Economic development and inequality of opportunity: Kuznets meets the Great Gatsby?[1,2]

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Abstract: According to the Kuznets hypothesis, inequality first tends to increase and then decrease as a country develops. Whether borne out empirically, this inverted-U Kuznets curve, as a stylized 'fact', has shaped the discourse on economic development and income inequality for decades. In this paper we investigate whether a similar relationship holds between national income per capita and inequality of opportunity: the inequality associated with inherited individual circumstances such as gender, ethnicity, and family background. As, empirically, inequality of opportunity is positively correlated with income inequality (a relationship known as the 'Great Gatsby' curve), the relationship between inequality of opportunity and 'development' is expected to display the same inverted-U shape. We suggest that the existence of a Kuznets inequality of opportunity curve can be the result of a 'triangular' relationship between development, income inequality, and inequality of opportunity. We then draw on the newly published Global Estimates of Opportunity and Mobility database to shed new light on this 'triangular' relationship, primarily in a cross-sectional context.

Key words: inequality, opportunity, development, Kuznets, Gatsby

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1 Introduction

Drawing on dual-economy models of development prevalent at the time such as Lewis (1954), Simon Kuznets's seminal 1955 paper hypothesized an inverted-U relationship between income inequality and economic development. During the initial stages of growth, he suggested that, as economic resources transition from a low-productivity, low-inequality sector (such as subsistence agriculture) to a higher-productivity, higher-inequality sector (such as manufacturing), overall inequality tends to rise, driven by surging between-sector inequality. This occurs because certain groups or regions benefit earlier from industrialization, leaving others behind. Over time, as development progresses and more and more workers move to the advanced sector, between-sector inequality declines and so does overall inequality.

Kuznets himself was hindered by what he described as an 'unusual scarcity of data' (Kuznets 1955:1), and the original article draws on income share data (e.g. for quintiles of the personal income distribution) for only three countries, namely the USA, the UK, and Germany. His concluding remarks begin by noting that the author was 'acutely conscious of the meagreness of reliable information presented. The paper is perhaps 5 per cent empirical information and 95 per cent speculation' (Kuznets 1955: 26).

As the availability of data on how income distributions evolve over time gradually increased, various authors sought to assess the degree of empirical support for the Kuznets hypothesis (e.g., Anand and Kanbur 1993; Deininger and Squire 1998; Huang and Lin 2007; Jovanovic 2018). On the whole, this literature provided, at best, partial support for the existence of a pattern of inequality *dynamics* consistent with the Kuznets hypothesis common across many countries.[6]

What support there was typically came from cross-sectional, rather than time-series, evidence. Although the hypothesis was originally framed in terms of the evolution of inequality within countries over time, the scarcity of such time-series data over sufficiently long periods often led researchers to look for support or refutation in inequality data across countries at different stages of development—typically proxied by their levels of gross domestic product (GDP) per capita. And in these cross-sectional data, an inverted-U relationship between inequality and GDP per capita was indeed present. Our own version of this curve is presented in Figure 2.

More recently,[7] it has been suggested that the absence of clear, single inverted-U trajectories in within-country data may reflect the fact that the development process may well consist of a sequence of technological shocks and advances, with new sectors arising and replacing older ones over time, as well as other major shocks, such as wars and epidemics. In such a view, even if there were truth to the key Kuznets mechanism—of inequality rising during periods of major changes in the sectoral

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[6] Gallup (2012) is categorical. In answering his own question 'Is there a Kuznets curve?', he writes 'No. There has never been good evidence for a pattern of rising inequality in low-income countries and falling inequality in higher income countries' (Gallup 2012: 1).

[7] Some contributions have analysed the relationship between development and inequality from a political economy perspective by focusing on the role of institutional transformations. In particular Acemoglu and Robinson (2002) propose a political economy theory of the Kuznets curve which is able to account for different (democratic and non-democratic) patterns that are historically observed in different geographical areas of the world such as the West and East Asia. In this paper we abstract from political factors and, in the spirit of the original Kuznets paper, we focus on economic factors.

composition of the economy—it would manifest not in a single curve but in 'Kuznets waves' (Milanovic 2016). Regardless of the nature and degree of empirical support, the fact is that the inverted-U Kuznets curve, as a stylized 'fact', has shaped the discourse on economic development and income inequality for decades.

In this paper we investigate whether a similar relationship holds between national income and inequality of opportunity (IOp), rather than income inequality. The IOp concept was introduced to economics in the 1990s and its measurement dates to the 2000s.[8] In simple terms IOp can be thought of as the inequality associated with inherited individual circumstances such as gender, ethnicity, place of birth, and family background. Some have argued that IOp is the active ingredient of inequality, both in terms of people's intrinsic inequality aversion and in terms of its negative effects on economic efficiency and growth (e.g. Ferreira 2022).

Our paper is also related to recent contributions that investigate the relationship between IOp and economic growth, with a focus on how IOp influences growth. Marrero and Rodríguez (2013) find that higher levels of IOp are associated with slower economic growth, suggesting that unequal access to opportunities can hinder a country's development (see also Ferreira et al. 2018; Marrero and Rodríguez 2023).[9] More recently, Arntz et al. (2025) suggest that the growth process itself—particularly certain technological changes—can reduce IOp by improving occupational opportunities for workers with low socioeconomic background.

There is some reason to expect that an 'opportunity Kuznets curve' might be observed, at least in the country-level cross-section. The reason for this is that the triangular relationship between economic development, income inequality, and IOp is characterized by two empirical regularities. The first is the cross-section Kuznets curve just described and shown in our Figure 2, which describes how income inequality initially rises and then falls as GDP per capita increases across countries. The second empirical regularity is a version of what is now known as the Great Gatsby curve. The original Great Gatsby curve is a negative cross-country correlation between income inequality and intergenerational mobility (Corak 2013). Because mobility is very closely associated with the (inverse of) IOp, one can also observe a clear positive empirical association between IOp and income inequality across countries (Brunori et al. 2013). This relationship suggests that, as income inequality increases, so does intergenerational persistence; a greater proportion of that inequality is attributable to inherited circumstances, reinforcing the barriers to mobility. Taken together these two stylized empirical relationships should imply that the cross-sectional relationship between GDP per capita and measures of IOp should also be characterized by an inverted-U curve: an opportunity Kuznets curve.

But if such a relationship were indeed observed in the cross-sectional data, would it be spurious or purely accidental, or might it instead reflect some meaningful characteristic of economic development? The two underlying empirical associations themselves suggest a plausible mechanism. The Great

[8] See e.g., van de Gaer (1993), Fleurbaey (1994), and Roemer (1993) for the first economic models of equality of opportunity and Peragine (2002), Bourguignon et al. (2007), Checchi and Peragine (2010), and Ferreira and Gignoux (2011) on measurement aspects. Ferreira and Peragine (2016) and Roemer and Trannoy (2015) provide surveys of the broad IOp literature.

[9] Other studies, for example Hassler and Mora (2000), argue for a similar relationship between intergenerational mobility and growth, suggesting that rapid growth is associated with children's incomes depending less on parental background and more on their own abilities.

Gatsby curve is typically interpreted as reflecting the two-way connection between outcomes and opportunities: more unequal outcomes among families today imply larger gaps in the opportunities they can provide to their children and, conversely, larger opportunity gaps will imply greater differences in future outcomes as well. The original Kuznets curve, on the other hand, is thought to arise from rising gaps as some people move to higher-productivity sectors, leaving others behind, and then from declines in those gaps, as those originally left behind also move across sectors and 'catch up'.

An opportunity Kuznets curve would arise, presumably, if the opportunities to move to the higher-productivity sector were shaped, at least in part, by inherited circumstances; that is, if families with higher incomes and better outcomes were somehow able to assist their children in seizing the better opportunities associated with the new, emerging sector. The downward-sloping part would correspond to the catch-up period, when the children of worse-off parents also manage to transition to the new sector or adopt the new technology. At the core of this discussion, therefore, lies the question of whether opportunities generated by economic growth are distributed independently of inherited circumstances or remain heavily influenced by them. Drawing on influential works on the inequality–growth nexus (Galor and Tsiddon 1997; Hassler and Mora 2000; among others) we argue that opportunities generated by economic development are, in fact, not independent of inherited circumstances.

The remainder of this paper does two main things. First, in Section 2, we provide a short discussion of the rich literature on the relationship between inequality and development, from the point of view of equality of opportunity. Section 3 contains the main contribution of the paper: we illustrate the empirical associations along each side of the income inequality—IOp—development triangle. Using data from an original and recently developed database (Global Estimates of Opportunity and Mobility—GEOM 2024), we document the existence of cross-sectional Great Gatsby curves, income Kuznets curves, and opportunity Kuznets curves. We also investigate whether the empirical associations are robust to different specifications. Section 4 concludes.

2 Theoretical background

In this section, we present some stylized facts, from the existing literature, that could provide some theoretical support for the existence of an opportunity Kuznets curve.

A vast literature examines the link between GDP growth and distributive issues such as inequality and intergenerational mobility within a theoretical framework. We focus in particular on intergenerational mobility, as it can be considered, under specific circumstances (notably, when the only inherited circumstance is parental income), as a proxy of equality of opportunity.

Prominent contributions include Galor and Tsiddon (1997) and Hassler and Mora (2000), who develop overlapping-generations models of endogenous growth in which parents transfer human capital to their children, enabling them to enhance their own human capital and achieve higher income prospects.

Similar intergenerational transmission mechanisms appear in other models, such as Galor and Zeira (1993), Owen and Weil (1998), and Maoz and Moav (1999). The intergenerational mobility literature also provides abundant evidence of a strong positive correlation between parents' and children's educational attainment (e.g., Neidhofer et al., 2018). Even more empirical evidence exists on the intergenerational link between parental and child income. Whether through human or physical capital, the literature broadly agrees that parents transmit advantages to their children, and these advantages translate into improved outcomes for the next generation.[10] In line with this literature, we can formulate the following stylized fact:

Stylized Fact 1: An individual's level of human (or physical) capital is an increasing function of the parental level of human (or physical) capital.

The same authors highlight that intergenerational persistence of advantages is not constant across time and countries. Both theoretical (Galor and Tsiddon 1997; Owen and Weil 1998; Maoz and Moav 1999; Hassler and Mora 2000) and empirical studies (Güell et al. 2018; Aydemir and Yazici 2019; Neidhofer 2019) support the idea that growth stimulates intergenerational mobility, ultimately reducing inequality.

This dynamic can be partly mechanical if we assume, as in Galor and Tsiddon (1997), that skilled and unskilled workers are complementary in production. In this case, GDP growth raises the wages of low-skilled workers, enabling children of low-skilled parents to invest in education and become high-skilled. Hassler and Mora (2000), by contrast, propose an explanation based on the speed of development: as economies grow faster, children's income depends less on parental human capital and more on their (randomly distributed) abilities. More recently, Arntz et al. (2025) show that technological shocks at later stages of development, such as the introduction of computer technology, can improve access to better occupations for workers from lower socioeconomic backgrounds.

Growth may also have an indirect effect on intergenerational mobility through policy intervention. Higher average income increases government resources available for financing public education and redistribution policies, which have been shown to reduce inequality and intergenerational persistence (e.g., Chetty et al. 2014; Hassler et al. 2007; Jerrim and Macmillan 2015; Neidhofer 2019).

Overall, endogenous growth models and empirical evidece seem to support the following stylized fact:

Stylized Fact 2: Development and growth foster intergenerational mobility, reducing inequality.

The above-mentioned papers, however, are very cautious about the speed at which the above dynamics will be observed: both economic and political mechanism can slow down and even prevent the inequality reduction to happen. Banerjee and Duflo (2003) are also cautious about the sign of this relationship, arguing a potential effect of inequality on growth. This effect is consistent with a political economy model but it can also reflect measurement errors due to the non-linear relation between growth and inequality (Banerjee and Duflo 2003). Non-linearities are also found by Forbes (2000), who concludes that inequality appears positively related to growth over short time spans, but negatively over long.

It is therefore reasonable to assume that, in the initial stages of technological change, children from more advantaged parental backgrounds realize higher incomes, consistent with Stylized Fact 1.[11] This advantage is then transmitted across generations until economic growth begins to enhance

[10] The reader should observe that in a theoretical setting where human capital is one of the main determinants of individual income, transfers of physical or human capital can be equivalent.

[11] Evidence for this mechanism is provided by Van der Weide and Milanovic (2018) and Lippi and Perri (2023), who show that inequality in the 1960s—before the IT revolution—in the United States fostered unequal, pro-rich growth, which in turn led to greater inequality.

intergenerational mobility (Stylized Fact 2). In other words, during the transition from an initial stage (before technological development) to the phase in which technological progress and development enhance intergenerational mobility (Stylized Fact 2), there exists a number of generations in which the persistence of advantages at time *t* (Stylized Fact 1) increases inequality at *t + 1*, which then raises IOp at *t + 2*, and so on. In line with the literature, this happens because only high skilled workers can access the new and more productive technology. Thus, if education is costly and credit markets are imperfect, sons of poor parents cannot borrow resources to finance their education. This excludes them from new (high skilled) sector, exacerbating the inequalities due to inherited factors (parental background in this case). IOp will eventually begin to decline once growth reaches a level sufficient to activate inequality-reducing mechanisms such as redistribution, public education, and the complementarity between skilled and unskilled workers.

This leads us to conclude that there are plausible theoretical arguments for the existence of an opportunity Kuznets curve which go beyond the simple positive correlation between inequality and IOp. In the remainder of the paper, we present some descriptive evidence of this.

3 Descriptive empirical evidence

As noted in the Introduction, the triangular relationship between income inequality, IOp, and economic development is characterized by two empirical regularities which have been repeatedly observed in the cross-section of countries: the income Kuznets curve and the Great Gatsby curve (which is a positive association between cross-sectional income inequality on the one hand and some measure of intergenerational persistence on the other). In this paper intergenerational persistence is measured by IOp.

Now, if both of these empirical relationships hold for a given set of countries, then the opportunity Kuznets curve we have been discussing should also hold. In this section we investigate whether this is indeed the case for a novel dataset, which we describe below. We first present evidence of the income Kuznets curve and the Great Gatsby curve, before showing our estimates of the opportunity Kuznets curve.

3.1 Data

To do so, we draw on data from the Global Estimates of Opportunity and Mobility (GEOM) database, a recently developed database that contains comparable estimates of income inequality and IOp for 72 countries, which account for over two-thirds of the global population.[12] GEOM contains estimates for two measures of income inequality, namely the Gini coefficient and the mean logarithmic deviation (MLD). It also contains Gini- and MLD-based estimates of IOp, computed both from an ex-ante and

[12] GEOM is a research project led by the International Inequalities Institute at the London School of Economics and the Department of Economics and Finance at the University of Bari in collaboration with the Asian Development Bank, the European Bank for Reconstruction and Development, the Centro de Estudios Espinosa Iglesias, Monash University, and the Center for Distributive, Labor and Social Studies at Universidad Nacional de La Plata, and the University of Florence, with the support of the VelezReyes+ Foundation. Original estimates and methodological notes are available at https://geom.ecineq.org/.

from an ex-post perspective. In both cases machine-learning techniques are used, so as to generate data-driven estimates. For the ex-post estimation, transformation trees are used, following Hothorn and Zeileis (2021) and Brunori, Ferreira, and Salas-Rojo (2023). For the ex-ante estimation, both conditional inference trees and random forests are presented, following Hothorn et al. (2006) and Brunori, Hufe, and Mahler (2023).

