03
Sargan test [H0: overidentifying restrictions are jointly valid]					10.95	0.36	35.41	0.04
Hansen test [H0: overidentifying restrictions are jointly valid]					10.86	0.37	19.83	0.59
Difference-in-Hansen test [H0: level equation restrictions are valid]							8.53	0.74

F. Disposable incomes elasticity for α = 1

Dependent variable:	**OLS**		**Within Groups**		**DIF-GMM**		**SYS-GMM**	
General mean lnμ(xt,α)	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
lnμ(xt-1,α)	0.85 ***	*0.02*	0.61 ***	*0.05*	0.28 **	*0.12*	0.74 ***	*0.08*
lnGDPt	0.90 ***	*0.07*	0.64 ***	*0.08*	0.39 **	*0.17*	0.94 ***	*0.23*
lnGDPt-1	-0.70 ***	*0.08*	-0.24 **	*0.09*	0.29	*0.24*	-0.61 **	*0.28*
NXt	-0.35 ***	*0.06*	-0.68 ***	*0.09*	-0.63 ***	*0.13*	-0.48 ***	*0.15*
Time trend	-0.02 ***	*0.00*	-0.02	*0.01*	-0.02	*0.02*	-0.03 ***	*0.01*
y2009-10	0.03 ***	*0.01*	0.02	*0.01*	-0.01	*0.01*	0.04 **	*0.02*
Constant	-0.54 ***	*0.11*	-0.30	*0.56*			-0.80 **	*0.38*
Long-run elasticity:								
lnμ(x,α) w.r.t. GDP	1.34 ***	*0.07*	1.05 ***	*0.15*	0.94 ***	*0.12*	1.28 ***	*0.14*
Number of observations	225		225		191		225	
Number of instruments					16		29	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	1.82	0.07			-1.53	0.13	-2.60	0.01
AR(2) test [H0: no serial correlation]	-0.11	0.91			0.08	0.94	-0.97	0.33
Sargan test [H0: overidentifying restrictions are jointly valid]					12.64	0.24	26.8	0.22
Hansen test [H0: overidentifying restrictions are jointly valid]					9.54	0.48	19.81	0.60
Difference-in-Hansen test [H0: level equation restrictions are valid]							8.82	0.72

G. Market incomes elasticity for α = 6

Dependent variable:	**OLS**			**Within Groups**			**DIF-GMM**			**SYS-GMM**		
General mean lnμ(xt,α)	Estimate		s.e.	Estimate		s.e.	Estimate		s.e.	Estimate		s.e.
lnμ(xt-1,α)	0.90	***	*0.02*	0.48	***	*0.06*	0.65	**	*0.25*	0.92	***	*0.08*
lnGDPt	0.96	***	*0.12*	0.85	***	*0.12*	0.85	***	*0.24*	1.38	***	*0.30*
lnGDPt-1	-0.78	***	*0.12*	-0.29	**	*0.14*	-0.60		*0.40*	-1.25	***	*0.37*
NXt	-0.42	***	*0.08*	-0.85	***	*0.15*	-0.93	***	*0.30*	-0.32		*0.29*
Time trend	-0.02	***	*0.01*	-0.01		*0.02*	0.01		*0.03*	-0.02		*0.01*
y2009-10	0.01		*0.02*	0.00		*0.01*	0.01		*0.02*	0.04		*0.03*
Constant	-0.77	***	*0.17*	-0.16		*0.91*				-0.47		*0.87*
Long-run elasticity:												
lnμ(x,α) w.r.t. GDP	1.82	***	*0.19*	1.08	***	*0.17*	0.75		*0.58*	1.67	*	*0.90*
Number of observations	225			225			191			225		
Number of instruments							16			29		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	0.51		0.61				-1.74		0.08	-3.02		0.00
AR(2) test [H0: no serial correlation]	-2.18		0.03				-1.74		0.08	-1.99		0.05
Sargan test [H0: overidentifying restrictions are jointly valid]							13.88		0.18	26.11		0.25
Hansen test [H0: overidentifying restrictions are jointly valid]							11.12		0.35	18.33		0.69
Difference-in-Hansen test [H0: level equation restrictions are valid]										11.00		0.53

H. Disposable incomes elasticity for α = 6

Dependent variable:	**OLS**			**Within Groups**			**DIF-GMM**			**SYS-GMM**		
General mean lnμ(xt,α)	Estimate		s.e.	Estimate		s.e.	Estimate		s.e.	Estimate		s.e.
lnμ(xt-1,α)	0.89	***	*0.02*	0.60	***	*0.05*	0.49	**	*0.19*	0.91	***	*0.09*
lnGDPt	0.91	***	*0.11*	0.71	***	*0.11*	0.59	**	*0.23*	1.34	***	*0.42*
lnGDPt-1	-0.76	***	*0.11*	-0.33	**	*0.13*	-0.05		*0.37*	-1.17	**	*0.48*
NXt	-0.35	***	*0.08*	-0.85	***	*0.13*	-0.85	**	*0.32*	-0.42		*0.26*
Time trend	-0.01	**	*0.01*	0.00		*0.02*	-0.01		*0.02*	-0.02	*	*0.01*
y2009-10	0.02		*0.01*	0.01		*0.01*	-0.01		*0.02*	0.05	*	*0.03*
Constant	-0.35	**	*0.15*	0.25		*0.83*				-0.74		*0.73*
Long-run elasticity:												
lnμ(x,α) w.r.t. GDP	1.34	***	*0.14*	0.95	***	*0.21*	1.05	***	*0.28*	1.80		*1.14*
Number of observations	225			225			191			225		
Number of instruments							16			29		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	0.07		0.94				-1.49		0.14	-2.03		0.04
AR(2) test [H0: no serial correlation]	-1.83		0.07				-0.86		0.39	-1.98		0.05
Sargan test [H0: overidentifying restrictions are jointly valid]							13.16		0.21	20.83		0.53
Hansen test [H0: overidentifying restrictions are jointly valid]							8.47		0.58	15.44		0.84
Difference-in-Hansen test [H0: level equation restrictions are valid]										6.05		0.91

Note: Standard errors in italic. See text for details about the underlying specifications. ***, **, * refer to the statistical significance at the 1%, 5% and 10% respectively, with cluster correction for the estimations. Standard errors for long-run elasticities are calculated by the delta method.

