25/25

Economic development and inequality of opportunity

Kuznets meets the Great Gatsby?

Francisco H.G. Ferreira,[1] Domenico Moramarco,[2] and Vito Peragine[2]

April 2025

WIDER WORKING PAPER

wider.unu.edu

United Nations University
World Institute for Development Economics Research

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 propose a simple theoretical model that links the three concepts and describes two possible mechanisms. A numerical simulation based on the model illustrates the process. 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

JEL classification: D31, D63, O15

Correction: An error in the ISBN displayed below was corrected on 19 September 2025.

[1] International Inequalities Institute, London School of Economics, London, UK; [2] Deparment of Economics and Finance, University of Bari, Bari, Italy, **vitorocco.peragine@uniba.it**

This study is published within the UNU-WIDER project **Inequality and structural transformation – Kuznets at 70**, which is part of the **Reducing inequalities across and within countries** research area.

Information and requests: publications@wider.unu.edu

ISSN 1798-7237 ISBN 978-92-9267-582-0

https://doi.org/10.35188/UNU-WIDER/2025/582-0

United Nations University World Institute for Development Economics Research provides economic analysis and policy advice with the aim of promoting sustainable and equitable development. The Institute began operations in 1985 in Helsinki, Finland, as the first research and training centre of the United Nations University. Today it is a unique blend of think tank, research institute, and UN agency—providing a range of services from policy advice to governments as well as freely available original research.

The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland and Sweden, as well as earmarked contributions for specific projects from a variety of donors.

Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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.[1]

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 7.

More recently,[2] 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,

---

[1] 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).

[2] 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.

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 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.[3] 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 some contributions in the recent literature that have investigated the relationship between IOp and economic growth, with a focus on how IOp influences growth. Notably, Marrero and Rodríguez (2013) found 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 and Marrero and Rodríguez 2023).

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 7, 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 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

[3] 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.

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.

The remainder of this paper does two main things. First, in Section 2, we propose a very simple model of wealth distribution dynamics and growth, where inherited wealth plays a role in technology adoption. A numerical simulation based on our toy model generates both income and opportunity Kuznets curves. Second, in Section 3, 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 and country inclusion criteria. Section 4 concludes.

2 A simple theoretical framework

To illustrate a process whereby movement into a more-productive sector is selective on inherited circumstances, we rely on a simple consecutive generation framework with intergenerational transmission of wealth. Inherited wealth will be our circumstance variable, in that it affects a person's outcomes in life but is entirely beyond their control.

Let there be a continuum of agents (indexed by *i*) with initial wealth $w \sim G_0(w)$. Agents are identical except for their initial wealth and preferences for leisure. Agents live for a single period and maximize a standard warm-glow bequest motive utility function of own consumption and bequests (Andreoni 1989), with separable disutility of effort. The original, 'traditional' technology is strictly convex in labour and capital and assumed to be atomistic, with each individual producing alone, using their own labour supply and their own wealth as capital. There are no capital or labour markets. So, agents maximize:

$$U(c, b, l) = c^{\alpha} b^{1-a} - V_i(l) \quad s.t. \quad c + b \leq y \tag{1}$$

where $y = f(k, l)$, with $f_k, f_l > 0$ and $f_{kk}, f_{ll} < 0$. Note that the disutility of effort function $V_i(l)$ is agent specific. This is intended to accommodate the fact that, in an IOp framework, agents make different choices about their level of effort reflecting, at least in part, some personal freedom of responsibility.

Hence, the first-order condition of (1) with respect to *l*, $V_i'(l) = \lambda f_l(k, l)$, has different solutions across individuals, reflecting their personal degrees of 'effort', or disutility of labour supply.[4]

Given the Cobb–Douglas form of the preferences between consumption and bequests, the first-order condition with respect to *c* yields the well-known linear bequest function given by (2) below:

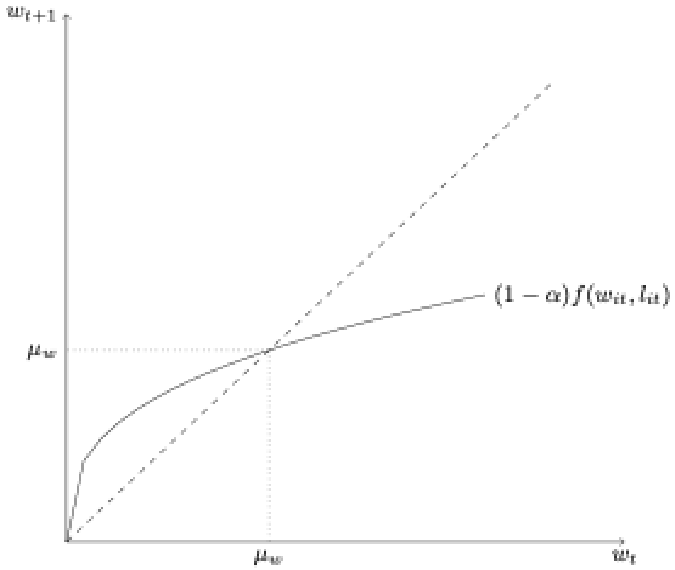
$$w_{t+1} = b_t = (1-\alpha)y_t \tag{2}$$