In what follows we use the database's recommended 'preferred' estimate of IOp, which is the random forest ex-ante Gini coefficient. Two versions are presented below: absolute IOp, which is simply the Gini coefficient in the smoothed distribution of types, and relative IOp, which is the ratio of the absolute IOp to the total Gini coefficient in incomes. Each of these estimates is computed by the GEOM team themselves from original, unit-record data from 193 household surveys. In all cases the income variable used is age-adjusted equivalized household income.[13] Inherited household wealth is typically not observed, so the following circumstance variables are used instead: sex; race, or ethnicity; place of birth; father's and mother's education levels; and father's and mother's occupational categories.

The fact that the same team of researchers used identical protocols to clean and harmonize the data from these different household surveys, defined income and circumstance variables in comparable ways, and used identical estimation methods across surveys makes GEOM a uniquely comparable database of information on inherited inequality and IOp.

To plot Kuznets curves, we also need estimates of per capita GDP; we use GDP per capita at market prices from the International Monetary Fund World Economic Outlook (IMF 2024) database.[14] Sectoral data on employment and value-added are drawn from the ten-sector database held by the University of Groningen (Timmer et al. 2015). Key summary statistics from both GEOM and on GDP per capita levels are shown in Table A1 in the Appendix.

3.2 Income Kuznets curves

We start by looking for evidence in support of the original Kuznets hypothesis, namely the inverted U-shaped relationship between development, captured by per capita GDP, and inequality, measured by the Gini coefficient of the income distribution. As noted earlier, Kuznets did propose it as a time-series concept: a pattern to be observed as a given country developed over time. Figure 1 shows the relationship for the country with the longest time series in our data, namely the USA, covering the period between 1980 and 2014. On the vertical axis we read income inequality measured by the Gini coefficient, while on the horizontal axis we approximate development via the logarithm of the per capita GDP. As we will do consistently below, the left panel of the figure shows a non-parametric regression line, while the right panel shows a parametric fit using a quadratic of the independent variable. The coefficients of the quadratic fits are all statistically significant and reported in Table A2 in the Appendix.

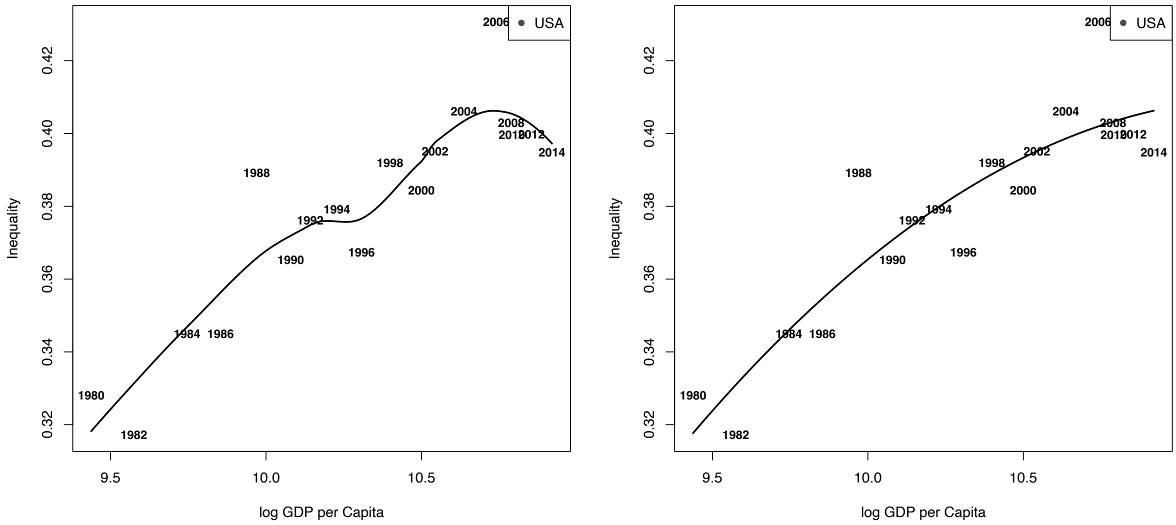
[13] The equivalence scale used is the square-root of household size scale. The age adjustment is carried out by using the residuals of an ordinary least squares (OLS) regression of income on the person's age and age squared.

[14] Purchasing Power Parity adjustments do not affect our results. See Figure A2 in the Appendix.

Figure 1: Time-series 'Kuznets curves' for the USA, 1980–2014

(a) Non-parametric fit

(b) Parametric fit



Note: inequality estimates based on the Panel Study of Income Dynamics data as in GEOM.

Source: elaboration on GEOM and IMF data.

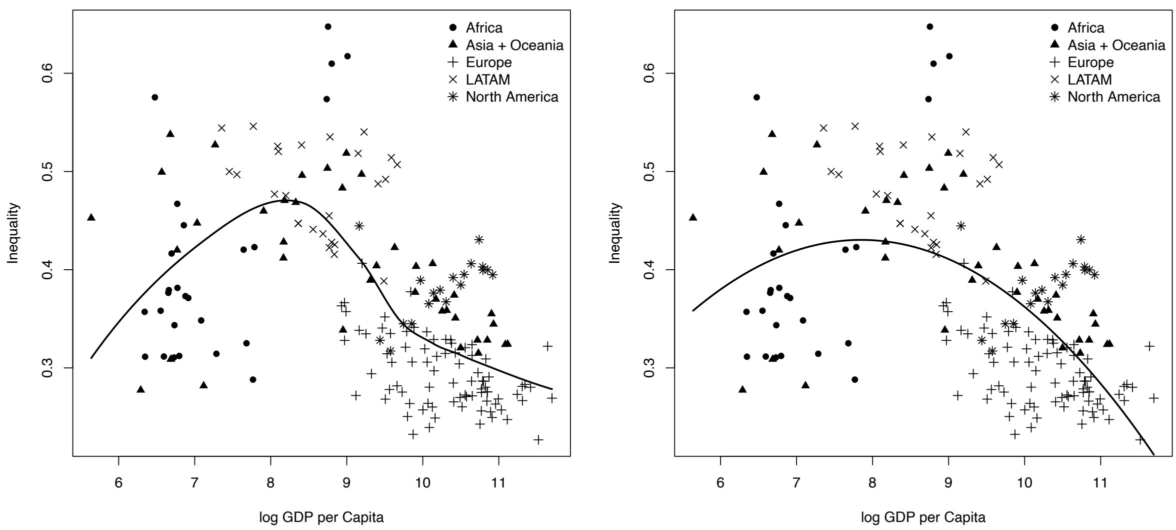
Although one might detect a local maximum—followed by a decline—at the very right of the non-parametric estimation in the left panel, it would probably be overoptimistic to claim that these US data offer much evidence of an inverted-U curve for this period. This is in keeping with the experience of many authors who have looked for Kuznets curves in time-series data, as noted earlier by Gallup (2012). For this particular country and period, the dominant tendency is of increasing inequality, perhaps with some flattening towards the end of the period.

Yet, it is not necessarily clear that the 1980–2014 period in the USA is the right time to test a model originally inspired by a view of development as a transition from backward agriculture towards more modern sectors. Indeed, a common, and not so easily dismissed, argument in defence of cross-sectional studies of the Kuznets curve is that there is limited data on these variables which covers a relevant and sufficiently long interval for any given country. In the case of the USA, however, the positive relation between inequality and GDP in Figure 1 is in line with the pro-rich growth dynamic highlighted by Van der Weide and Milanovic (2018) and Lippi and Perri (2023): a dynamic that may be consistent with significant advancements in Finance and Information Technologies, which could correspond to the initial stage of a (new) development process that increases inequality, as suggested by Kuznets.

Be that as it may, we too now move to the pooled cross-section available to us from GEOM, containing 192 observations. Figure 2 once again shows the Kuznets curves obtained by fitting a non-parametric (left panel) or a quadratic curve (right panel).

Figure 2: Cross-sectional Kuznets curves on pooled GEOM data

(a) Non-parametric fit (b) Parametric fit



Note: pooled cross-section data.

Source: elaboration on GEOM and IMF data.

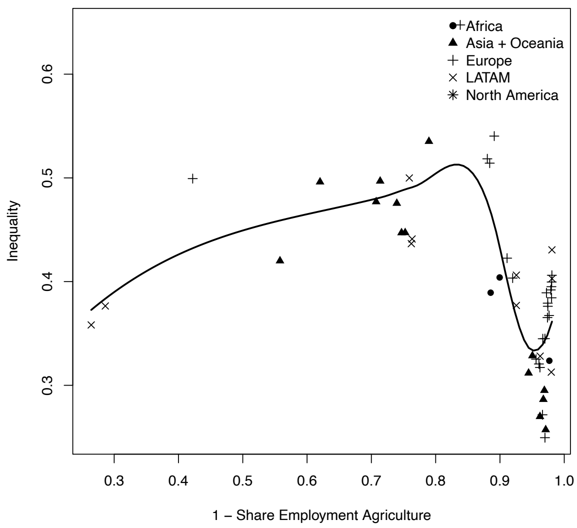
On these data both the parametric and non-parametric estimations offer strong support for Kuznets's hypothesis. Both panels show clear inverted-U shaped relationships between inequality and development. The result is clearly driven by the positions occupied by different groups of countries, which correspond to different stages of development, while there is substantial heterogeneity within the different geographical clusters.

It should also be noted that the visual relationship is reliant on the log transformation of the per capita GDP proxy for development. Given the skewed global cross-sectional distribution of per capita GDP, these curves are not observed when the horizontal axis is in levels rather than in logs. The corresponding figures can be seen in Figure A1 in the Appendix.

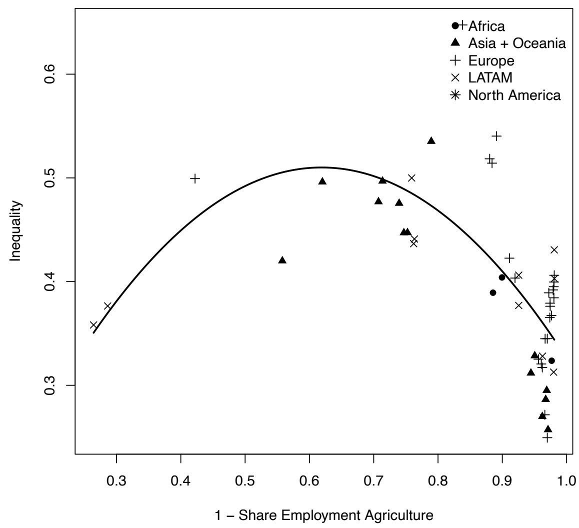
In line with our model and in the spirit of Kuznets's hypothesis, we can alternatively approximate the level of development by the share of the population employed in the agricultural sector. The idea is that, when this share is particularly high, we are in the presence of an economy at the initial stages of development, as described in our model. Conversely, when this share is very low, then most of the population has moved toward the more-productive technology, which is likely to be represented by the industrial and advanced services sectors. Figure 3 shows the pattern first using employment shares (Panels (a) and (b)) and then shares in total value-added (Panels (c) and (d)). An inverted-U relationship between inequality and development is also supported by these four figures, using this alternative measure of development. Analogous graphs for the manufacturing and service sectors (Figure A3 in Appendix) yield results that are less clear.

Figure 3: Kuznets curves when development is proxied by (inverse) agricultural shares: employment and valued-added

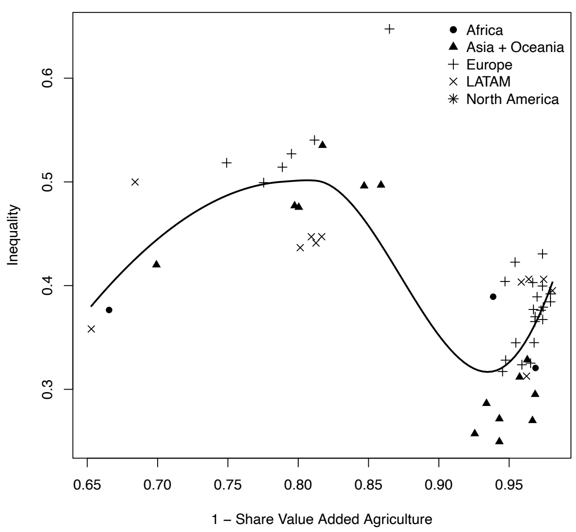
(a) Kuznets Curve (employment agriculture)



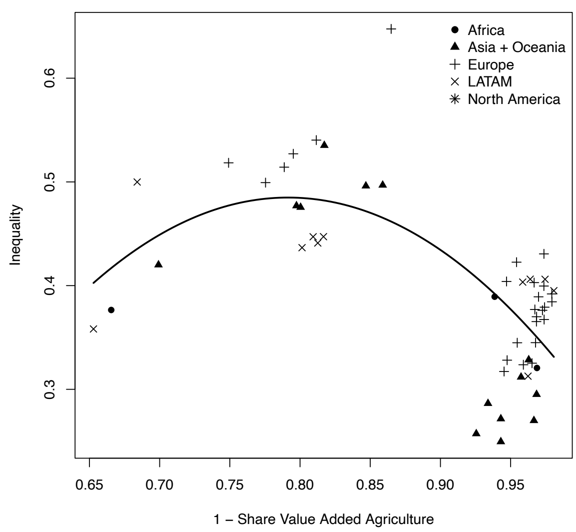
(b) Kuznets Curve (employment agriculture)



(c) Kuznets Curve (value-added agriculture)



(d) Kuznets Curve (value-added agriculture)



Note: pooled cross-section data.

Source: elaboration on GEOM and ten-sector (Timmer et al. 2015) data.

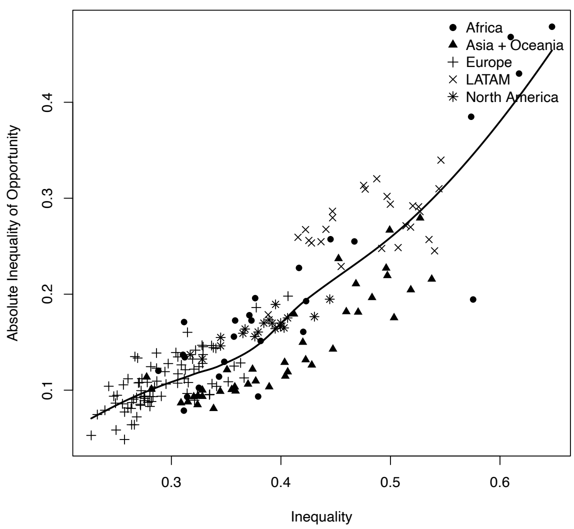
3.3 Great Gatsby curves

Let us now turn to the second side of the income inequality-IOp-development triangle, namely the Great Gatsby curve. This name was originally given to graphs that show a positive association between income inequality and intergenerational earnings elasticities (IGEs) across a few developed countries, shown in Corak (2013). IGEs are inverse measures of intergenerational mobility, so the relationship was interpreted as documenting a negative correlation between cross-sectional inequality and mobility across countries. A similar relationship using measures of IOp instead of IGEs was documented by Brunori et al. (2013).