Table A3.2. Household incomes elasticity to labour productivity and labour utilisation

A. Market incomes elasticity for α = -4

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.95 ***	*0.02*	0.59 ***	*0.05*	0.23	*0.30*	0.74 ***	*0.08*
lnLPt	1.03 ***	*0.26*	0.56 *	*0.29*	0.25	*0.91*	-0.04	*0.50*
lnLPt-1	-0.97 ***	*0.26*	-0.18	*0.28*	0.27	*1.19*	-0.08	*0.54*
lnLUt	2.66 ***	*0.22*	2.28 ***	*0.25*	2.58 ***	*0.80*	3.09 ***	*0.51*
lnLUt-1	-2.39 ***	*0.22*	-0.71 **	*0.30*	-0.22	*0.98*	-2.28 ***	*0.49*
NXt	-0.46 ***	*0.13*	-0.66 **	*0.26*	-0.61	*0.59*	-0.10	*0.41*
Time trend	0.01	*0.01*	-0.09 ***	*0.03*	-0.13	*0.09*	-0.02	*0.02*
y2009-10	0.00	*0.03*	-0.02	*0.02*	-0.01	*0.04*	-0.01	*0.04*
Constant	-0.04	*0.39*	0.70	*1.86*			4.29 *	*2.39*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.13 *	*0.61*	0.94 **	*0.43*	0.68	*0.86*	-0.45	*0.74*
lnμ(x,α) w.r.t. LU	4.95 ***	*1.61*	3.87 ***	*0.53*	3.06 ***	*0.75*	3.09 ***	*1.08*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	0.50	0.61			-0.72	0.47	-3.01	0.00
AR(2) test [H0: no serial correlation]	-0.65	0.52			-0.17	0.86	0.04	0.97
Sargan test [H0: overidentifying restrictions are jointly valid]					26.84	0.00	36.67	0.04
Hansen test [H0: overidentifying restrictions are jointly valid]					13.81	0.18	21.96	0.52
Difference-in-Hansen test [H0: level equation restrictions are valid]							7.97	0.85

B. Disposable incomes elasticity for α = -4

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.97 ***	*0.02*	0.53 ***	*0.05*	0.00	*0.16*	0.81 ***	*0.10*
lnLPt	0.96 ***	*0.16*	0.49 ***	*0.15*	0.11	*0.51*	0.59	*0.42*
lnLPt-1	-0.92 ***	*0.15*	-0.08	*0.15*	0.84	*0.69*	-0.45	*0.46*
lnLUt	1.41 ***	*0.13*	0.85 ***	*0.13*	0.30	*0.40*	1.24 ***	*0.29*
lnLUt-1	-1.30 ***	*0.13*	-0.21	*0.15*	0.70 *	*0.38*	-0.87 **	*0.34*
NXt	-0.27 ***	*0.08*	-0.80 ***	*0.13*	-0.77 **	*0.33*	-0.20	*0.18*
Time trend	0.00	*0.01*	-0.04 **	*0.01*	-0.08	*0.05*	-0.03 *	*0.02*
y2009-10	0.04 **	*0.02*	0.01	*0.01*	-0.03	*0.03*	0.02	*0.03*
Constant	-0.10	*0.24*	0.37	*0.93*			0.54	*0.72*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.39 **	*0.7*	0.88 ***	*0.19*	0.94 **	*0.37*	0.74 **	*0.34*
lnμ(x,α) w.r.t. LU	3.83 **	*1.91*	1.35 ***	*0.22*	1.00 ***	*0.37*	1.96 ***	*0.46*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	2.66	0.01			-0.99	0.32	-2.56	0.01
AR(2) test [H0: no serial correlation]	-0.79	0.43			0.43	0.67	-0.08	0.93
Sargan test [H0: overidentifying restrictions are jointly valid]					17.45	0.06	71.64	0.00
Hansen test [H0: overidentifying restrictions are jointly valid]					6.49	0.77	25.70	0.32
Difference-in-Hansen test [H0: level equation restrictions are valid]							14.61	0.33

C. Market incomes elasticity for α = 0

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.91 ***	*0.02*	0.47 ***	*0.05*	0.09	*0.25*	0.77 ***	*0.09*
lnLPt	0.91 ***	*0.13*	0.60 ***	*0.14*	0.22	*0.34*	-0.11	*0.38*
lnLPt-1	-0.78 ***	*0.14*	-0.03	*0.15*	0.30	*0.50*	0.29	*0.45*
lnLUt	1.62 ***	*0.11*	1.29 ***	*0.12*	1.45 ***	*0.37*	1.73 ***	*0.31*
lnLUt-1	-1.41 ***	*0.12*	-0.41 ***	*0.15*	0.10	*0.53*	-1.32 ***	*0.34*
NXt	-0.39 ***	*0.07*	-0.68 ***	*0.13*	-0.43	*0.29*	-0.35 *	*0.18*
Time trend	-0.01 *	*0.01*	-0.05 ***	*0.01*	-0.03	*0.03*	-0.04 *	*0.02*
y2009-10	0.02	*0.01*	0.00	*0.01*	0.00	*0.02*	-0.01	*0.02*
Constant	-0.43 **	*0.21*	-0.34	*0.88*			0.61	*0.76*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.52 ***	*0.20*	1.08 ***	*0.16*	0.57 **	*0.29*	0.81 ***	*0.31*
lnμ(x,α) w.r.t. LU	2.41 ***	*0.42*	1.67 ***	*0.18*	1.70 ***	*0.27*	1.80 ***	*0.58*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	1.54	0.12			-0.54	0.59	-2.77	0.01
AR(2) test [H0: no serial correlation]	-0.92	0.36			-1.33	0.19	0.50	0.61
Sargan test [H0: overidentifying restrictions are jointly valid]					15.30	0.12	35.25	0.05
Hansen test [H0: overidentifying restrictions are jointly valid]					11.21	0.34	18.68	0.72
Difference-in-Hansen test [H0: level equation restrictions are valid]							6.39	0.93