As there is no capital market, hence no lending, borrowing, or wealth pooling, (2) can be rewritten as:

$$w_{i,t+1} = b_{it} = (1-\alpha)f(w_{it}, l_{it}) \tag{3}$$

Equation (3) gives the law of motion of wealth in this society. If $V_i(l)$ were identical across individuals, this dynamic process would be a deterministic Markov process and the convexity of f would ensure convergence to a steady-state wealth level w*, to which all lineages would converge. Although heterogeneous labour supply complicates this slightly, (3) will still follow a (stochastic) Markov process provided $l_{it} \sim L_t(l_i)$, with a finite variance, is independently and identically distributed over time: $Cov(l_{it}, l_{i,t+j}) = 0, \forall j$. That is, so long as our allowance for freedom of choice in the supply of labour generates a well-behaved, finite-variance distribution of labour supply with no intergenerational correlation, this system will still yield a long-run steady-state ergodic wealth distribution $G_\infty^*(w)$, centred around a mean value such as μ_w in Figure 1 (see e.g., Theorem 11.12 in Stokey and Lucas 1989).

Figure 1: Wealth steady state 'before development'



Source: authors' illustration.

---

[4] λ is the standard Lagrange multiplier associated with the budget constraint.

2.1 Development

Now let us introduce economic growth and development as arising from a process of exogenous technological progress, where a new, more efficient production function $\tilde{f}(k,l)$, becomes available, such that:

$$\tilde{f}_t(k,l) = \begin{cases} 0, & if\ k < \phi_t \\ \hat{f}_t(k,l), & if\ k \geq \phi_t \end{cases}. \quad (4)$$

and $\hat{f}_t(k',l') > f(k',l')\ , \forall l', \forall k' \geq \phi_t$.[5] Such a formulation implies two things: first, there are barriers to entry into the sector using this new technology: there is a non-convexity, in that a minimum amount of capital, ϕ_t, is necessary for production in this sector. Second, at levels of capital greater than this threshold, the new technology is more productive than the traditional one: for any given combination of capital and labour, it generates higher value-added.

Now suppose that $G^*_\infty(w)$ has finite support $[\underline{w}, \overline{w}]$ and that initially, $\phi_0 > \overline{w}$. Under the above assumptions, technology $\hat{f}_t(k,l)$ is then unavailable, and the economy produces in a single sector using technology $f(k,l)$. The steady state is still characterized by the ergodic wealth distribution $G^*_\infty(w)$, centred around a mean value such as μ_w, as shown in Figure 1.

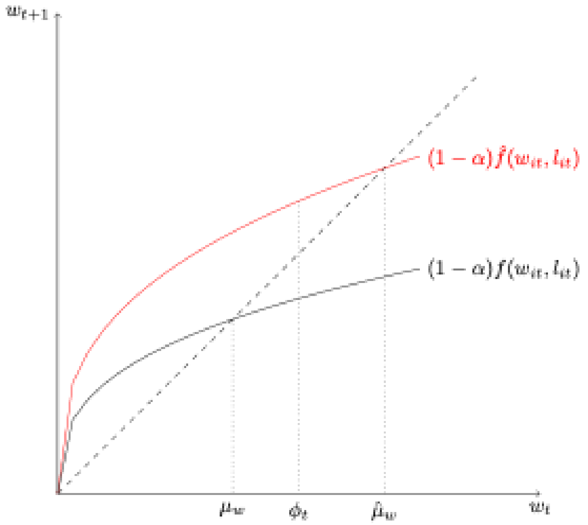
Development—or at least a particular phase of development—can be seen as a gradual reduction in the minimum access requirement to the more-productive technology, with ϕ_t falling over time. As soon as $\phi_t < \overline{w}$, some mass of agents $1 - G(\phi_t)$ will adopt the new technology, which has a different ergodic distribution, $\hat{G}^*_\infty(w)$, with support $[\underline{\hat{w}}, \hat{\overline{w}}]$. Quite likely, $\underline{\hat{w}} > \underline{w}$ and $\hat{\overline{w}} > \overline{w}$.[6] These agents will be attracted to a new steady state, around a higher mean wealth level, such as $\hat{\mu}_w$ in Figure 2.