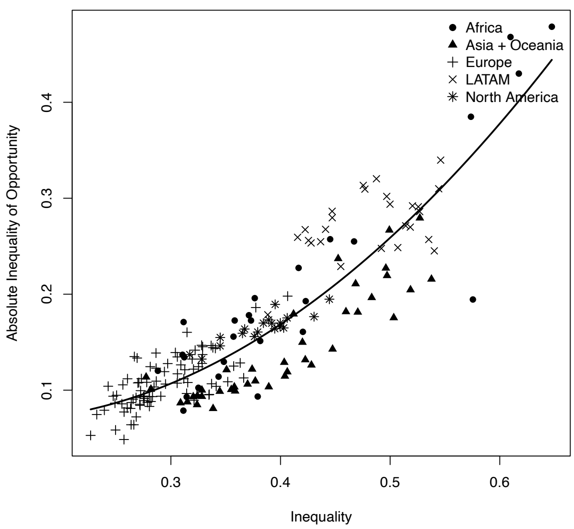
Figure 4 plots the Great Gatsby curves present in the GEOM data, both for absolute and relative measures of IOp, following the same pattern as above: non-parametric estimates on the left; quadratic fits on the right.

Figure 4: Great Gatsby curves for both absolute and relative IOp

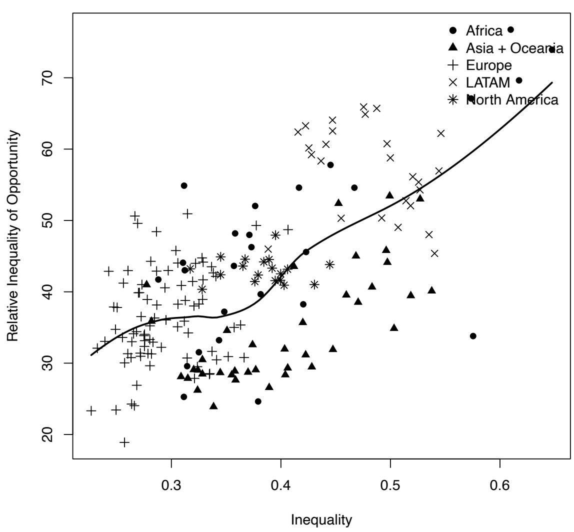
(a) Absolute IOp, non-parametric fit



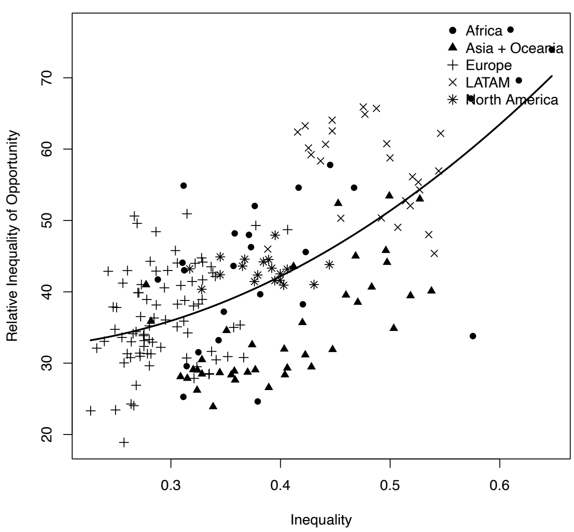
(b) Absolute IOp, parametric fit



(c) Relative IOp, non-parametric fit



(d) Relative IOp, parametric fit



Note: pooled cross-section data.

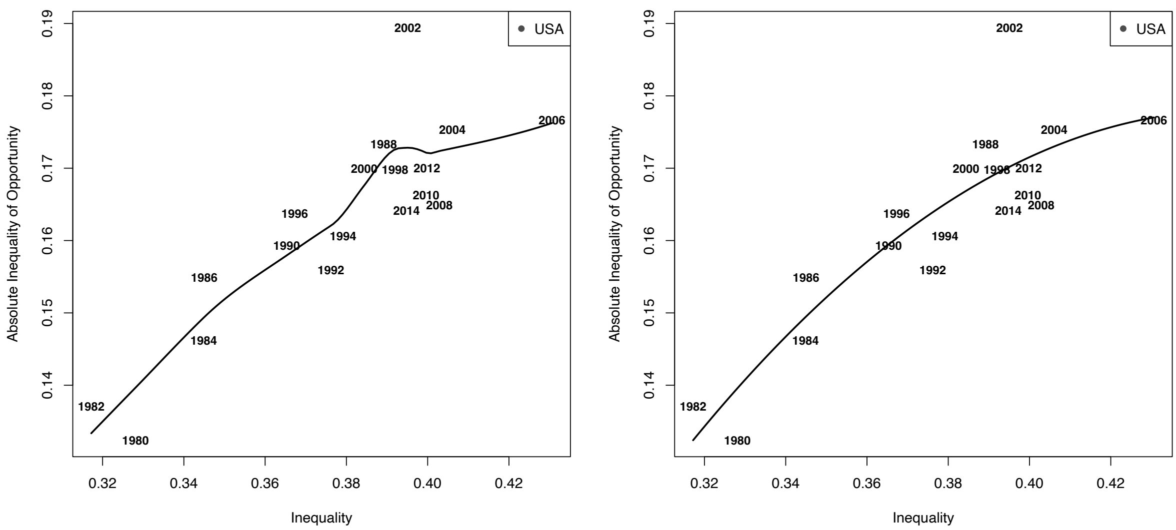
Source: elaboration on GEOM and IMF data.

All four plots show a clear positive association between income inequality, on the one hand, and both relative and absolute IOp on the other. It is worth noting that, while one might expect some mechanical association between absolute IOp and income inequality, as the former is a component of the latter, there is no a priori reason to expect that *relative* IOp and income inequality would be strongly positively correlated. So the fact that they are (at least in our sample and in a pooled cross-sectional framework) is important. In fact the existence of a Great Gatsby curve indicates that more unequal societies also have an increasing share of 'unfair', inherited inequality, reflecting the mutually reinforcing association between unequal outcomes and unequal opportunities.

This positive associations in Figure 4 are clearer when looking across regions rather than within them. In fact there is substantial variation in the IOp measures—particularly the relative ones—around the regression lines. Nevertheless, the empirical associations are clear and significant. And as shown in Figure 5, they are also present in the time series for the USA, using GEOM data for 1980–2014, as in Figure 1.

Figure 5: Time-series 'Great Gatsby curves' for the USA, 1980–2014

(a) Non-parametric fit (b) Parametric fit



Note: inequality and IOp estimates based on the Panel Study of Income Dynamics data as in GEOM.

Source: elaboration on GEOM data.

Taken together with the standard income Kuznets relationship documented earlier, the existence of this Great Gatsby curve both in the US time series and in the GEOM pooled cross-section should imply that we should also observe a Kuznets relationship between IOp and GDP per capita – an opportunity Kuznets curve, at least in the GEOM cross-sectional data.

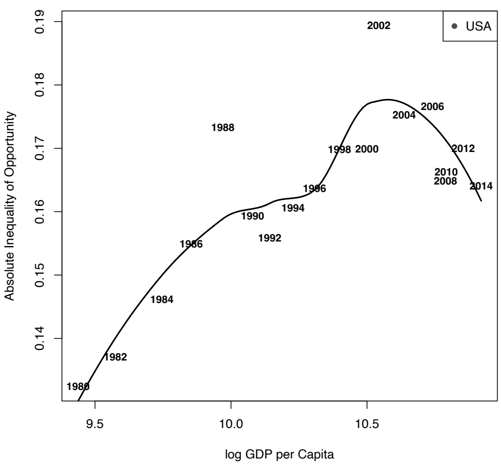
3.4 Opportunity Kuznets curves

The following figures show the Kuznets IOp curves obtained by fitting a non-parametric (left panel) or a quadratic (right panel) curve. On the vertical axis we have either absolute ex-ante IOp (measured by the Gini coefficient for the smoothed distribution), or the relative IOp measure, which is the ratio between absolute IOp and income inequality, also measured by the Gini. On the horizontal axis of Figures 6 and 7, we again use the logarithm of per capita GDP as a proxy for development. Figure 6 follows on from Figures 1 and 5 and plots the Kuznets IOp relationships for the USA time series between 1980 and 2014. As before the top row uses the absolute measure of IOp, while the bottom row uses the relative measure. Plots on the left use non-parametric regressions, while those on the right fit a quadratic polynomial.

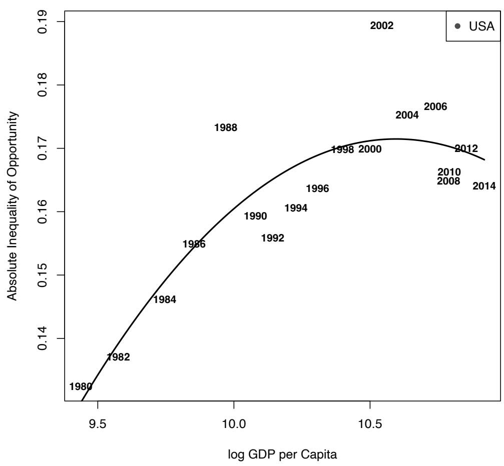
The curves for absolute IOp look similar to the income Kuznets curves in Figure 1, but the turning point around 2002 is now more marked. The downturn after that point is appreciable in the non-parametric figure and discernible even in the quadratic one. Naturally, with the numerator and denominator following reasonably similar trajectories but with a more pronounced ∩-shape for absolute IOp, the relative IOp Kuznets curve is actually quite pronounced in Figure 6.

Figure 6: Time-series ‘Kuznets opportunity curves’ for the USA, 1980–2014

(a) Absolute IOp, non-parametric fit

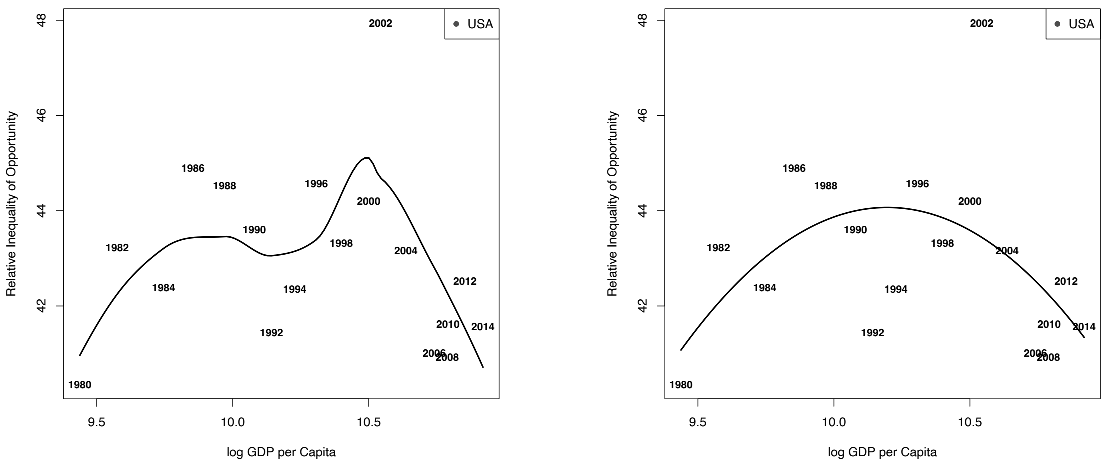


(b) Absolute IOp, parametric fit



(c) Relative IOp, non-parametric fit

(d) Relative IOp, parametric fit



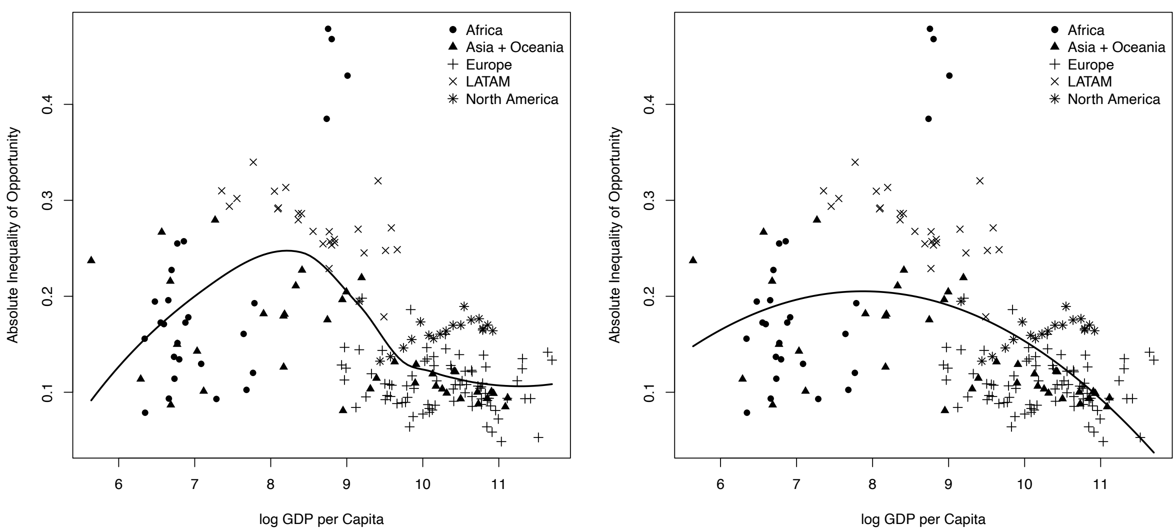
Note: IOp estimates based on the Panel Study of Income Dynamics data as in GEOM.

Source: elaboration on GEOM and IMF data.

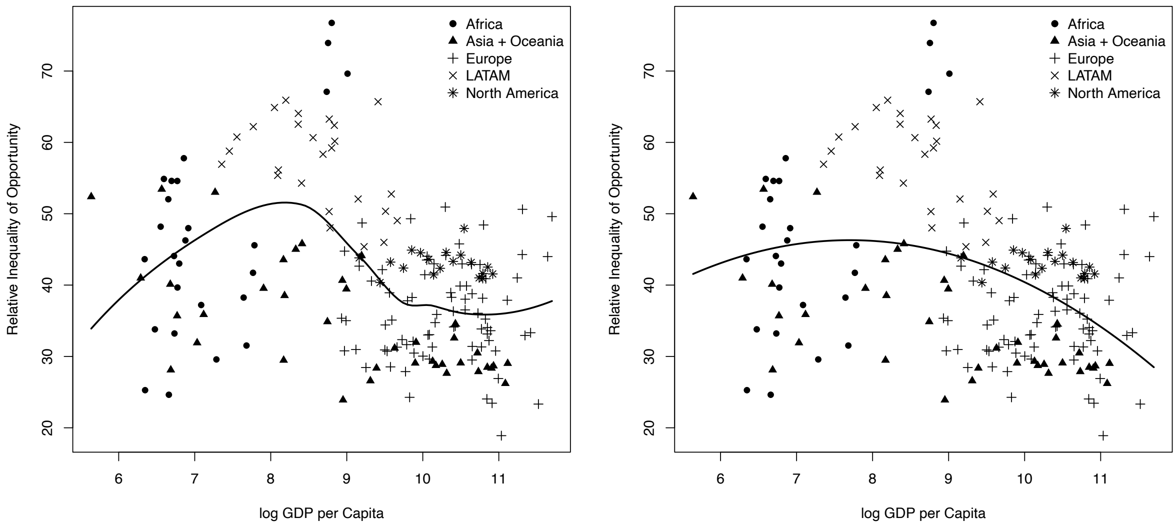
Next, we present the Opportunity Kuznets relationships as observed in the GEOM pooled cross-section in graphs analogous to Figure 2. Figure 7 contains the full 192 observations from that dataset, once again with absolute IOp in the top row and relative IOp in the bottom. All four panels reveal clearly discernible ∩-shapes. These are a little less pronounced (have a lower second derivative) for the parametric curves, because the more rigid quadratic functional form, when imposed over the entire span of the data, is unable to detect that the inverted-U seems to end around USD18,000 per capita, as shown by the non-parametric estimates.