D. Disposable incomes elasticity for α = 0

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.88 ***	*0.02*	0.60 ***	*0.04*	0.17	*0.20*	0.70 ***	*0.08*
lnLPt	0.85 ***	*0.11*	0.54 ***	*0.11*	0.25	*0.29*	0.20	*0.35*
lnLPt-1	-0.69 ***	*0.11*	-0.14	*0.11*	0.12	*0.45*	0.05	*0.39*
lnLUt	1.02 ***	*0.09*	0.71 ***	*0.09*	0.75 **	*0.34*	0.96 ***	*0.22*
lnLUt-1	-0.83 ***	*0.10*	-0.23 **	*0.11*	0.25	*0.30*	-0.52 *	*0.27*
NXt	-0.31 ***	*0.06*	-0.63 ***	*0.10*	-0.31	*0.25*	-0.32 **	*0.15*
Time trend	-0.02 ***	*0.01*	-0.02 *	*0.01*	0.01	*0.04*	-0.03 ***	*0.01*
y2009-10	0.04 ***	*0.01*	0.01	*0.01*	0.00	*0.02*	0.01	*0.02*
Constant	-0.45 **	*0.17*	0.03	*0.69*			0.51	*0.50*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.36 ***	*0.12*	0.97 ***	*0.16*	0.45	*0.35*	0.86 ***	*0.15*
lnμ(x,α) w.r.t. LU	1.59 ***	*0.24*	1.18 ***	*0.19*	1.20 ***	*0.30*	1.48 ***	*0.26*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	2.80	0.01			-0.52	0.61	-2.53	0.01
AR(2) test [H0: no serial correlation]	0.40	0.69			0.31	0.76	0.14	0.89
Sargan test [H0: overidentifying restrictions are jointly valid]					10.94	0.36	49.10	0.00
Hansen test [H0: overidentifying restrictions are jointly valid]					8.18	0.61	16.81	0.82
Difference-in-Hansen test [H0: level equation restrictions are valid]							5.19	0.97

E. Market incomes elasticity for α = 1

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.91 ***	*0.02*	0.44 ***	*0.05*	0.12	*0.23*	0.80 ***	*0.09*
lnLPt	0.86 ***	*0.13*	0.64 ***	*0.14*	0.30	*0.29*	-0.10	*0.39*
lnLPt-1	-0.71 ***	*0.13*	-0.03	*0.15*	0.20	*0.44*	0.32	*0.46*
lnLUt	1.31 ***	*0.11*	1.00 ***	*0.12*	1.14 ***	*0.32*	1.36 ***	*0.30*
lnLUt-1	-1.11 ***	*0.11*	-0.33 **	*0.14*	0.05	*0.38*	-1.09 ***	*0.33*
NXt	-0.38 ***	*0.07*	-0.72 ***	*0.12*	-0.47 *	*0.27*	-0.37 *	*0.19*
Time trend	-0.02 ***	*0.01*	-0.03 **	*0.01*	0.00	*0.03*	-0.04 *	*0.02*
y2009-10	0.02	*0.01*	0.01	*0.01*	0.00	*0.02*	-0.01	*0.03*
Constant	-0.56 ***	*0.20*	-0.48	*0.87*			-0.13	*0.79*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.62 ***	*0.19*	1.08 ***	*0.15*	0.56 **	*0.26*	1.11 ***	*0.34*
lnμ(x,α) w.r.t. LU	2.06 ***	*0.37*	1.19 ***	*0.17*	1.35 ***	*0.23*	1.37 **	*0.66*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	0.98	0.33			-0.61	0.54	-2.71	0.01
AR(2) test [H0: no serial correlation]	-1.45	0.15			-1.95	0.05	0.02	0.99
Sargan test [H0: overidentifying restrictions are jointly valid]					14.72	0.14	27.13	0.25
Hansen test [H0: overidentifying restrictions are jointly valid]					10.23	0.42	19.03	0.70
Difference-in-Hansen test [H0: level equation restrictions are valid]							7.14	0.89

F. Disposable incomes elasticity for α = 1

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate	s.e.	**Within Groups** Estimate	s.e.	**DIF-GMM** Estimate	s.e.	**SYS-GMM** Estimate	s.e.
lnμ(xt-1,α)	0.86 ***	*0.02*	0.62 ***	*0.05*	0.29 *	*0.15*	0.69 ***	*0.08*
lnLPt	0.78 ***	*0.10*	0.57 ***	*0.11*	0.31	*0.24*	0.07	*0.31*
lnLPt-1	-0.59 ***	*0.11*	-0.19	*0.12*	0.04	*0.40*	0.22	*0.36*
lnLUt	0.98 ***	*0.09*	0.68 ***	*0.10*	0.76 **	*0.32*	0.95 ***	*0.25*
lnLUt-1	-0.77 ***	*0.09*	-0.28 **	*0.11*	0.11	*0.26*	-0.53 *	*0.28*
NXt	-0.35 ***	*0.06*	-0.66 ***	*0.10*	-0.37	*0.26*	-0.42 ***	*0.15*
Time trend	-0.02 ***	*0.00*	-0.02	*0.01*	0.01	*0.03*	-0.03 **	*0.01*
y2009-10	0.03 ***	*0.01*	0.01	*0.01*	0.00	*0.02*	0.01	*0.02*
Constant	-0.46 ***	*0.16*	-0.12	*0.72*			0.32	*0.54*
Long-run elasticities:								
lnμ(x,α) w.r.t. LP	1.30 ***	*0.09*	1.01 ***	*0.18*	0.50	*0.35*	0.92 ***	*0.16*
lnμ(x,α) w.r.t. LU	1.39 ***	*0.19*	1.05 ***	*0.20*	1.22 ***	*0.32*	1.34 ***	*0.37*
Number of observations	225		225		191		225	
Number of instruments					18		32	
	t-stat	p-value			t-stat	p-value	t-stat	p-value
AR(1) test [H0: no serial correlation]	1.74	0.08			-1.11	0.27	-2.25	0.02
AR(2) test [H0: no serial correlation]	0.04	0.97			-0.35	0.72	-0.09	0.93
Sargan test [H0: overidentifying restrictions are jointly valid]					15.05	0.13	31.31	0.12
Hansen test [H0: overidentifying restrictions are jointly valid]					8.51	0.58	20.62	0.60
Difference-in-Hansen test [H0: level equation restrictions are valid]							9.02	0.77