As ϕ_t continues to fall, a larger and larger mass of workers in the traditional sector (using technology *f*) moves to the advanced sector (using technology $\hat{f}$), At some point t+k, $\phi_{t+k} < \underline{w}$. At that point everyone is able to exit the traditional—by now, 'backward'—sector and to adopt the technology of the advanced sector. At this point all agents are in the attraction zone of the 'final' ergodic distribution $\hat{G}^*_\infty(w)$. Between t and t+k, development is characterized by a dualistic economy, with two sectors employing different technologies. During this period the wealth distribution in society, which we can denote by F_t, is a mixture of two time-varying distributions, $G_t(\phi)$ and $\hat{G}_t(w)$, corresponding respectively to the distribution of those workers left in the (shrinking) traditional sector and the distribution of those who have moved to the (growing) advanced sector. Inequality in F_t will naturally comprise inequality within each sector, as well as inequality between them.

[5] Above ϕ_t, the sign restrictions described above for f also apply to $\hat{f}$.

[6] An exact characterization of the ergodic distributions depends on the distribution of labour supply choices, about which we remain agnostic in this paper. The purpose of our simple model is illustrative.

Figure 2: Wealth steady state 'during development'



Source: authors' illustration.

2.2 Simulations

To illustrate the distributional dynamics that the simple framework above would imply, we run some numerical simulations. This requires some specific parameterization, beginning with the distribution of labour supply levels $l_{it} \sim L_t(l_i)$, which arises from heterogeneous preferences for effort. We model it as a uniform distribution $l_{it} \sim Unif(0.1,1)$, from which values are drawn randomly and independently across generations.

The production functions are parameterized as follows:

$$\text{Traditional production function: } f(k,l) = 2k_t^{0.5}\, l_t^{0.5} \tag{5}$$

$$\text{Modern production function: } \tilde{f}_t(k,l) = \begin{cases} 0, & if\ k < \phi_t \\ \hat{f}_t(k,l) = 4k_t^{0.5}\, l_t^{0.5}, & if\ k \geq \phi_t \end{cases} \tag{6}$$

The exogenous process of technological progress, modelled as a decline in entry costs $\phi_0^j \geq \phi_t^j \geq \phi_{t+1}^j \geq \cdots \geq 0$ is specifically parameterized as follows for the simulation: we set the initial threshold as $\phi_0 = 1.5$, and then let ϕ_t evolve discontinuously, so that $\phi_t = \phi_{t+1}$ if t is even, and $\phi_{t+1} = \phi_t - 0.4$ if t is odd.[7] In our main simulation we consider 12 generations of 5,000 agents. We set $G_0(w) = Unif(1,1)$, so that there is no wealth inequality in the initial generation.

At each subsequent generation a level of labour supply is drawn for each agent from $L_t(l_i)$, as described above. Given their wealth levels this determines their final income and bequest, and thus

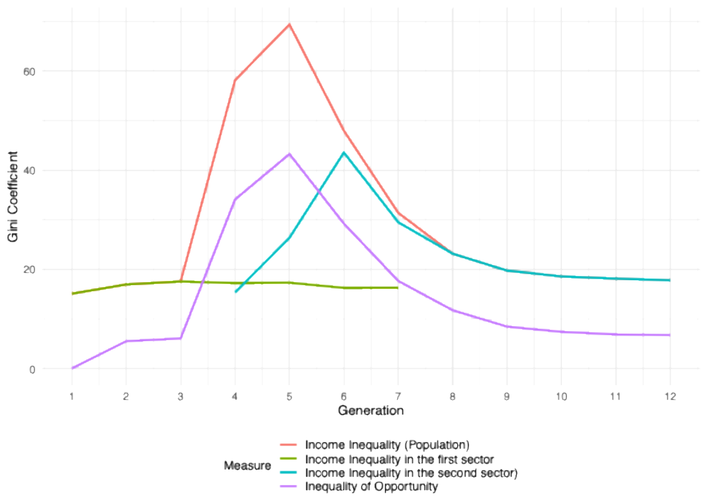
[7] The sequence of ϕ is therefore 1.5 in $t = 1$, 1.1 in $t = \{2,3\}$, 0.7 in $t = \{4,5\}$, 0.3 in $t = \{6,7\}$ and 0 in $t = \{8, \ldots, 12\}$.

the initial wealth level of the next generation. At some point some agents have wealth levels that exceed ϕ_t. At that point all of those agents are moved to the more-productive sector. That is, they start producing with $\hat{f}_t(k, l) = 4k_t^{0.5}\, l_t^{0.5}$. In other words, access to the more-productive sector, in this benchmark version of the model, depends entirely on wealth. Note that this entry cost in terms of physical capital could be interpreted as a human capital entry cost in models where education can only be financed by parental investment.

For each generation we measure income inequality by the Gini coefficient of the income distribution. We define IOp as the income inequality between the sons of rich parents and the sons of poor parents. Specifically, we define a wealth threshold $\widetilde{w_t}$, corresponding to the median wealth. Agents are then categorized into a 'poor type' ($w_t < \widetilde{w_t}$) and a 'rich type' ($w_t \geq \widetilde{w_t}$). IOp is computed as the Gini coefficient of the smoothed distribution, where individual incomes are replaced with their type's average income.[8]

Figure 3 displays the graphical results of our simulation. Agents are all employed in the traditional production sector up to the fourth generation; the Gini coefficient for the second sector is therefore not defined over this period, and the observed income inequality corresponds to inequality in the traditional sector. By the eighth generation, instead, all agents have moved to the new sector. These transitions take place at different speeds depending on the entry costs. Nevertheless, once the economy is entirely employed in one sector, both income inequality and IOp converge toward long-run levels which reflect the influence of intergenerational transmission of incomes.