Figure 7: Cross-sectional opportunity Kuznets curves on pooled GEOM data

(a) Absolute IOp, non-parametric fit (b) Absolute IOp, parametric fit



(c) Relative IOp, non-parametric fit (d) Relative IOp, parametric fit



Note: pooled cross-section data.

Source: elaboration on GEOM and IMF data.

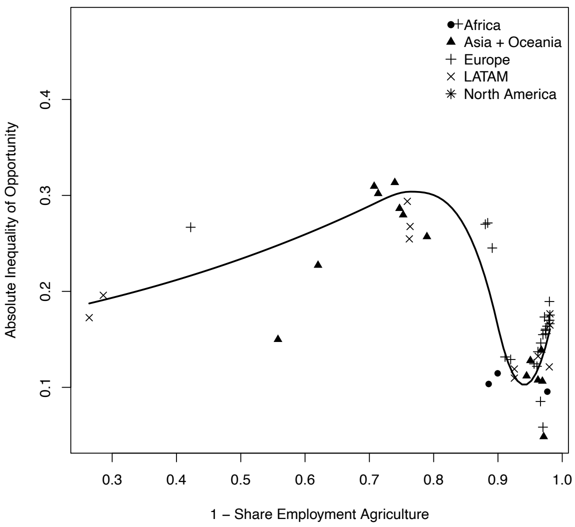
For the more flexible non-parametric fits, the opportunity Kuznets curve looks like a ∩ with an L attached, consistent with what one would observe if countries followed similar development paths to one another and those now richer than USD18,000 per capita had completed a process of migration of economic activity from a less-productive to a more-productive sector.

Next, just as Figure 3 did for the income Kuznets curve, Figure 8 uses the share of workers employed in the agricultural sector (top four panels) or of agriculture value-added in GDP (bottom four panels) as inverse proxies for development, replacing GDP per capita. Here too we see interesting patterns that suggest the existence of a Kuznets IOp curve. Figure A4 in the Appendix contains analogous graphs—also both for absolute and relative IOp—for the employment and value-added shares of the manufacturing and services sectors. Unlike the Kuznets curve graphs in Figure A4, those graphs in Figure 8 do display relatively clear inverted-U patterns, hence supporting the picture obtained from agriculture below.

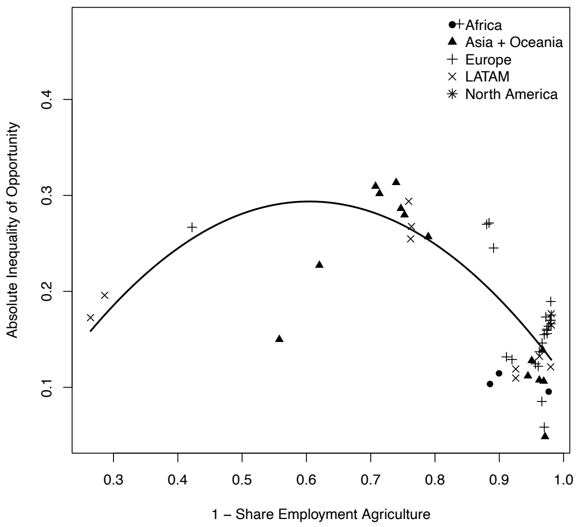
Figure 8: Opportunity Kuznets curves when development is proxied by (inverse) agricultural shares: employment and valued added

(a) Absolute IOp, non-parametric fit (employment agriculture)

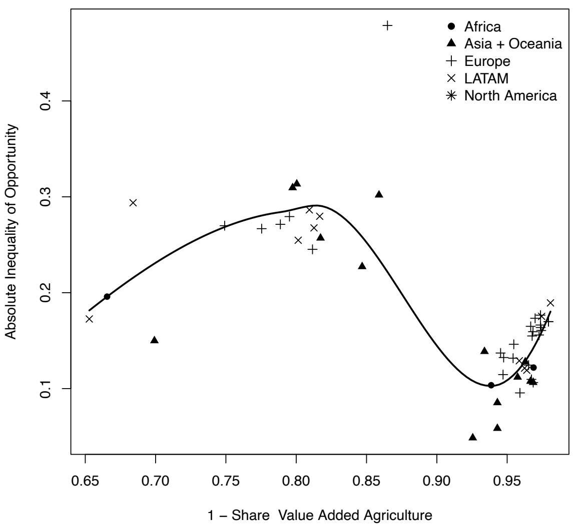
(b) Absolute IOp, parametric fit (employment agriculture)



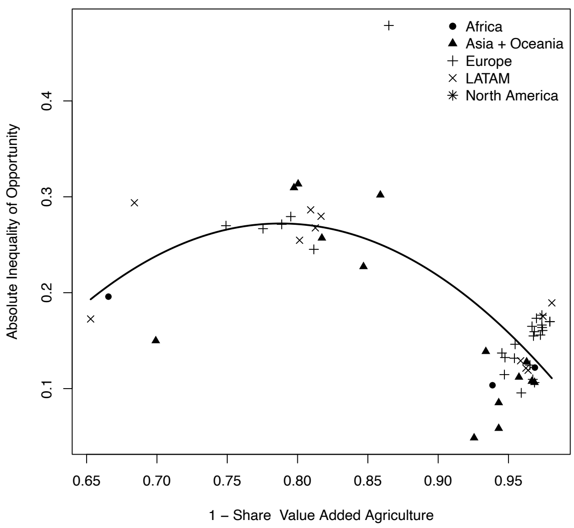
(c) Absolute IOp, non-parametric fit (value-added agriculture)



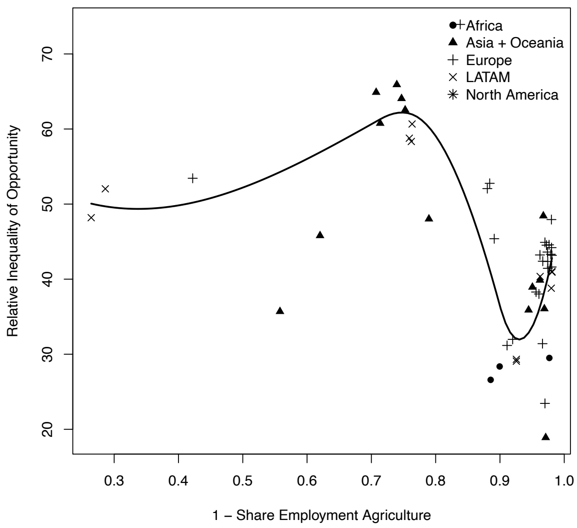
(d) Absolute IOp, parametric fit ((value-added agriculture)



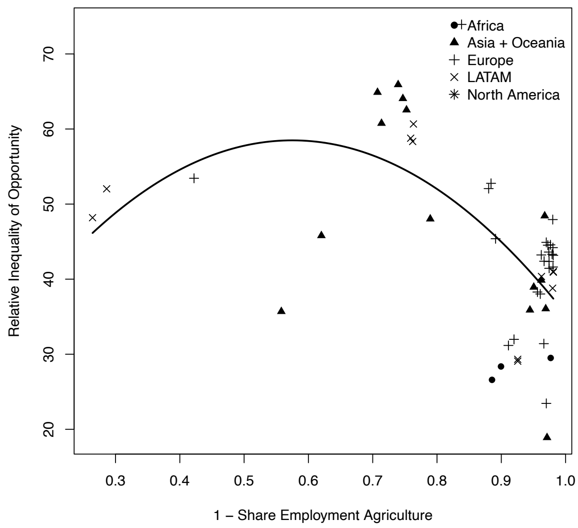
(e) Relative IOp, non-parametric fit (employment agriculture)



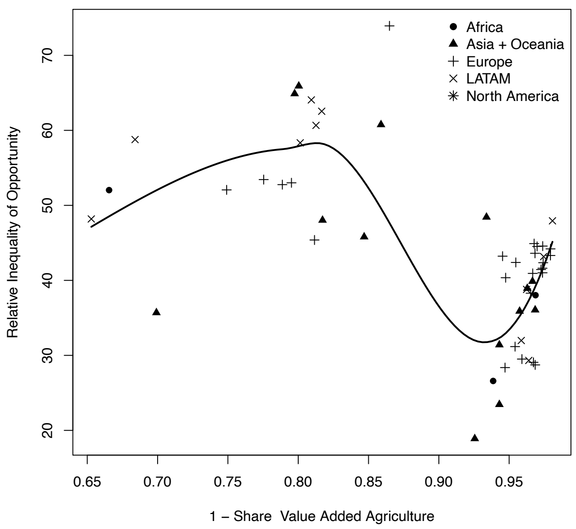
(f) Relative IOp, parametric fit (employment agriculture)

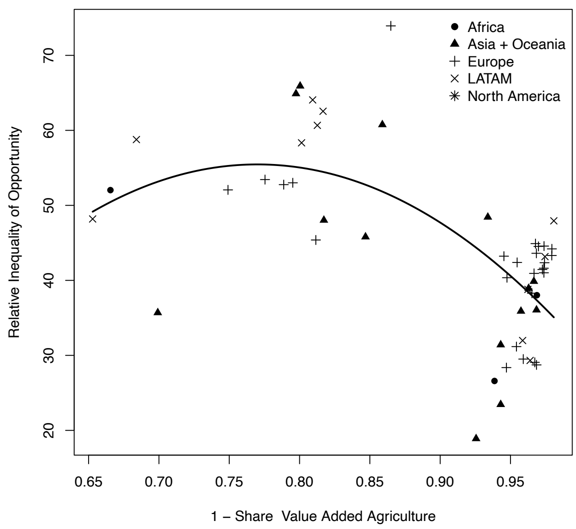


(g) Relative IOp, non-parametric fit (value-added agriculture)



(h) Relative IOp, parametric fit (value-added agriculture)





Note: pooled cross-section data.

Source: elaboration on GEOM and ten-sector (Timmer et al. 2015) data.

3.5 Some additional robustness

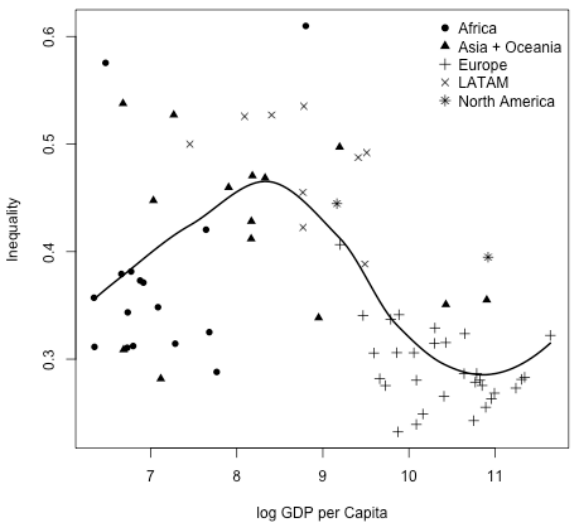
The evidence presented so far appears to be broadly supportive of the existence of an opportunity Kuznets curve, at least in the global cross-section of countries. This is consistent both with the discussion in Section 2 and with the combination of an income Kuznets curve and a Great Gatsby curve in the same cross-section.

Given data restrictions, we are only able to look for similar curves in country-specific time series for one country, namely the USA, for which we have data from 1980 to 2014. Those time-series data display a clear Great Gatsby curve. The income Kuznets curve is less clearly visible, although there is a hint of it in the curvature of the non-parametric plot at the higher levels of GDP per capita. Nonetheless, the pattern is sufficient to translate into quite marked opportunity Kuznets curves for the USA, particularly when relative IOp is used.

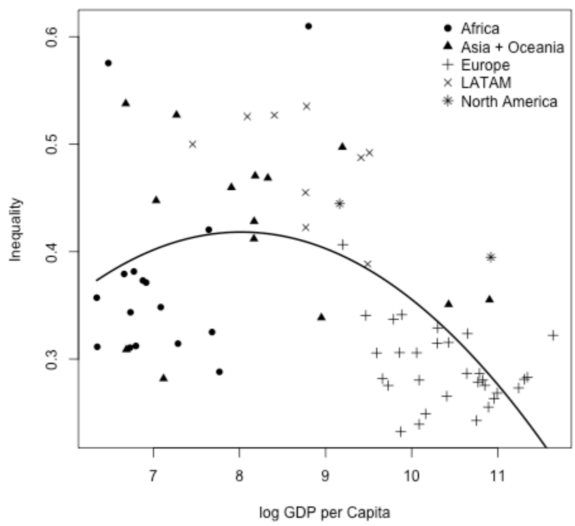
To end this empirical section by way of a brief ‘robustness analysis’, we look at two additional sets of figures for the three sides of the income-IOp-growth triangle. The first set, in Figure 9, contains eight graphs: non-parametric and quadratic fits for standard Kuznets curves, Great Gatsby curves, and opportunity Kuznets curves, for both absolute and relative measures. This analysis revisits the cross-country GEOM data, but replaces the pooled cross-section with a simple cross-section, using only the latest observation for each county.