G. Market incomes elasticity for α = 6

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate		s.e.	**Within Groups** Estimate		s.e.	**DIF-GMM** Estimate		s.e.	**SYS-GMM** Estimate		s.e.
lnμ(xt-1,α)	0.89	***	*0.02*	0.47	***	*0.06*	0.63	***	*0.19*	0.90	***	*0.10*
lnLPt	0.76	***	*0.17*	0.79	***	*0.18*	0.47		*0.42*	0.09		*0.49*
lnLPt-1	-0.58	***	*0.17*	-0.13		*0.19*	-0.31		*0.61*	0.05		*0.57*
lnLUt	1.08	***	*0.14*	0.77	***	*0.15*	0.98	**	*0.39*	1.23	***	*0.33*
lnLUt-1	-0.89	***	*0.14*	-0.37	**	*0.16*	-0.68	*	*0.35*	-1.19	***	*0.39*
NXt	-0.43	***	*0.09*	-0.95	***	*0.16*	-0.82	**	*0.38*	-0.30		*0.27*
Time trend	-0.03	***	*0.01*	-0.02		*0.02*	0.02		*0.03*	-0.03	*	*0.02*
y2009-10	0.00		*0.02*	0.00		*0.01*	0.00		*0.03*	-0.02		*0.03*
Constant	-0.72	***	*0.25*	-1.25		*1.16*				-0.34		*0.96*
Long-run elasticities:												
lnμ(x,α) w.r.t. LP	1.75	***	*0.22*	1.24	***	*0.21*	0.43		*0.74*	1.36	*	*0.75*
lnμ(x,α) w.r.t. LU	1.79	***	*0.41*	0.76	***	*0.24*	0.81		*0.71*	0.35		*1.48*
Number of observations	225			225			191			225		
Number of instruments							18			32		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	0.23		0.82				-2.14		0.03	-2.67		0.01
AR(2) test [H0: no serial correlation]	-2.05		0.04				-1.47		0.14	-1.16		0.25
Sargan test [H0: overidentifying restrictions are jointly valid]							14.54		0.15	26.99		0.26
Hansen test [H0: overidentifying restrictions are jointly valid]							10.81		0.37	20.93		0.59
Difference-in-Hansen test [H0: level equation restrictions are valid]										10.86		0.62

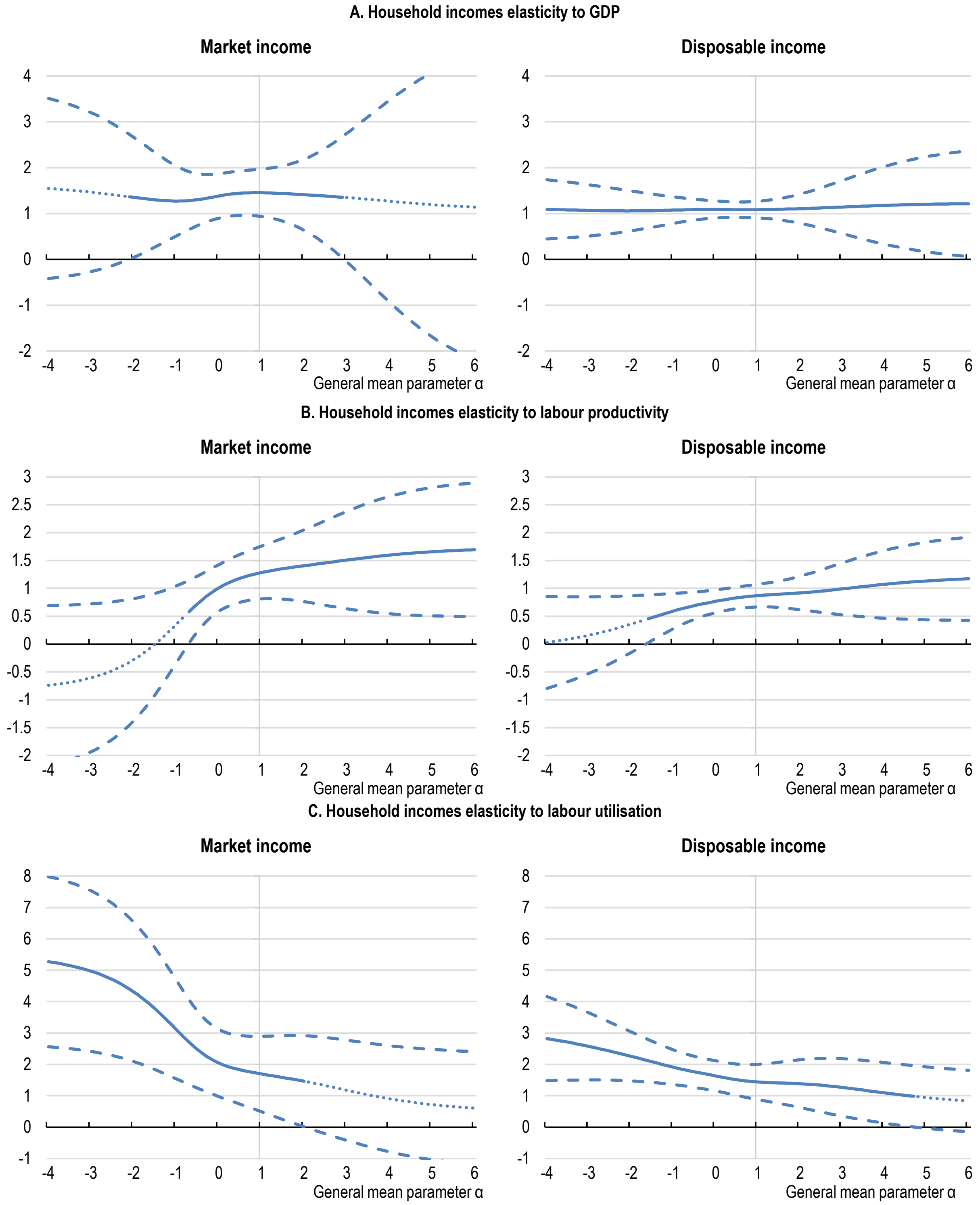
H. Disposable incomes elasticity for α = 6