Figure 3: Simulations – evolution of inequality and inequality of opportunity across generations



Source: authors' illustration based on simulated data.

[8] This measure of IOp is consistent with the theoretical and empirical literature on IOp and is known as the 'ex ante, between types, non-parametric measure of IOp' (see Checchi and Peragine 2010 and Ferreira and Peragine 2016). It is also consistent with the measures of IOp that will be used in our empirical analysis (see the next section).

Between generations 4 and 8 the economy displays a dualistic structure, with a traditional and an advanced sector co-existing. Between generations 3 and 4, as the minimum capital requirement falls to 0.7, thus below maximum level of wealth, agents with the richest parents move to the advanced sector. Inequality within the traditional sector (in green) remains constant, but there is now some inequality in the advanced sector (in blue). Importantly, total income inequality (in red) jumps from a Gini of 0.2 to almost 0.6, greater than the sum of the within-group inequalities and thus reflecting the onset of between-sector inequality. Total income inequality rises further until generation 5, before it starts declining. This decline reflects a diminishing role for between-sector inequality, as a majority of the population transitions to the advanced sector. The last generation that still has some agents in the traditional sector is generation 7. From generation 8 onwards the economy is single sector again, and total inequality converges to within-advanced-sector inequality. The model thus generates a standard Kuznets curve, with income inequality first rising and then declining over the course of economic development as agents move from a low-productivity to a higher-productivity sector.

More interestingly from the point of view of this paper are the dynamics of the pink line, which measures IOp, here proxied by inequality between those with 'rich' and 'poor' parents, i.e. those who had wealth levels above and below the median in each period. There are two points to note in particular: first, IOp arises in generation 2, even before the advanced sector comes into being. This reflects the fact that differences in income that arise in generation 1 as a result purely of unequal efforts, $l_{it} \sim L_t(l_i)$ translate into IOp in the next generation, as different incomes at the end of generation 1 yield different bequests at the beginning of generation 2. This is an important point: even though there was no initial IOp, outcome differences arising from differences in effort become IOp once they are transmitted to the next generation. Unequal outcomes today yield unequal opportunities tomorrow (see e.g., Ferreira 2022).

The second point is that IOp jumps from a Gini of 0.061 to 0.341 between generations 3 and 4, when the children of the rich have access to a more-productive technology, while those poorer than a certain threshold are confined to the backward sector. This is a key part of the mechanics of the opportunity Kuznets curve: if access to the advanced, more-productive sector, is selective on the basis of inherited circumstances, the transition phase will be marked not only by high (income) inequality between sectors but also by high inequality (of opportunity) between types, here defined as children with family wealth below or above the median.

To better understand these two different, but related, drivers behind the opportunity Kuznets curve, it is informative to compare this benchmark simulation with an alternative version of the model, in which initial conditions and the nature of the exogenous process of technological progress are the same as above, but in which selection into the advanced sector is not dependent on wealth but, instead, on effort. This would arise, for example, if the production function in the advanced sector were of the form:

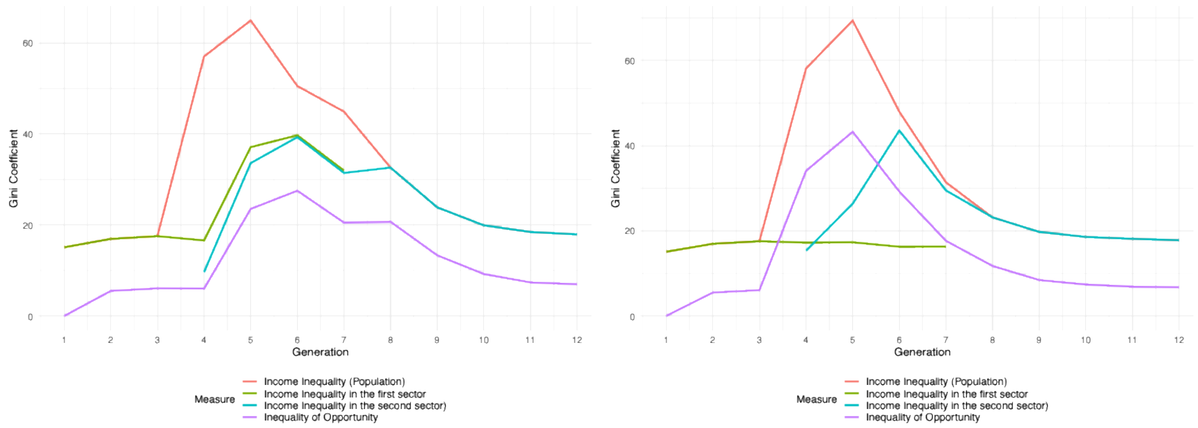
$$\text{Modern production function: } \tilde{f}_t(k,l) = \begin{cases} 0, & if\ l < \phi_t^l \\ \hat{f}_t(k,l) = 4k_t^{0.5}\, l_t^{0.5}, & if\ l \geq \phi_t^l \end{cases}. \qquad (7)$$

One could see this type of entry cost as equivalent to a human capital entry cost in models where skills are acquired only through effort in education, with no effects from parental investment. Alternatively, one can see this cost as a mechanism that remunerates individual entrepreneurial initiatives.