Figure 9: Cross-sectional Kuznets curves on latest-year GEOM data

(a) Kuznets Curve, non-parametric fit

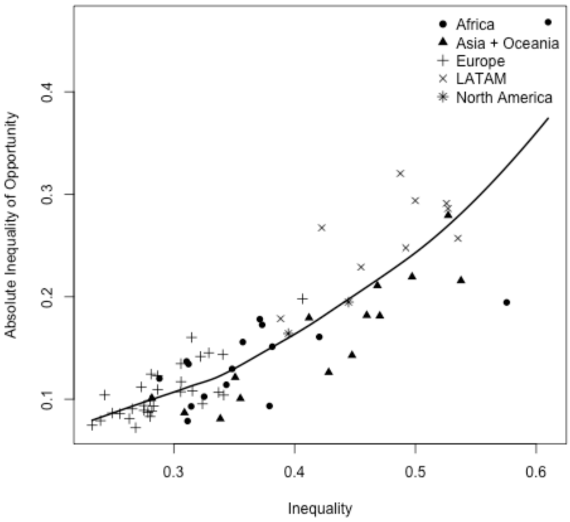


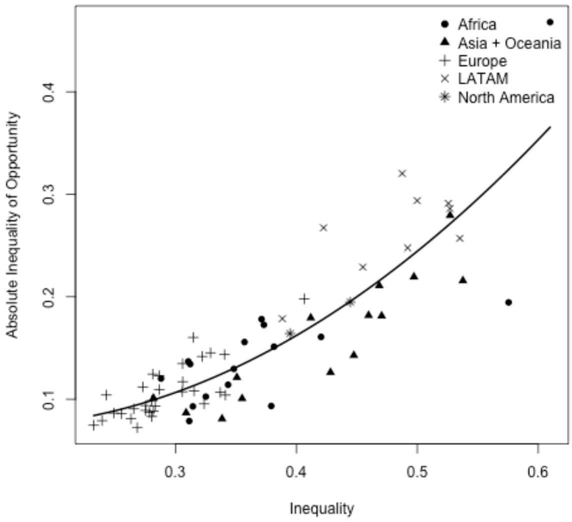
(b) Kuznets Curve, parametric fit



(c) Gatsby Curve, non-parametric fit

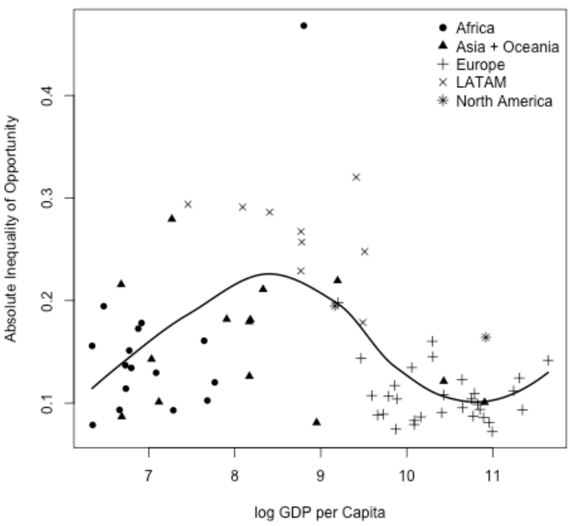
(d) Gatsby Curve, parametric fit

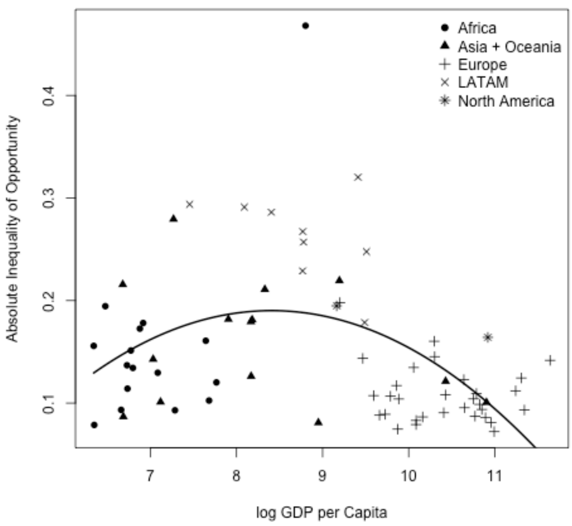




(e) Opportunity Kuznets Curve, non-parametric fit, Absolute IOp

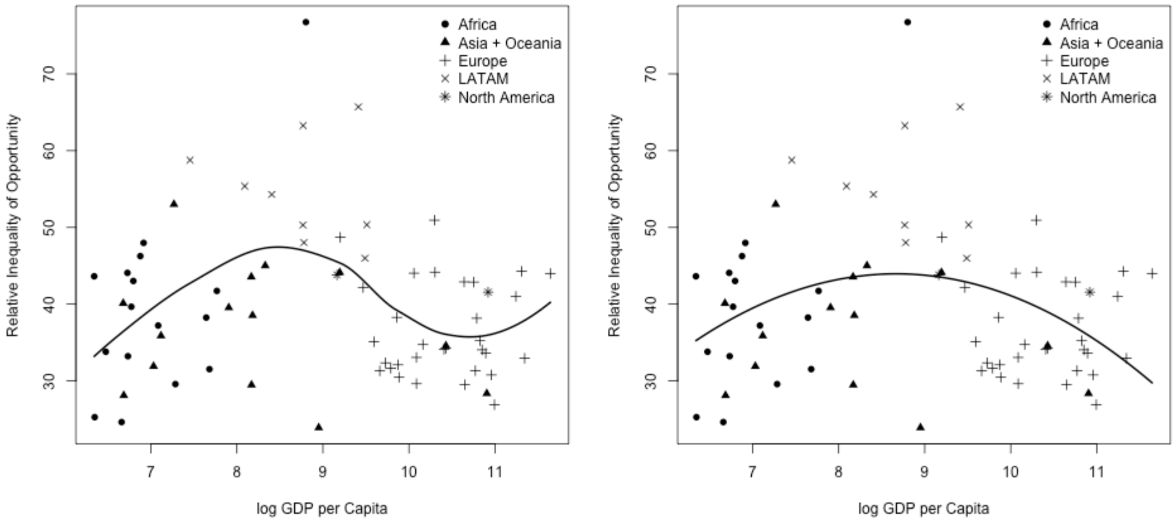
(f) Opportunity Kuznets Curve, parametric fit, Absolute IOp





(g) Opportunity Kuznets Curve, non-parametric fit, Relative IOp

(h) Opportunity Kuznets Curve, parametric fit, Relative IOp



Note: inequality and IOp estimates refer to the last available observations from the GEOM data.

Source: elaboration on GEOM and IMF data.

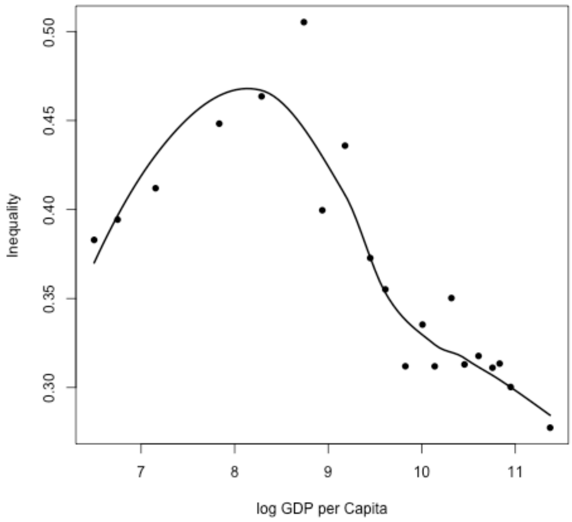
The use of this smaller, single cross-section sample does not meaningfully alter the main results discussed earlier. All three sets of curves—including the absolute and relative opportunity Kuznets curves—are still clearly distinguishable. As before, the non-parametric graphs suggest an inverted-U that ends strictly inside the support for per capita GDP, with a flat line or, in this case, even an upward-sloping segment for the highest income levels. The quadratic pictures still show 'well-behaved' Kuznets pictures.

Our second set of 'robustness graphs' mimics the previous one but is based on a binned scatter plot. We divide the horizontal axis in 20 intervals and plot the average inequality or IOp within each bin.[15] Interestingly, by reducing the noise, the binned scatterplot display sharper Kuznets dynamics.

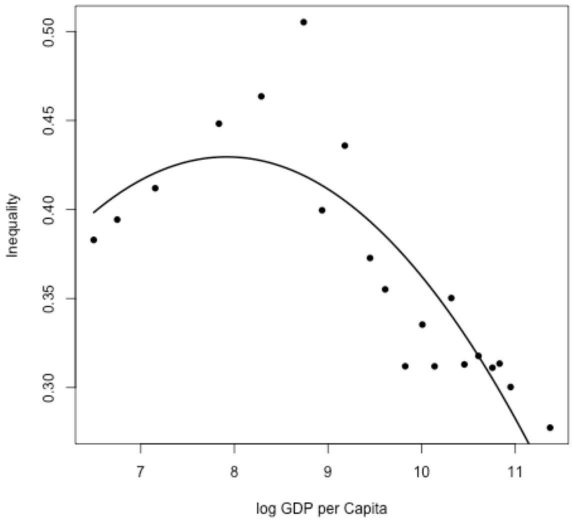
Figure 10: Cross-sectional Kuznets curves on GEOM data (binned scatterplots)

(a) Kuznets Curve, non-parametric fit (b) Kuznets Curve, parametric fit

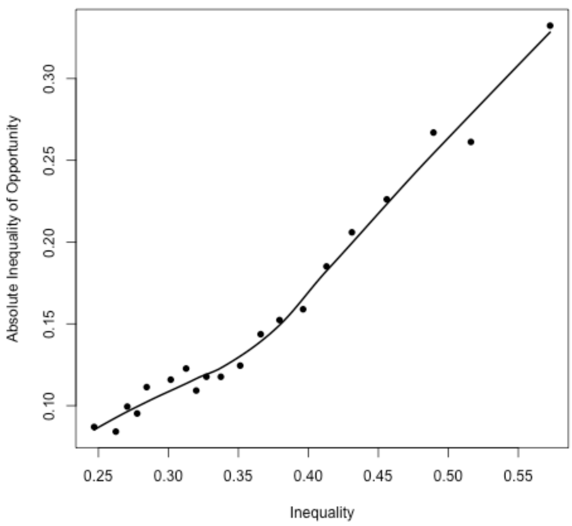
[15] When plotting the Kuznets curves, each country-year approximates a specific level of development. To prevent populated economies from influencing our result, country-year observations are equally weighted. A version of Figure 10 where countries are weighted by the population size is available upon request.

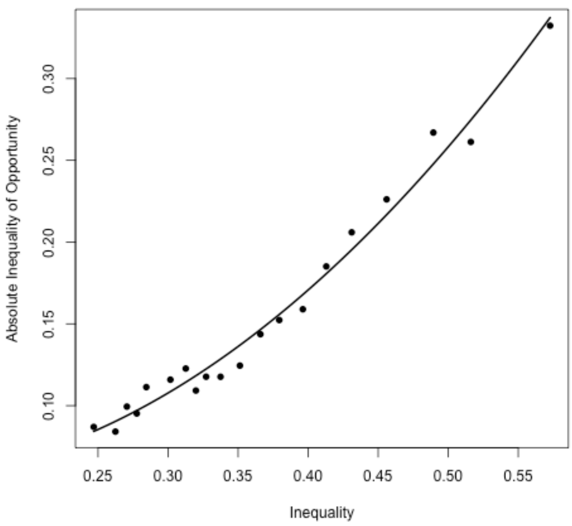


(c) Gatsby Curve, non-parametric fit

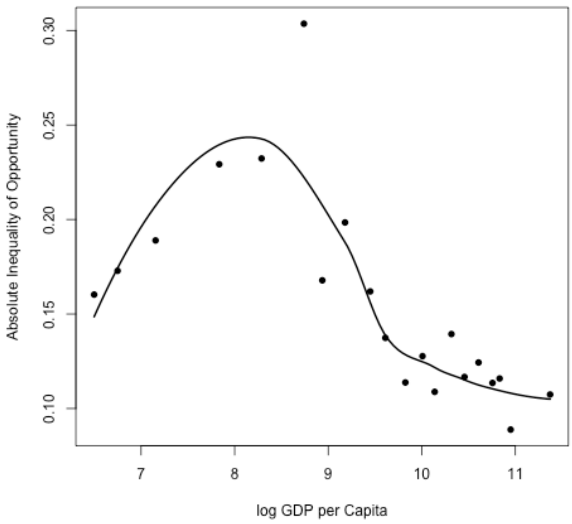


(d) Gatsby Curve, parametric fit

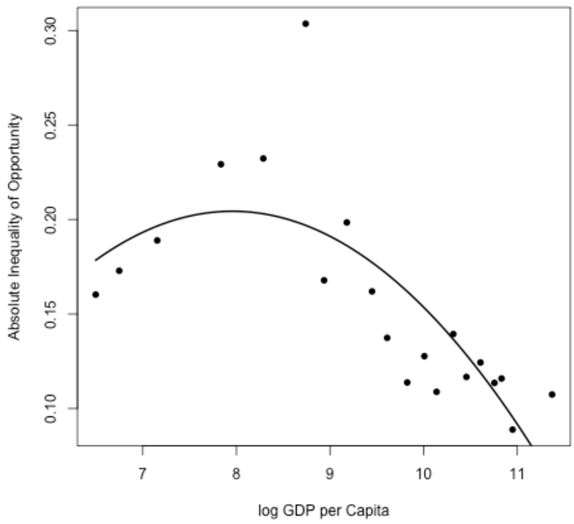




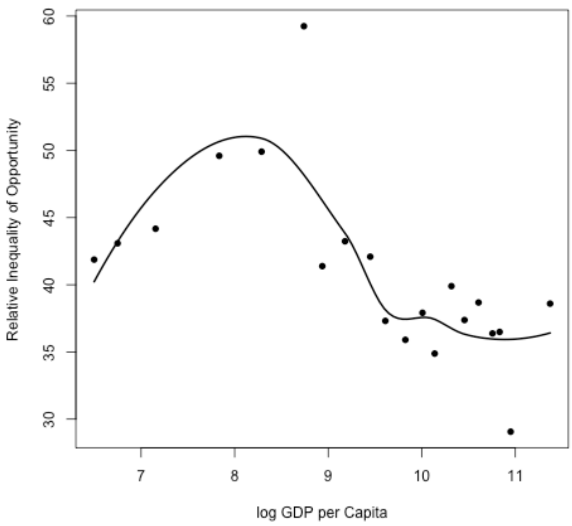
(e) Opportunity Kuznets Curve, non-parametric fit, Absolute IOp



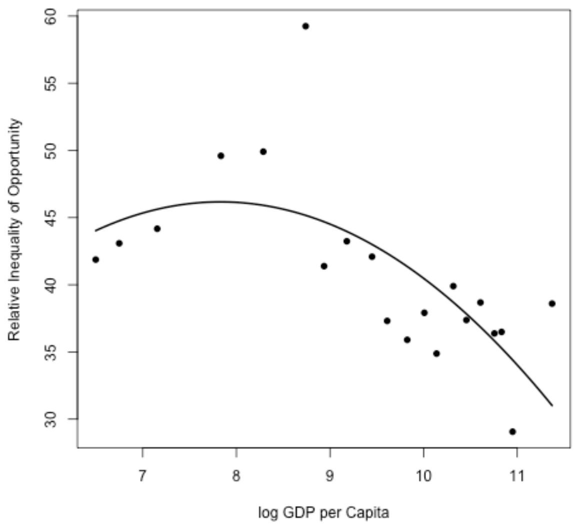
(f) Opportunity Kuznets Curve, parametric fit, Absolute IOp



(g) Opportunity Kuznets Curve, non-parametric fit, Relative IOp



(h) Opportunity Kuznets Curve, parametric fit, Relative IOp



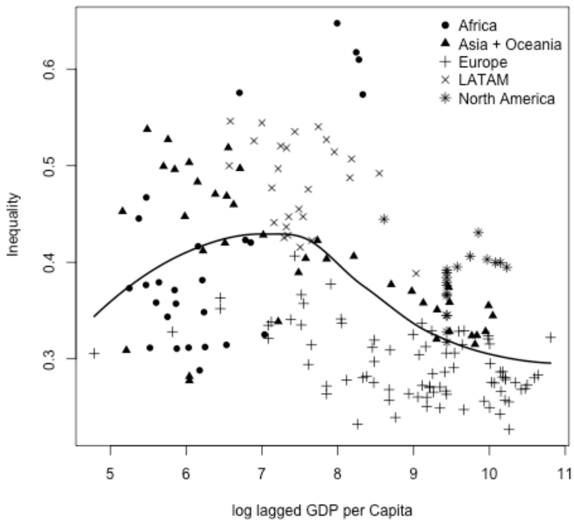
Note: pooled cross-section data, binned scatteplot.