Dependent variable: General mean lnμ(xt,α)	**OLS** Estimate		s.e.	**Within Groups** Estimate		s.e.	**DIF-GMM** Estimate		s.e.	**SYS-GMM** Estimate		s.e.
lnμ(xt-1,α)	0.88	***	*0.02*	0.60	***	*0.05*	0.47	**	*0.18*	0.86	***	*0.09*
lnLPt	0.70	***	*0.15*	0.72	***	*0.17*	0.30		*0.31*	0.27		*0.38*
lnLPt-1	-0.54	***	*0.16*	-0.24		*0.17*	0.14		*0.48*	-0.09		*0.43*
lnLUt	1.01	***	*0.12*	0.61	***	*0.14*	0.69	*	*0.35*	1.23	***	*0.42*
lnLUt-1	-0.88	***	*0.13*	-0.37	**	*0.15*	-0.12		*0.37*	-1.10	**	*0.51*
NXt	-0.36	***	*0.08*	-0.96	***	*0.15*	-0.77	*	*0.40*	-0.42	*	*0.24*
Time trend	-0.02	**	*0.01*	-0.01		*0.02*	0.00		*0.03*	-0.02	**	*0.01*
y2009-10	0.02		*0.01*	0.01		*0.01*	-0.01		*0.02*	0.01		*0.03*
Constant	-0.39	*	*0.22*	-0.90		*1.05*				-0.41		*0.75*
Long-run elasticities:												
lnμ(x,α) w.r.t. LP	1.34	***	*0.17*	1.19	***	*0.24*	0.84	**	*0.42*	1.30	**	*0.50*
lnμ(x,α) w.r.t. LU	1.14	***	*0.32*	0.58	**	*0.28*	1.06	**	*0.45*	0.93		*0.87*
Number of observations	225			225			191			225		
Number of instruments							18			32		
	t-stat		p-value				t-stat		p-value	t-stat		p-value
AR(1) test [H0: no serial correlation]	-0.15		0.88				-1.54		0.12	-1.82		0.07
AR(2) test [H0: no serial correlation]	-1.76		0.08				-0.78		0.44	-1.48		0.14
Sargan test [H0: overidentifying restrictions are jointly valid]							13.95		0.18	28.96		0.18
Hansen test [H0: overidentifying restrictions are jointly valid]							9.48		0.49	16.33		0.84
Difference-in-Hansen test [H0: level equation restrictions are valid]										5.03		0.97

Note: Standard errors in italic. See text for details about the underlying specifications. ***, **, * refer to the statistical significance at the 1%, 5% and 10% respectively, with cluster correction for the estimations. Standard errors for long-run elasticities are calculated by the delta method.

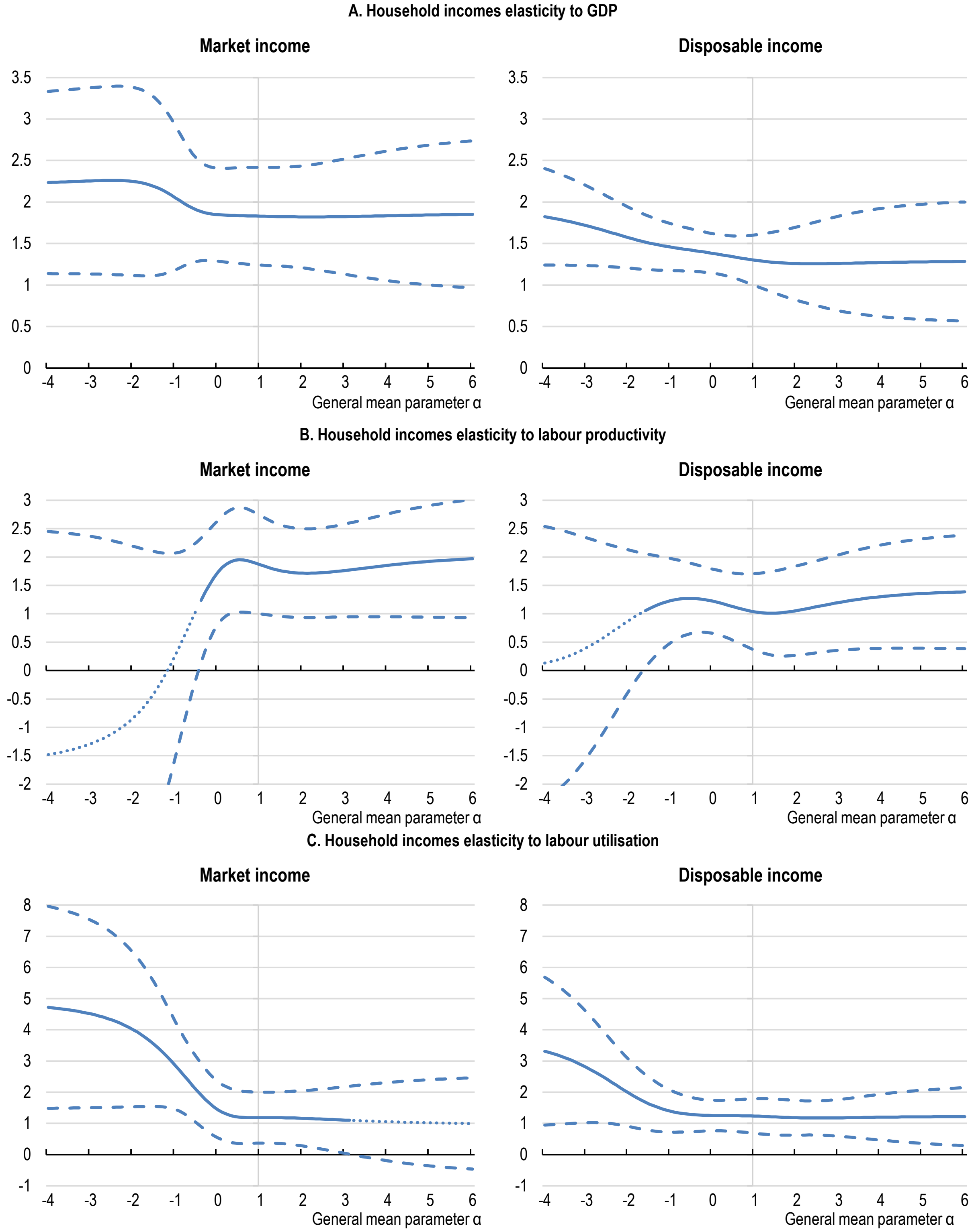
APPENDIX 4: ROBUSTNESS ESTIMATION RESULTS