Figure 4 plots the evolution of income inequality within each sector, total income inequality, and IOp for this alternative version of the model in panel (a). For ease of comparison, panel (b) repeats Figure 3, so the two trajectories can be seen next to each other. From an equality of opportunity perspective, in which individuals are seen as deserving of rewards to effort but not to circumstances they do not control, one might consider this second process of selection into the advanced sector (in panel (a)) as a fairer development process.

Figure 4: Kuznets and opportunity Kuznets curves under different mechanisms for entry into the advanced sector

(a) Effort-based entry cost (b) Wealth-based entry cost



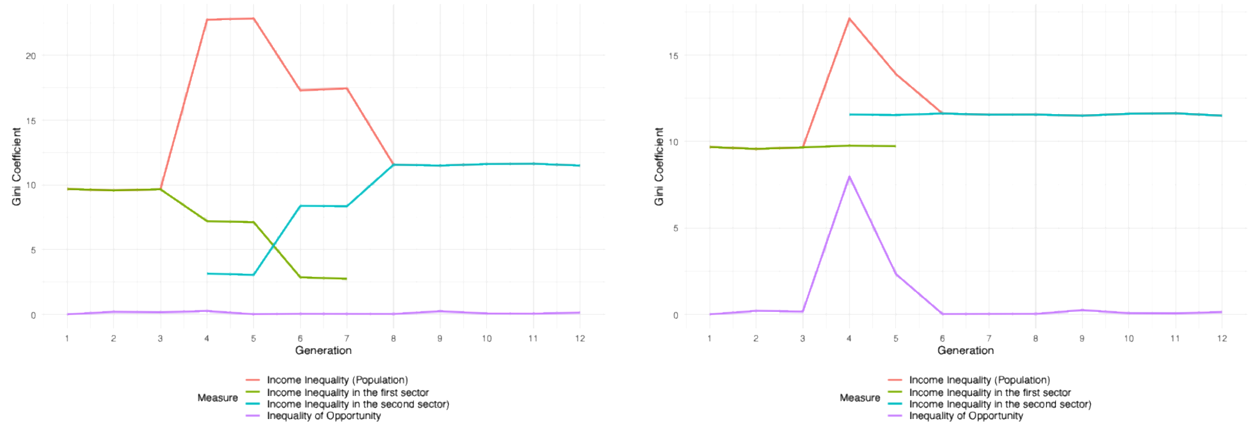
Source: authors' illustration based on simulated data.

It is interesting to observe, nonetheless, how this greater fairness does not prevent the appearance of an inverted-U shape curve for IOp, even in panel (a). This arises because, while it is true that access to the new sector is now based on effort, capital is still an input into the production technology, and it can only be obtained through inherited wealth. So long as this is true, some of the income inequality from the parents' generation will always be transmitted to the children's generation, for whom they become circumstances. In addition, during the period of transitions from the old to the new sector (generations 4 to 8), the role of circumstances is exacerbated by the higher productivity of wealth in the new sector. But of course, even though the different entry costs generate qualitatively similar dynamics, our benchmark process, in which selectivity into the new sector is directly driven by inherited wealth, exacerbates the growth in IOp during the transition. IOp peaks at more than 40 Gini points in panel (b), as opposed to about 28 Gini points in panel (a).

To see the centrality of the role of inherited wealth in generating the opportunity Kuznets curve in both panels of Figure 4, contrast it with Figure 5, in which capital is no longer an input into production in either sector. Here we let $f(k,l) = l_t$ and $\hat{f}_t(k,l) = 1.5 + 2l_t$. As in in Figure 4, panel (a) shows the case in which selection into the advanced sector is based on effort levels, while panel (b) shows the case where it is based on wealth levels. In panel (a), where wealth (which is still inherited) matters neither for production nor for selection into the advanced sector, there is no opportunity Kuznets curve. Indeed, there is no IOp at all. In panel (b), where wealth is of no use as a production input but does matter for selection into the advanced sector, IOp exists only during the sectoral transition, and an opportunity Kuznets curve to match the income one reappears.

Figure 5: Kuznets and opportunity Kuznets curves when capital is not an input into production

(a) Effort-based entry cost (b) Wealth-based entry cost



Source: authors' illustration based on simulated data.