Source: elaboration on GEOM and IMF data.

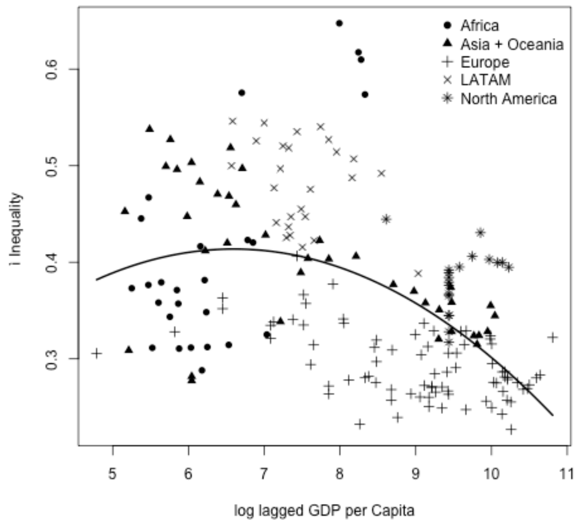
A third set of robustness graphs replaces current with lagged GDP. Assuming that there is a 20 years gap between the moment in which parents and children enter the job market, Figure 11 plots inequality and IOp against log GDP from 20 years before.

Figure 11: Kuznets curves with lagged GDP.

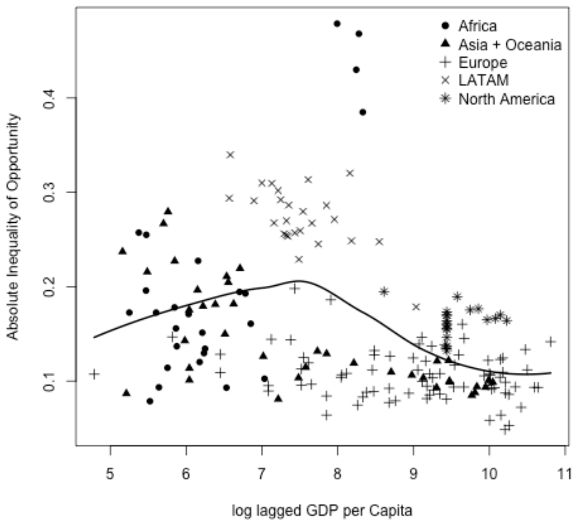
(a) Kuznets Curve, non-parametric fit



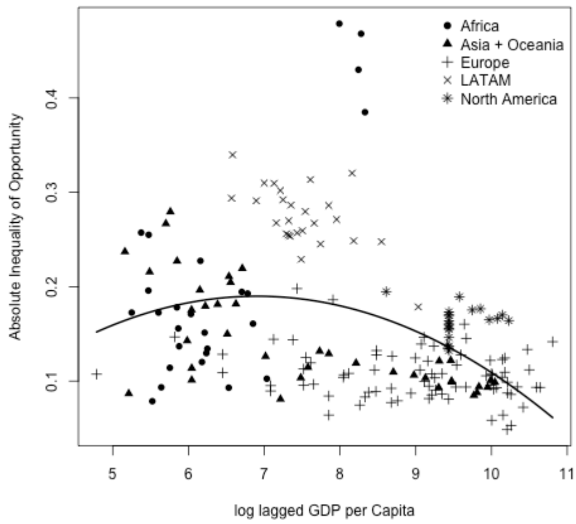
(b) Kuznets Curve, parametric fit



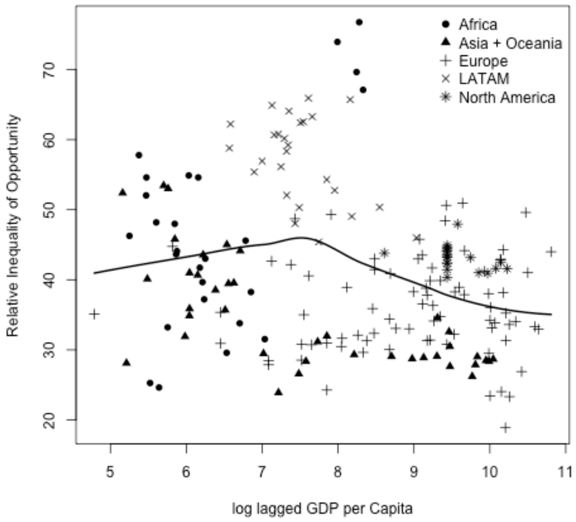
(c) Opportunity Kuznets Curve, non-parametric fit, absolute IOp



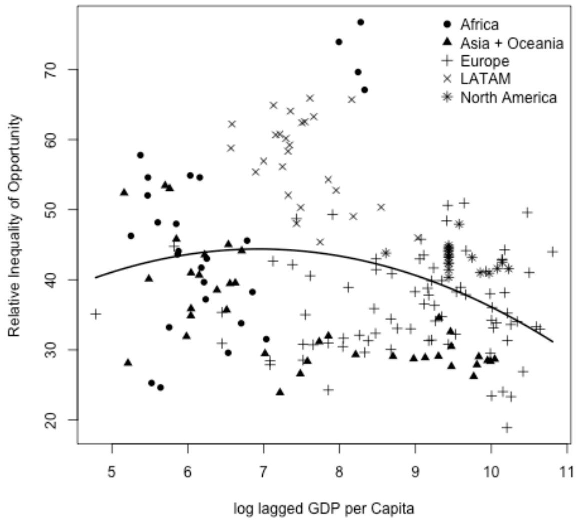
(d) Opportunity Kuznets Curve, parametric fit, absolute IOp



(e) Opportunity Kuznets Curve, non-parametric fit, relative IOp



(f) Opportunity Kuznets Curve, parametric fit, relative IOp



Note: pooled cross-section data with GDP per capita from 20 years before.

Source: elaboration on GEOM and IMF data.

This robustness check, in particular panels (c) and (d), shows a weaker yet clear inverted-U shape in line with our Opportunity Kuznets curve hypothesis.

4 Conclusions

Although the empirical status of the original Kuznets (1955) hypothesis is far from established in *time-series* data for individual countries, the famous inverted-U relationship between inequality and 'development' that it postulates has become a powerful, highly influential stylized fact in development economics ever since. This is, at least in part, because something very much like that curve is in fact observed in the *cross-section* of countries—with a range of middle-income countries displaying higher income inequality levels than both poorer and richer nations.

We set out to ask whether a similar relationship might exist—whether in the time series or the cross-section—between IOp and economic development. As is now standard, we understand IOp as that part of inequality which is attributable to factors beyond the control of individuals, typically measured as the inequality that can be predicted by inherited circumstances.

Our question was motivated in part by another cross-country empirical regularity, namely the positive association between income inequality, on the one hand, and intergenerational persistence (whether measured by IOp or by the inverse of intergenerational mobility), on the other: the so-called Great Gatsby curve. Abstracting from variations around the fitted lines, if both the income Kuznets curve and the Great Gatsby curve were present in a given dataset—that is, if IOp and income inequality moved together, and the latter displayed an inverted-U as countries developed—then we would expect IOp to display a similar pattern: an opportunity Kuznets curve.

We argue that the existence of an opportunity Kuznets curve may not only be a mechanical consequence of the above empirical regularities. Rather, it can be the result of the combined effect of intergenerational mobility, economic growth and inequality, under the assumption that opportunities generated by economic development are heavily influenced by inherited circumstances. We then discuss influential results in the growth and inequality literatures that support our hypothesis of an opportunity Kuznets curve.

We use the GEOM database, which contains 192 estimates of inequality of both income and opportunity for 72 countries, to investigate our hypothesis empirically. First, we document that income Kuznets curves and Great Gatsby curves are indeed observed in the global cross-section. We also find evidence in support of opportunity Kuznets curves on the same data, which are robust across various specifications, including moving between pooled data and a single cross-section, using lagged GDP values, or using agricultural employment and value-added shares as alternative proxies of the stage of development. There is even fairly strong support for opportunity Kuznets curves in the time-series data for the USA in the 1980–2014 period, even though the other two sides of the income inequality-IOp-development triangle are less clearly visible in that data.

These findings are broadly consistent with the view that IOp is an important component of overall income inequality. They complement earlier findings in the literature that higher levels of IOp may retard economic growth and are certainly aligned with the opportunity Great Gatsby curve, first documented by Brunori et al. (2013).

We would be cautious, however, in inferring f that the opportunity Kuznets curve or, for that matter, the original Kuznets curve, represents an automatic, self-correcting mechanism which ensures that high inequality is an inherently transitory phenomenon. Indeed, the US time series provides an interesting example of a country where an opportunity Kuznets curve is present alongside a clear upward trend in inequality over time.

It is true that, if the original Kuznets hypothesis operates through the sectoral dynamics that feature in our model—and in predecessors at least as far back as Lewis (1954)—then there *is* an element of automatic inequality reduction as migration to a new sector is completed. But if development is indeed better characterized as a sequence of Kuznets waves, as Milanovic (2016) suggested, rather than by a single curve, then that element may provide scant ground for optimism, particularly if new sectors are, as in the original models, marked by higher within-sector inequality. If that were the case, then the lower levels of inequality that we observe in the global cross-section may reflect active redistributive policy choices in richer countries in Europe, Japan, and Canada. These would be consistent with another longstanding stylized fact of development economics, namely Wagner's Law. But that lies beyond our current scope in this paper.

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Appendix

Table A1 contains some key summary statistics for the 72 countries covered by the GEOM database, which were used in the main text.

Table A1: Summary statistics for all countries in the cross-sectional analysis

Country	Number of waves	Latest year	GDP per capita (latest year)	Income Gini (latest year)	Relative IOP % (latest year)
Argentina	1	2014	13,209	0.388	46.0
Armenia	1	2016	3,524	0.412	43.6
Australia	8	2019	54,391	0.355	28.4
Austria	3	2019	50,192	0.28	35.2
Belgium	3	2019	46,783	0.243	42.9
Benin	1	2018	1,194	0.348	37.2
Bolivia	1	2008	1,729	0.5	58.8
Brazil	1	2014	12,231	0.488	65.7
Bulgaria	2	2019	9,910	0.406	48.7
Burkina Faso	1	2018	780	0.379	24.6
Chile	5	2015	13,494	0.492	50.3
China	5	2018	9,849	0.497	44.1
Colombia	1	2010	6,499	0.535	48.0
Croatia	1	2011	14,659	0.306	35.1
Cyprus	3	2019	29,626	0.315	50.9
Czech Rep.	3	2019	24,013	0.239	33.1
Denmark	3	2019	59,490	0.268	26.9
Ecuador	2	2014	6,422	0.455	50.3
Estonia	3	2019	24,024	0.28	29.6
Finland	3	2019	48,396	0.287	38.2
France	3	2019	41,831	0.286	42.9
Gambia	1	2015	650	0.576	33.8
Georgia	1	2016	4,142	0.469	45.0
Germany	3	2019	47,629	0.279	31.3
Ghana	2	2017	2,087	0.42	38.2
Greece	3	2019	19,141	0.306	38.3
Guatemala	3	2011	3,265	0.526	55.4
Guinea Bissau	1	2018	895	0.312	43.0
Hungary	3	2019	16,782	0.275	32.4
Iceland	1	2005	57,406	0.263	30.8
India	2	2012	1,434	0.527	53.0
Indonesia	2	2014	3,533	0.428	29.5
Ireland	3	2019	81,506	0.281	44.3
Italy	3	2019	33,767	0.315	34.2
Ivory Coast	1	2018	2,167	0.325	31.5
Kazakhstan	1	2016	7,715	0.338	23.9
Kyrgyzstan	1	2016	1,132	0.448	31.9
Latvia	3	2019	17,828	0.337	31.7
Lithuania	3	2019	19,624	0.341	30.5
Luxembourg	3	2019	113,860	0.322	44.0

Malawi	1	2020	568	0.357	43.6
Mali	1	2019	840	0.344	33.2
Malta	2	2019	33,106	0.266	34.1
Mexico	1	2017	9,543	0.445	43.8
Mongolia	1	2016	3,575	0.47	38.5
Nepal	2	2011	795	0.538	40.1
Netherlands	3	2019	53,755	0.255	33.6
Niger	1	2018	571	0.311	25.3
Nigeria	1	2019	2,361	0.288	41.7
Norway	3	2019	76,304	0.273	41.0
Panama	1	2003	4,470	0.527	54.3
Peru	11	2015	6,436	0.422	63.3
Poland	3	2019	15,695	0.282	31.3
Portugal	3	2019	23,333	0.306	44.0
Romania	2	2019	12,928	0.341	42.2
Senegal	1	2018	1,459	0.314	29.6
Sierra Leone	2	2018	835	0.311	44.1
Slovakia	3	2019	19,397	0.232	32.1
Slovenia	3	2019	25,910	0.249	34.7
South Africa	4	2017	6,647	0.61	76.7
South Korea	11	2019	33,827	0.351	34.6
Spain	3	2019	29,798	0.329	44.2
Sweden	1	2019	51,529	0.276	34.0
Switzerland	2	2019	84,481	0.283	32.9
Tajikistan	1	2016	801	0.309	28.1
Tanzania	3	2013	970	0.373	46.3
Timor Leste	2	2014	1,234	0.282	35.9
Togo	1	2018	874	0.382	39.7
Uganda	4	2014	1,008	0.371	48.0
United Kingdom	2	2011	42,107	0.324	29.5
USA	18	2014	55,264	0.395	41.6
Uzbekistan	1	2016	2,713	0.46	39.5

Note: GDP per capita expressed in US dollars at market.

Source: income Gini and relative IOp from GEOM data.

Table A2 reports the coefficients of the quadratic fit in the main figures.