Figure A4.1. Alternative set of internal instruments: 3rd lag for income, 2nd lag for GDP, and no collapse



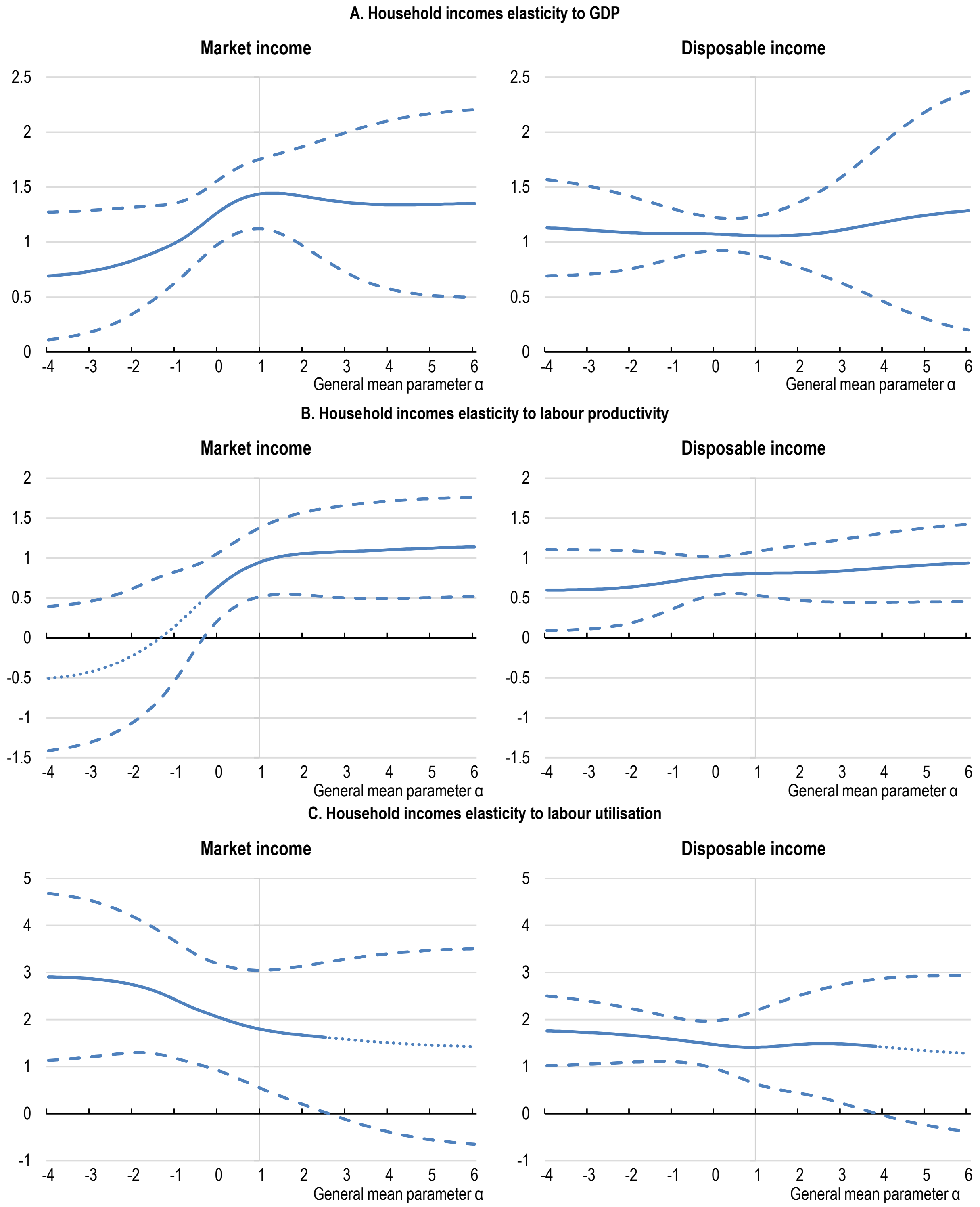
Note: Elasticity estimated by System GMM. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

Figure A4.2. Alternative set of internal instruments: all lags for income and GDP and instruments collapsed