The simple model of development with intergenerational transmission of wealth that we presented and simulated above therefore suggests two mechanisms through which economic growth may be accompanied by first rising and then falling inequality—both in income and in opportunity. Like the original Lewis (1954) model that inspired Simon Kuznets, the existence of two sectors with different technologies and of a gradual flow of resources between them plays a crucial role. From the perspective of IOp, two drivers of the appearance of a Kuznets curve are, first, the transmission of wealth inequality across generations (given that capital markets are imperfect)—a feature reminiscent of earlier work by, for example, Galor and Zeira (1993) and Banerjee and Newman (1993). This is the only driver at work in Figure 4(a). But as we also show, there is reason to expect the temporary increase in IOp during such periods of economic transition to be greater if access to opportunities in the new, more-productive sector is itself selective on circumstances, such as inherited wealth. This second driver of the opportunity Kuznets curve is the only factor at work in Figure 5(b). The more pronounced opportunity Kuznets curve shown in Figure 3 (and again in Figure 4(b)), arises from a combination of both mechanisms.

This leads us to conclude that there are plausible theoretical foundations 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.[9] 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 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.[10] 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. Sectoral

[9] 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/.

[10] 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.

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.

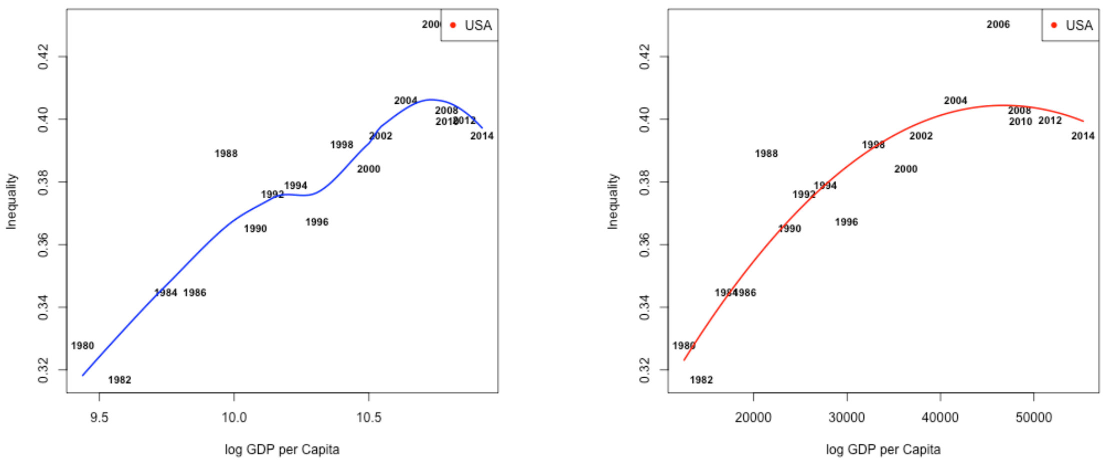
3.2 Income Kuznets curves

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 6 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.

Figure 6: 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.

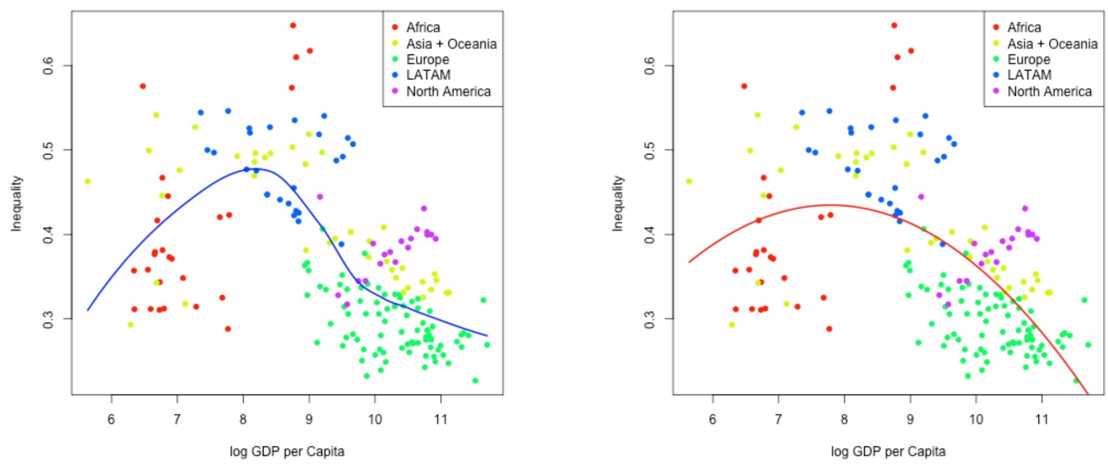
Although one might detect a local maximum—followed by a decline—at the very right of the non-parametric estimation in the left panel, it would probably be overoptimistic to claim that these US data offer much evidence of an inverted-U curve for this period. This is in keeping with the experience of many 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.