Table A2: Coefficients of the quadratic fit, development expressed as log of per capita GDP

Figure in the text:	Fig.2 (b)	Fig. 7 (b)	Fig. 7 (d)	Fig.1 (b)	Fig. 6 (b)	Fig. 6 (d)
Countries:	All	All	All	USA	USA	USA
	Ineq.	Abs. IOp	Rel. IOp	Ineq.	Abs. IOp	Rel. IOp
(Intercept)	-47.849**	-50.647***	-19.767	-305.830	-331.416***	-497.266**
	(20.411)	(18.593)	(28.368)	(174.520)	(99.742)	(222.354)
GDP per capita	23.158***	18.079***	17.157***	61.521*	65.796***	106.185**
	(4.676)	(4.259)	(6.498)	(34.196)	(19.544)	(43.569)
GDP per capita ^2	-1.475***	-1.148***	-1.114***	-2.728	-3.105***	-5.207**
	(0.262)	(0.239)	(0.365)	(1.673)	(0.956)	(2.131)
R^2	0.346	0.272	0.159	0.829	0.752	0.288
Note: * p < 0.1, ** p < 0.05, *** p < 0.01						

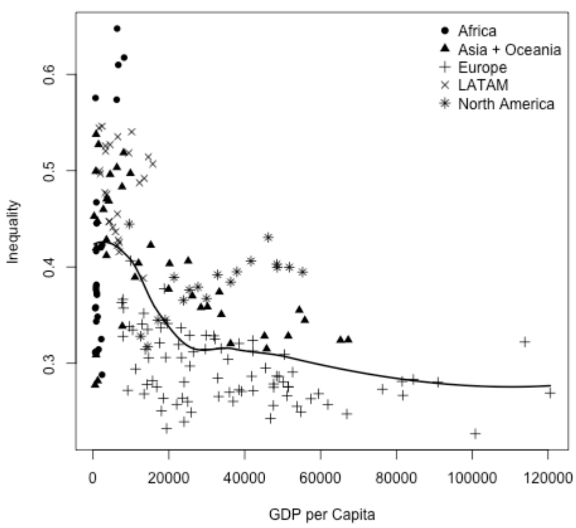
Note: GDP per capita expressed in US dollars at market.

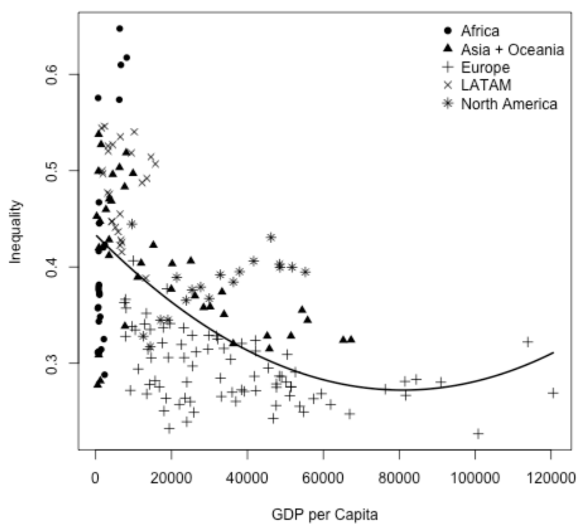
Source: income Gini and relative IOp from GEOM data.

Figure A1: (No) Kuznets curve when GDP per capita is in levels

(a) Kuznets Curve, non-parametric fit

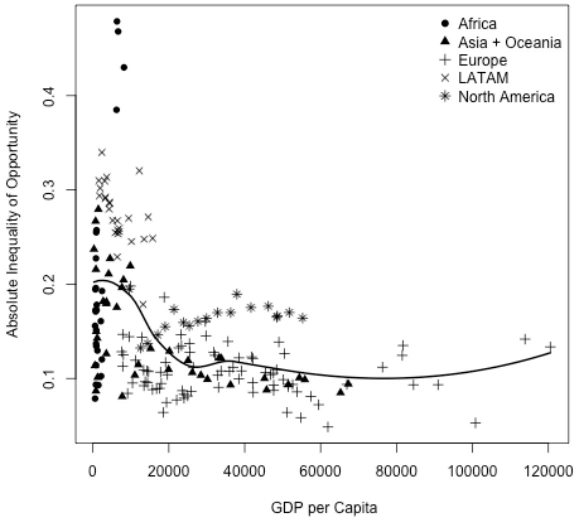
(b) Kuznets Curve, parametric fit

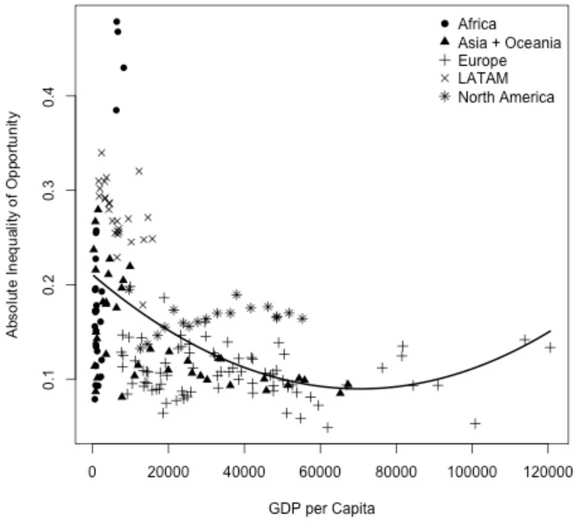




(c) Opportunity Kuznets Curve, non-parametric fit, absolute IOp

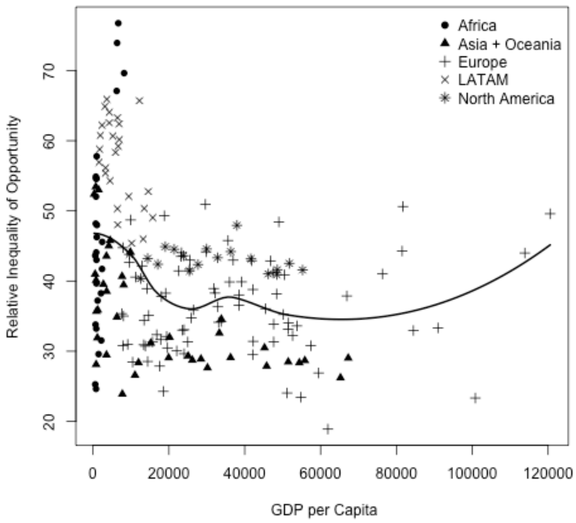
(d) Opportunity Kuznets Curve, parametric fit, absolute IOp

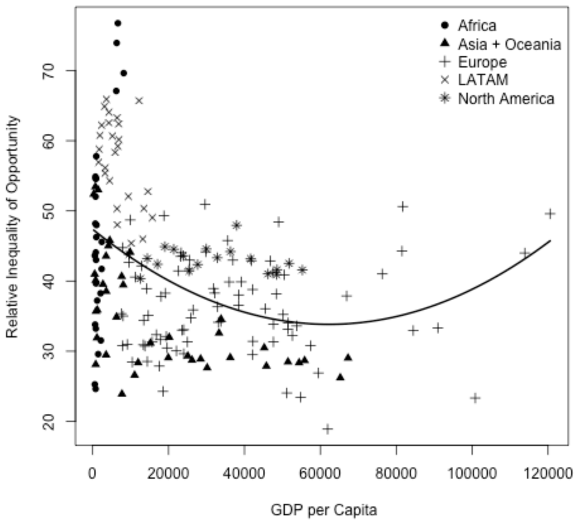




(e) Opportunity Kuznets Curve, non-parametric fit, relative IOp

(f) Opportunity Kuznets Curve, parametric fit, relative IOp



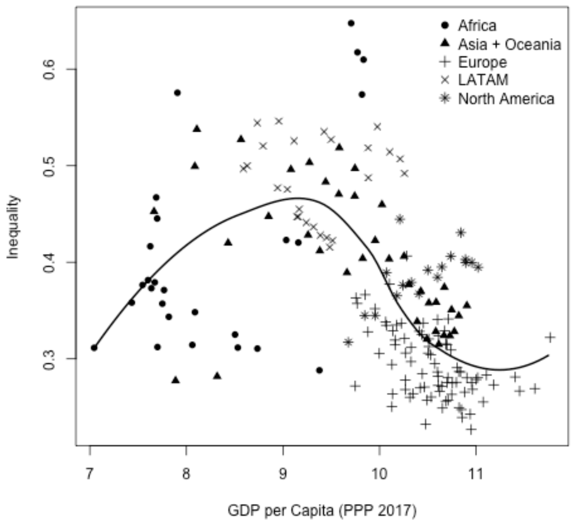


Note: pooled cross-section data.

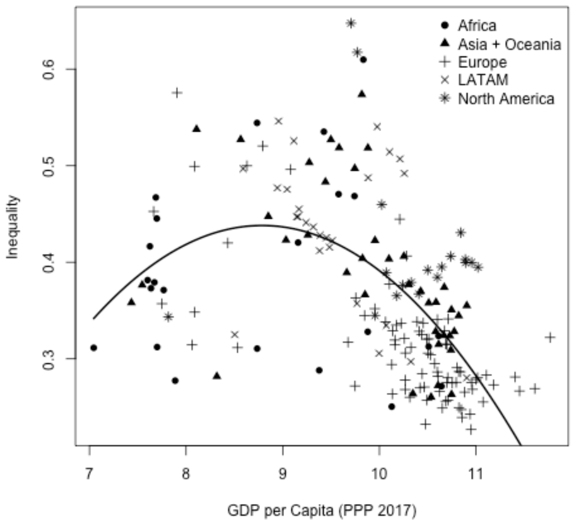
Source: elaboration on GEOM and IMF data.

Figure A2: Kuznets curves when GDP per capita is PPP adjusted.

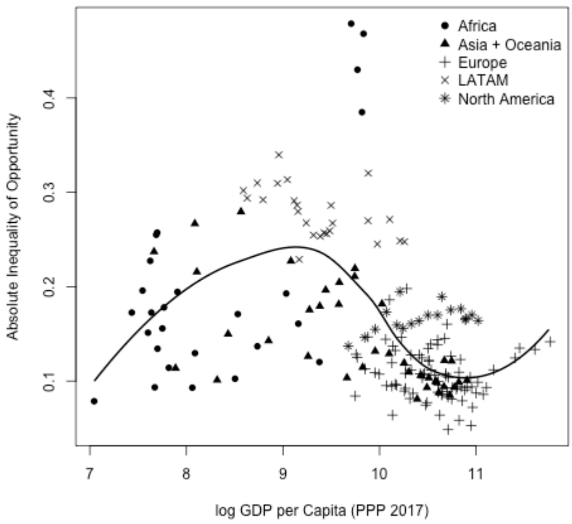
(a) Kuznets Curve, non-parametric fit



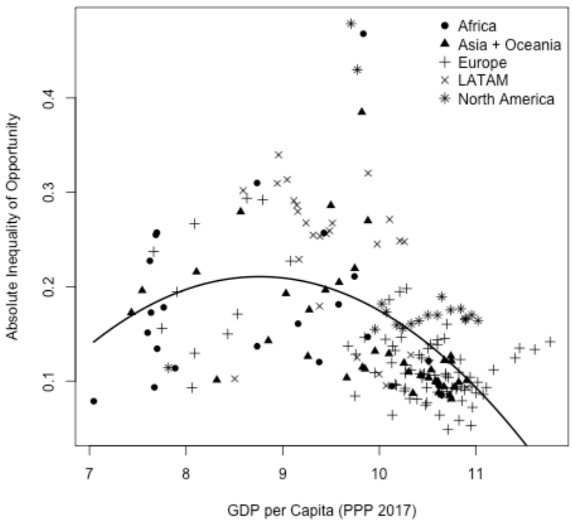
(b) Kuznets Curve, parametric fit



(c) Opportunity Kuznets Curve, non-parametric fit, absolute IOp

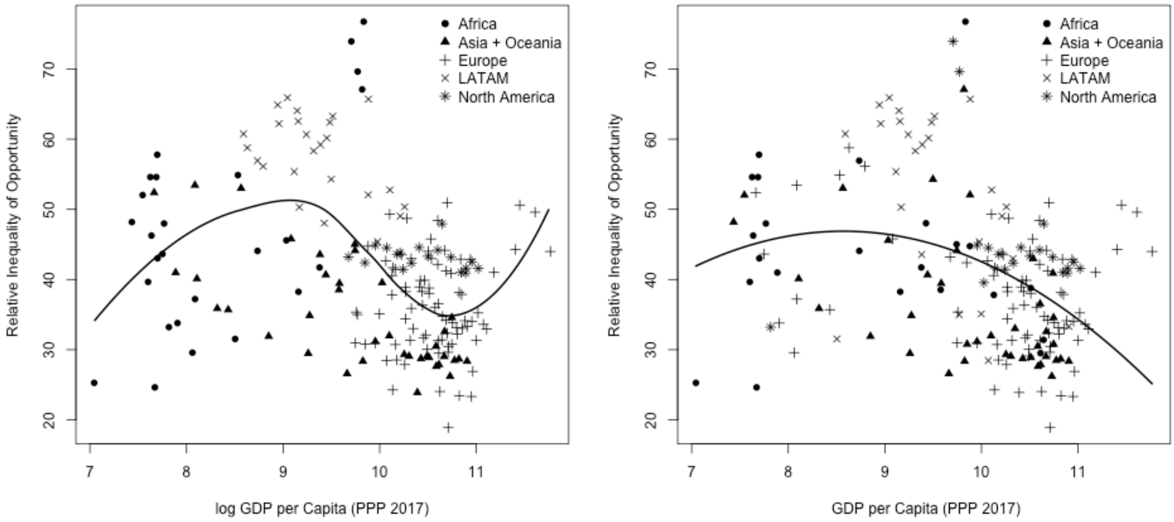


(d) Opportunity Kuznets Curve, parametric fit, absolute IOp



(e) Opportunity Kuznets Curve, non-parametric fit, relative IOp

(f) Opportunity Kuznets Curve, parametric fit, relative IOp

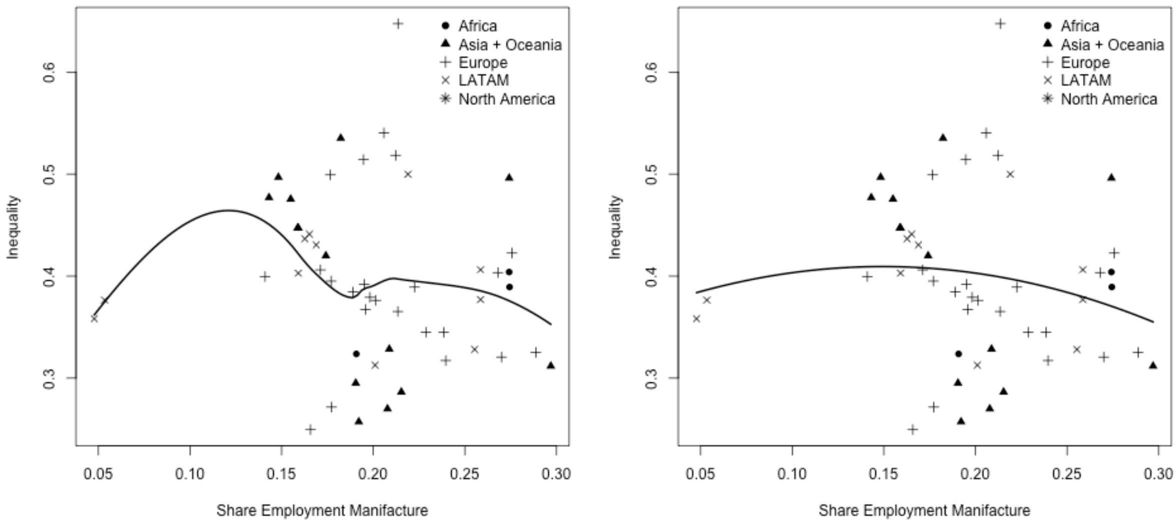


Note: pooled cross-section data. GDP per capita is adjusted at 2017 PPP.