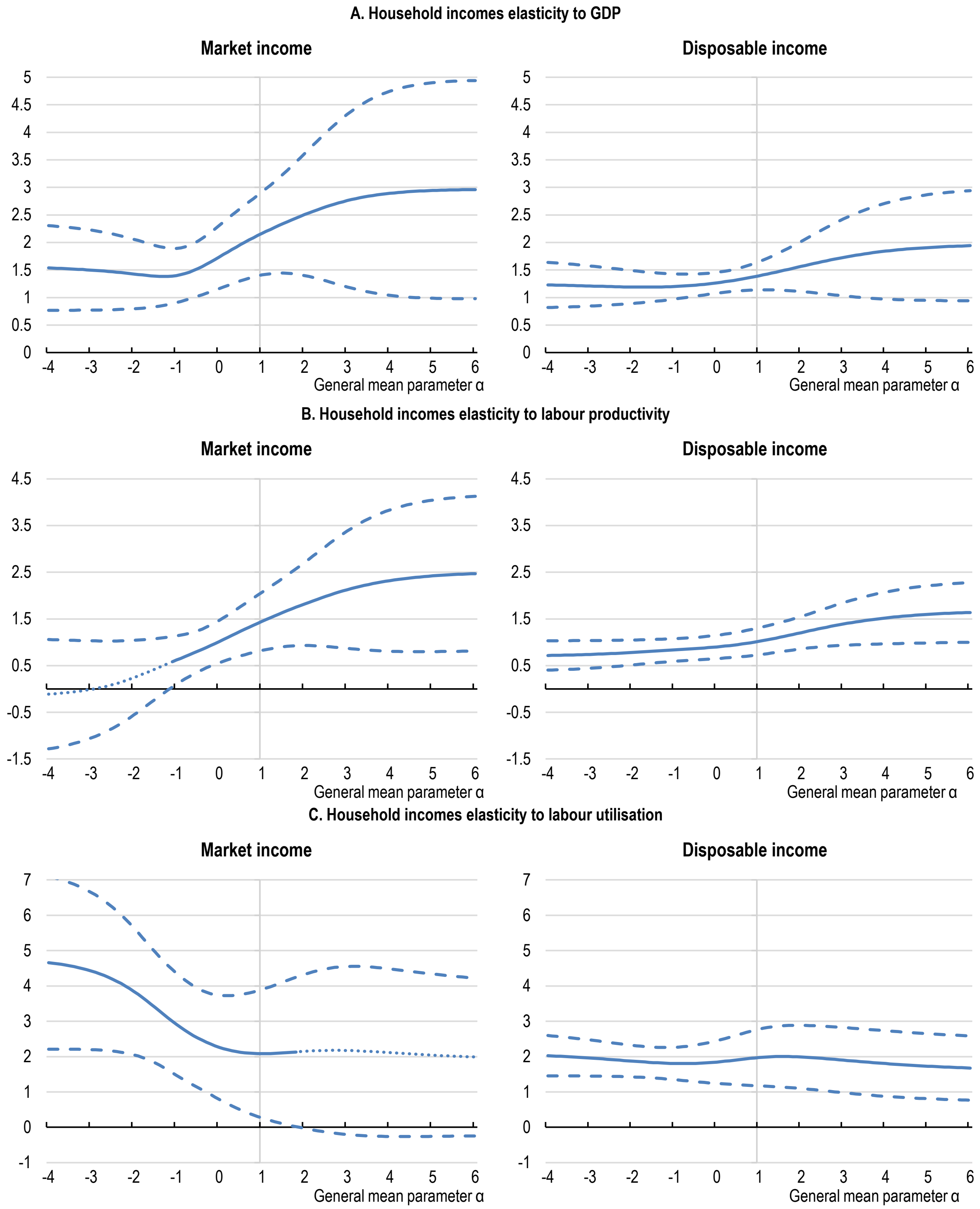
Note: Elasticity estimated by System GMM. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

Figure A4.3. Net exports replaced by terms-of-trade



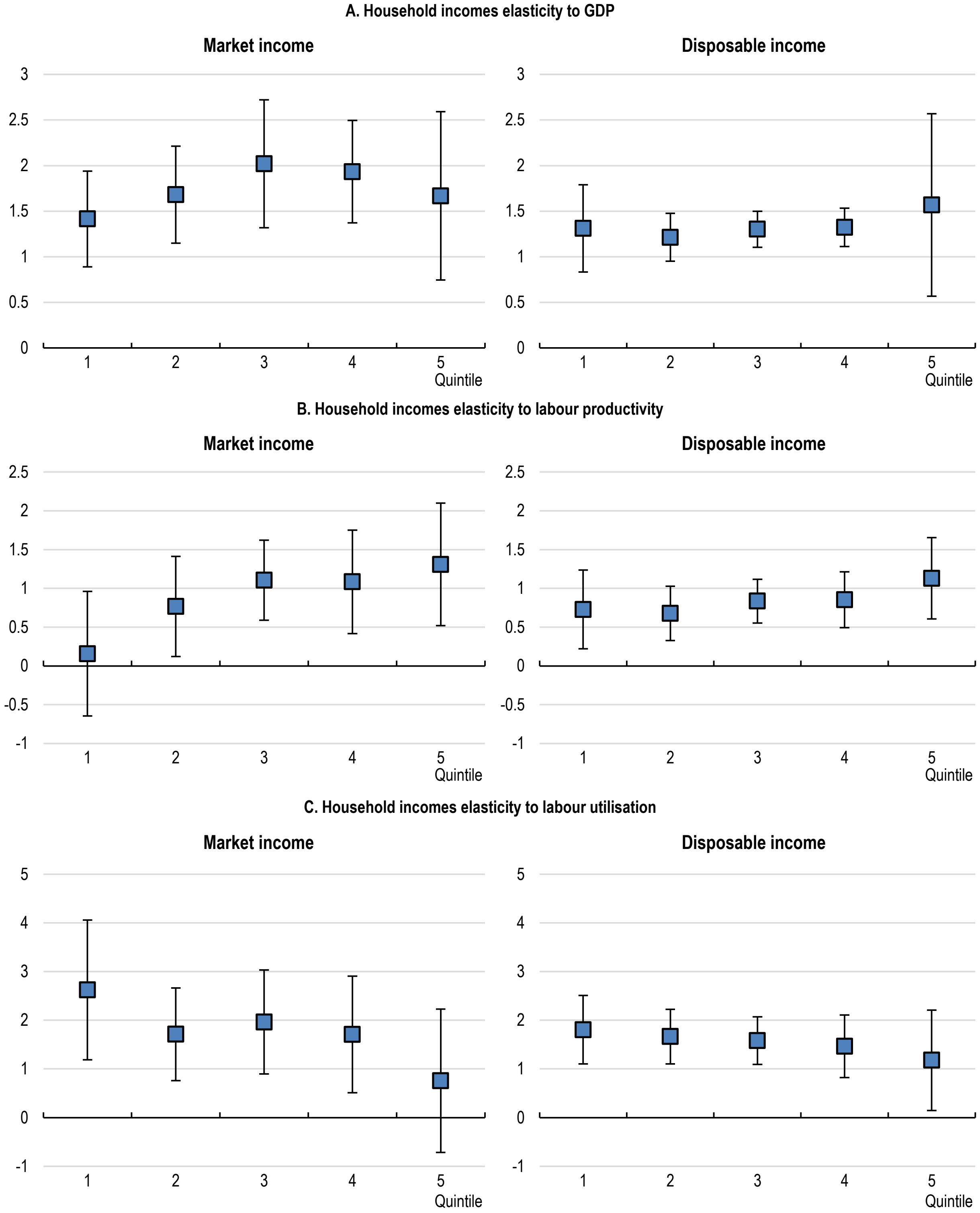
Note: Elasticity estimated by System GMM. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