Be that as it may, we too now move to the pooled cross-section available to us from GEOM, containing 192 observations. Figure 7 once again shows the Kuznets curves obtained by fitting a non-parametric (left panel) or a quadratic curve (right panel).

Figure 7: 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.

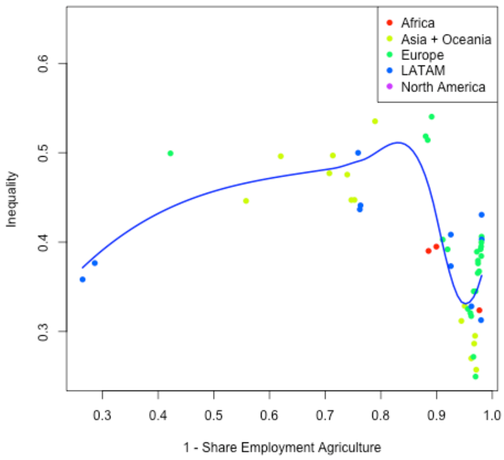
On these data both the parametric and non-parametric estimations offer strong support for Kuznets's hypothesis. Both panels show clear inverted-U shaped relationships between inequality and development. The result is clearly driven by the positions occupied by different groups of countries, which correspond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

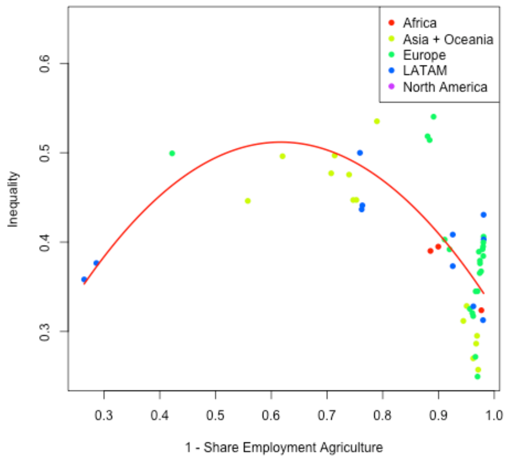
In line with our model and in the spirit of Kuznets's hypothesis, we can alternatively approximate the level of development by the share of the population employed in the agricultural sector. The idea is that, when this share is particularly high, we are in the presence of an economy at the initial stages 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 8 shows the pattern first using employment shares (Panels (a) and (b)), and then shares in total value-added (Panels (c) and (d)).[11]

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

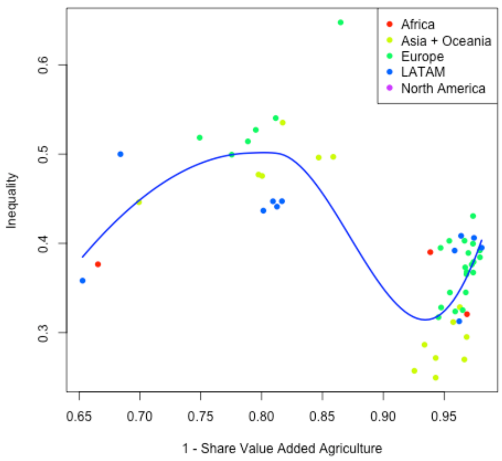
(a) Kuznets Curve (employment agriculture)



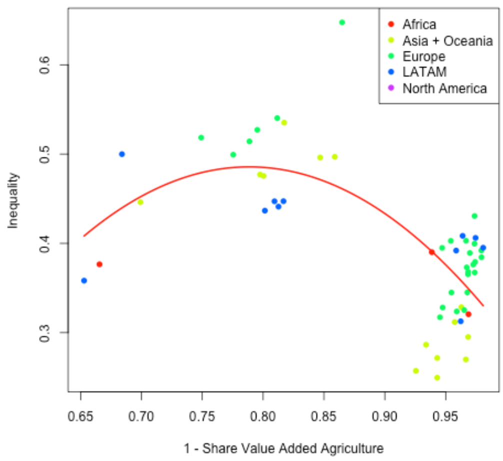
(b) Kuznets Curve (employment agriculture)



(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.

An inverted-U relationship between inequality and development is also supported by these four figures, using this alternative measure of development.

[11] Analogous graphs for the manufacturing and service sectors yield results that are less clear. See Appendix Figure A2.

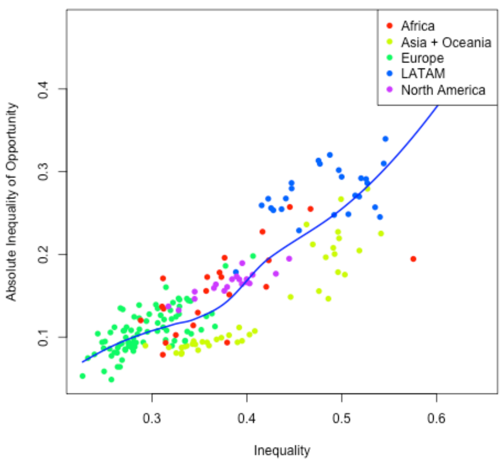
3.3 Great Gatsby curves

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).