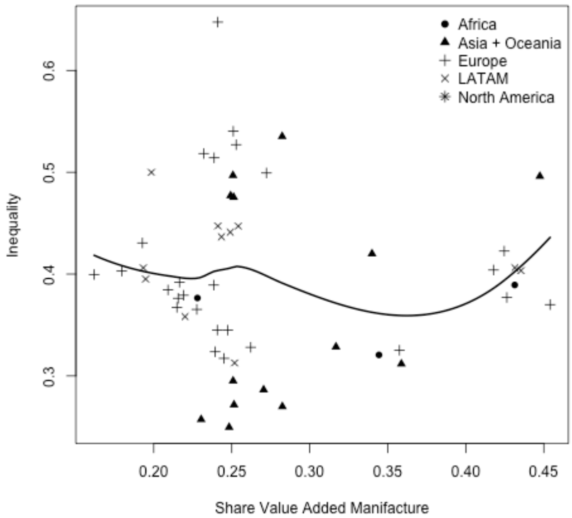
Source: elaboration on GEOM and IMF data.

Figure A3: 'Kuznets curves' when development is proxied by employment and valued-added shares in manufacturing and the service sectors

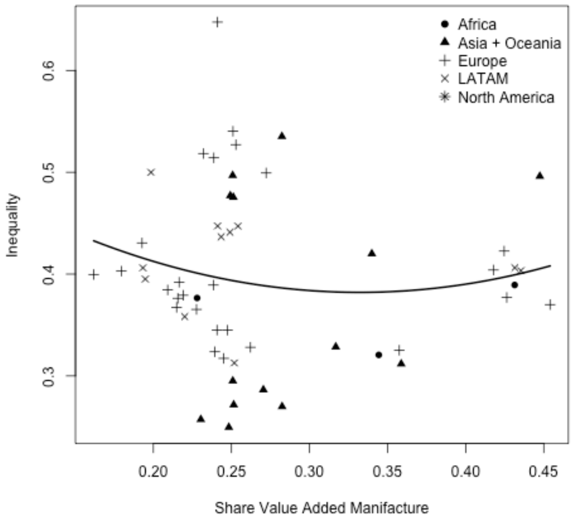
(a) Non-parametric fit (employment manufacture) (b) Parametric fit (employment manufacture)



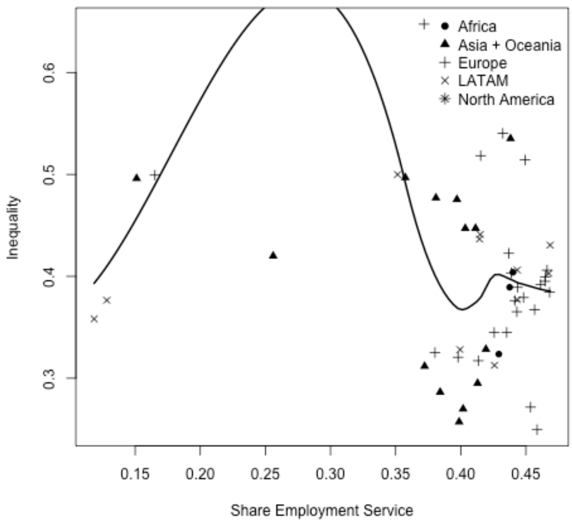
(c) Non-parametric fit (value-added manufacture) (d) Parametric fit (value-added manufacture)



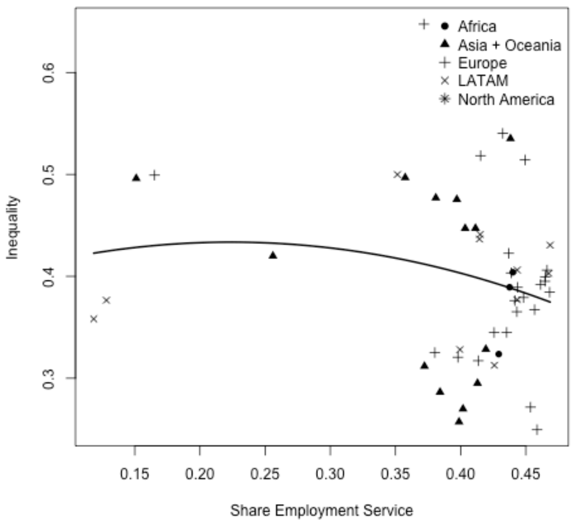
(e) Non-parametric fit (employment services)



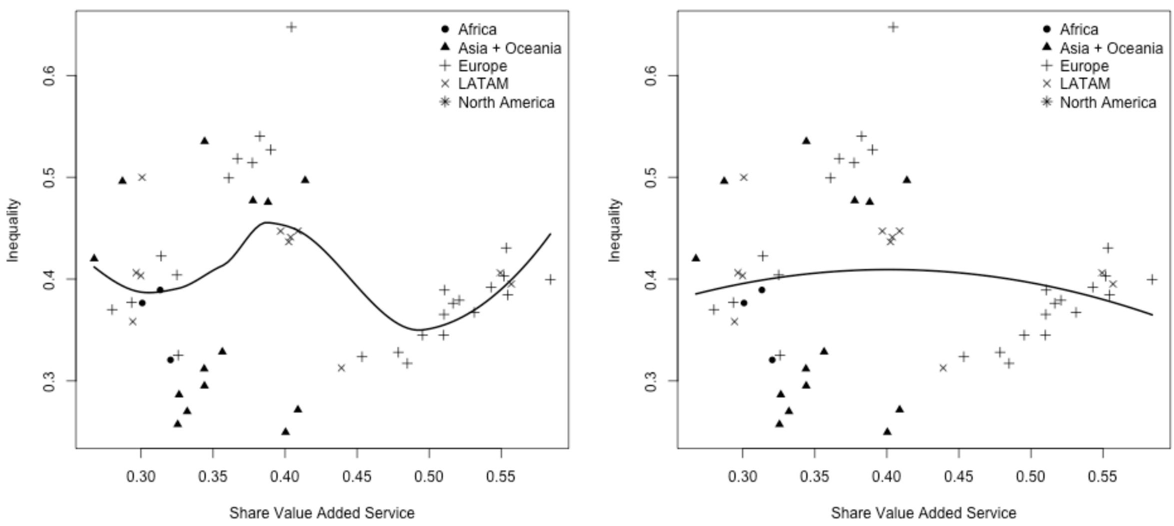
(f) Parametric fit (employment services)



(g) Non-parametric fit (value-added services)



(h) Parametric fit (value-added services)

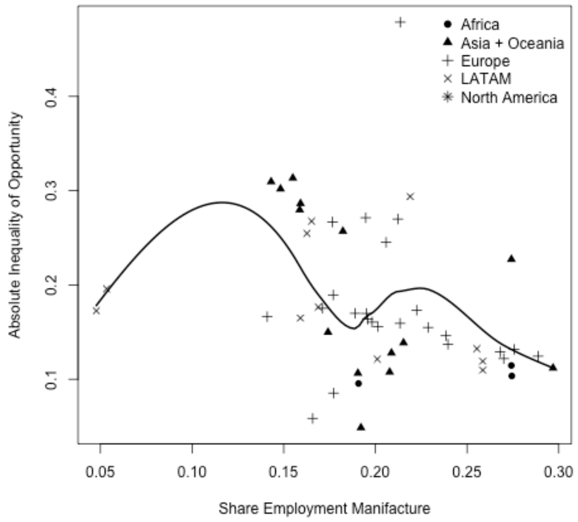


Note: pooled cross-section data.

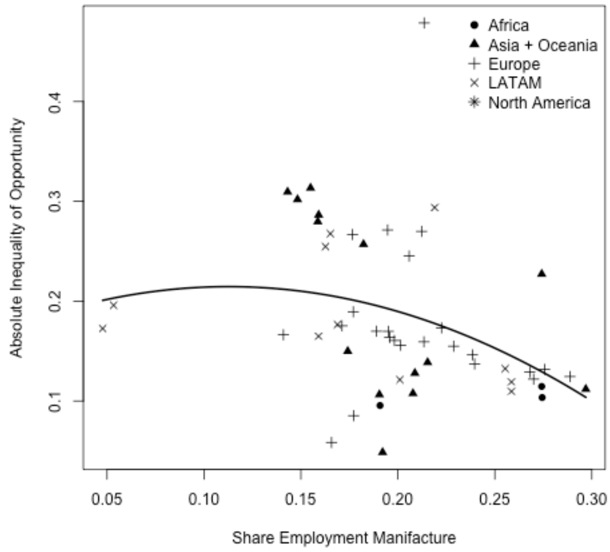
Source: elaboration on GEOM and ten-sector (Timmer et al. 2015) data.

Figure A4: 'Opportunity Kuznets curves' when development is proxied by employment and valued-added shares in manufacturing and the service sectors

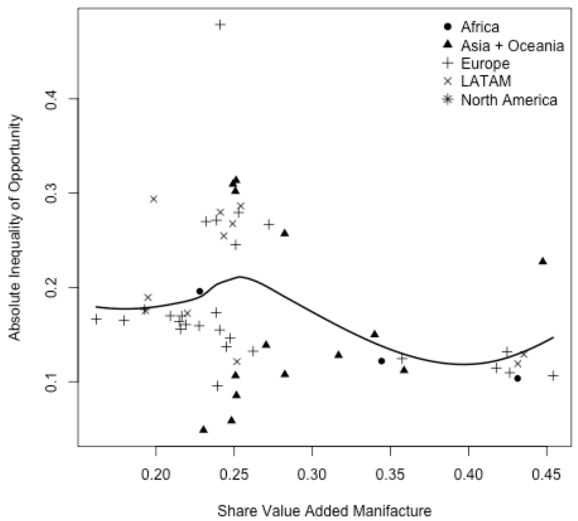
(a) Non-parametric fit (employment manufacture)



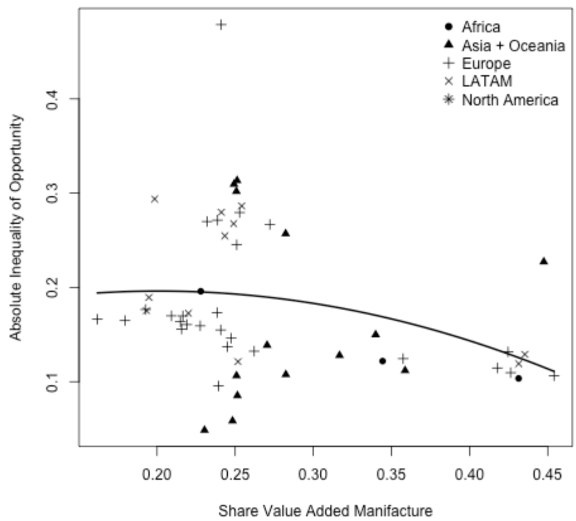
(b) Parametric fit (employment manufacture)



(c) Non-parametric fit (value-added manufacture)

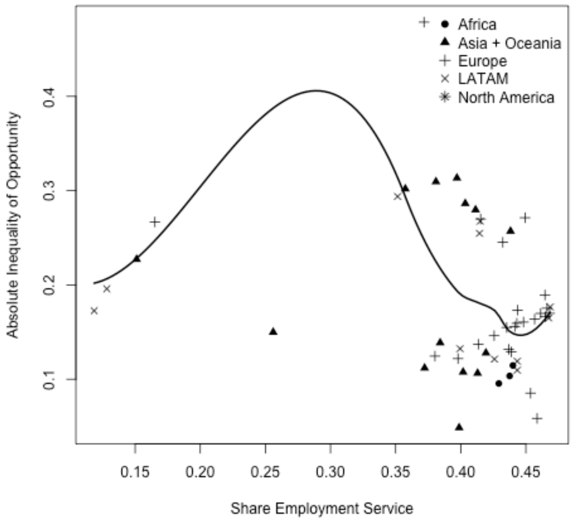


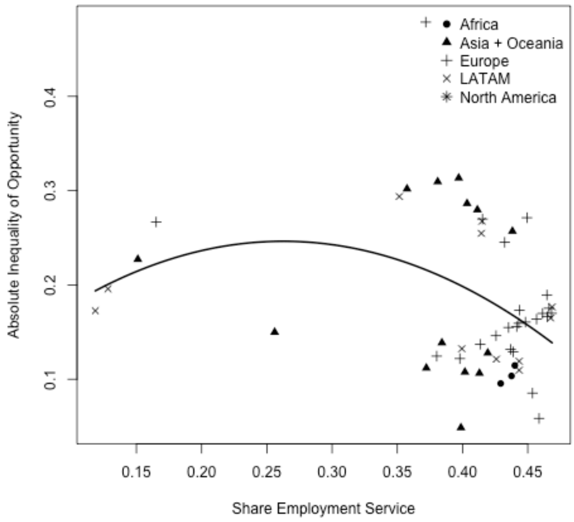
(d) Parametric fit (value-added manufacture)



(e) Non-parametric fit (employment services)

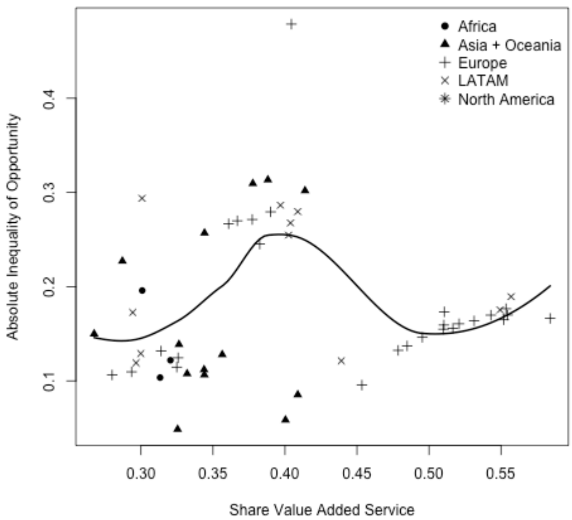
(f) Parametric fit (employment services)

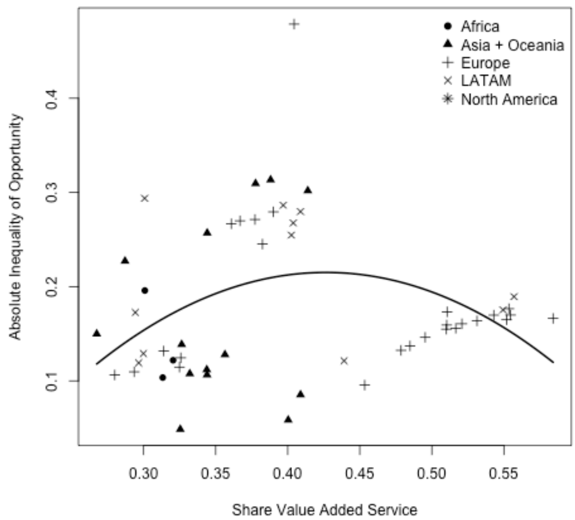




(g) Non-parametric fit (value-added services)

(h) Parametric fit (value-added services)





Note: pooled cross-section data.

Source: elaboration on GEOM and ten-sector (Timmer et al. 2015) data.