Figure A4.4. Chile, Mexico and Turkey excluded



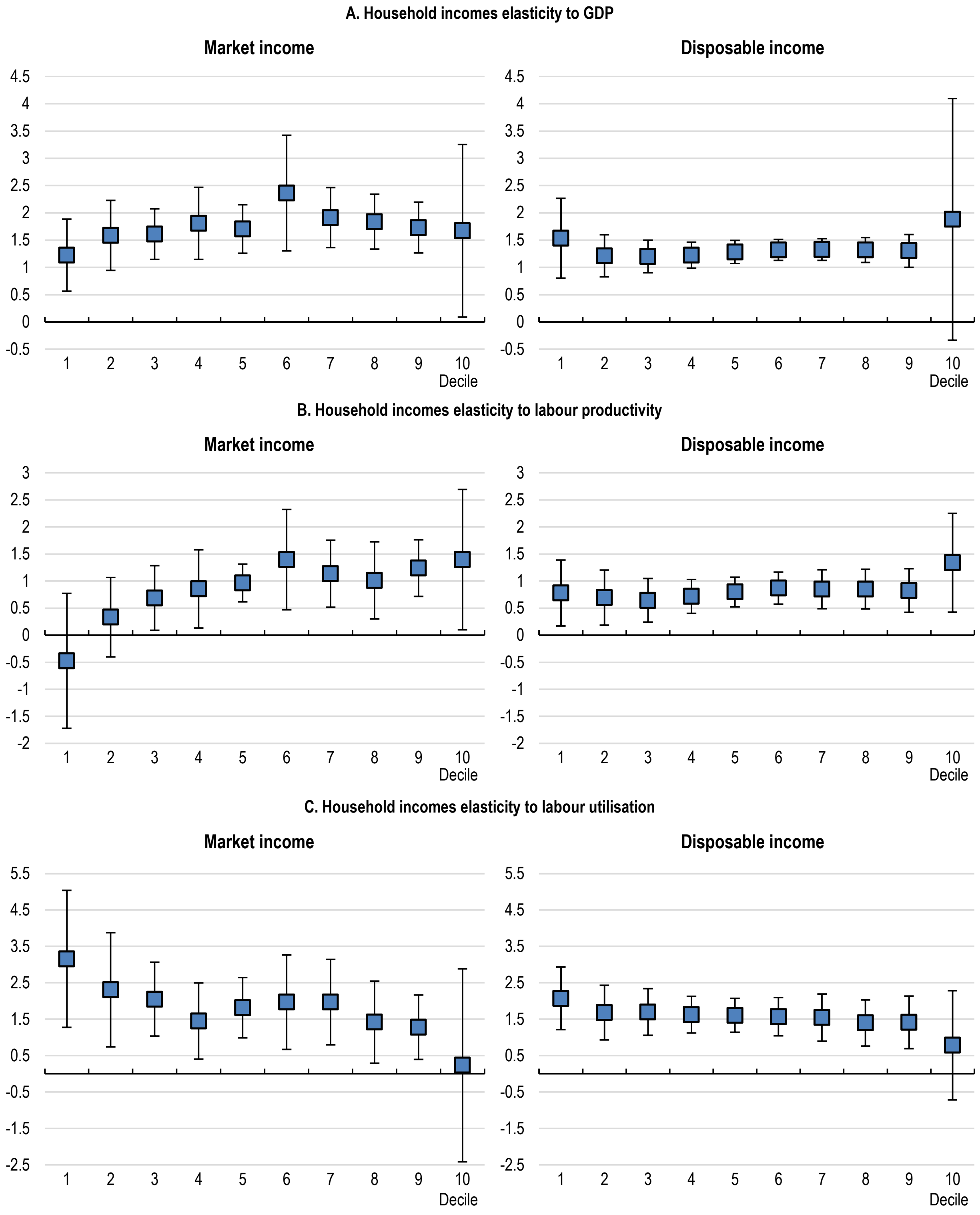
Note: Elasticity estimated by System GMM. See text for details. Starred portion of the curves represent non-significant estimations at the 90% level; dashed lines represent the 90% confidence interval bands calculated by the delta method.

Figure A4.5. General mean replaced by quintile mean income



Note: Elasticity estimated by System GMM. See text for details. Lines represent the 90% confidence interval bands calculated by the delta method.

Figure A4.6. General mean replaced by decile mean income



Note: Elasticity estimated by System GMM. See text for details. Lines represent the 90% confidence interval bands calculated by the delta method.