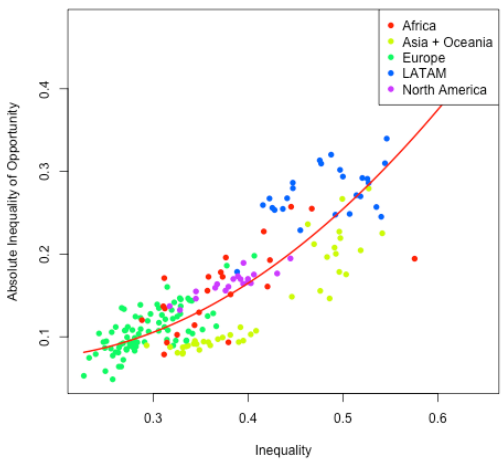
Figure 9 plots the Great Gatsby curves present in the GEOM data, both for absolute and relative measures of IOp, following the same pattern as above: non-parametric estimates on the left; quadratic fits on the right.

Figure 9: Great Gatsby curves for both absolute and relative IOp

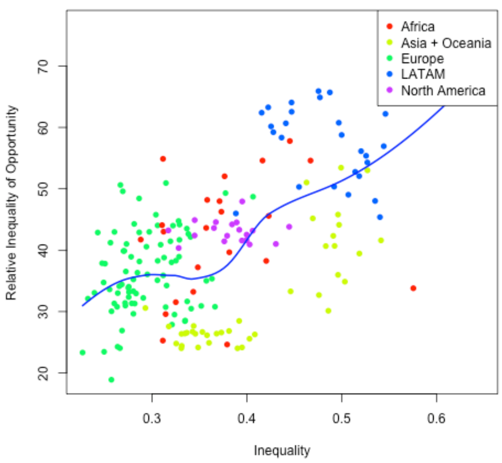
(a) Absolute IOp, non-parametric fit



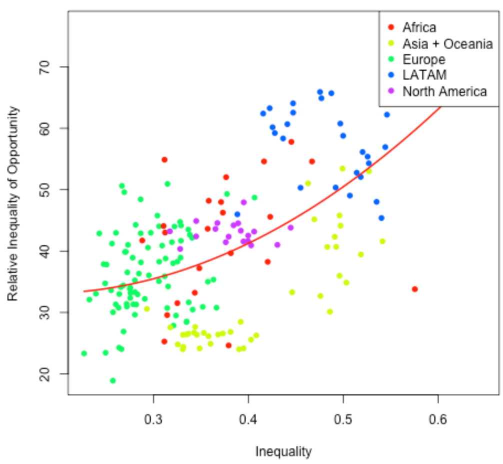
(b) Absolute IOp, parametric fit



(c) Relative IOp, non-parametric fit



(d) Relative IOp, parametric fit



Note: pooled cross-section data.

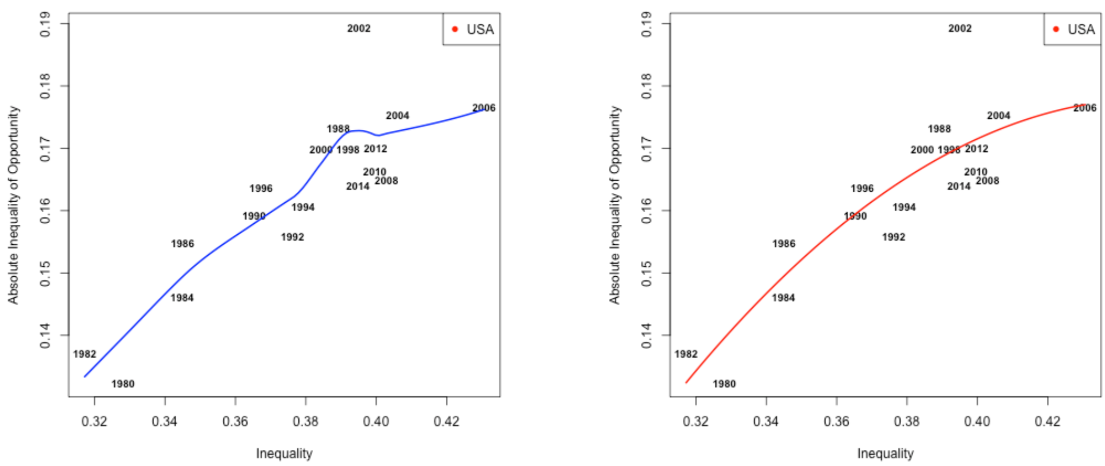
Source: elaboration on GEOM and IMF data.

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 9 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 10, they are also present in the time series for the USA, using GEOM data for 1980–2014, as in Figure 6.

Figure 10: 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.

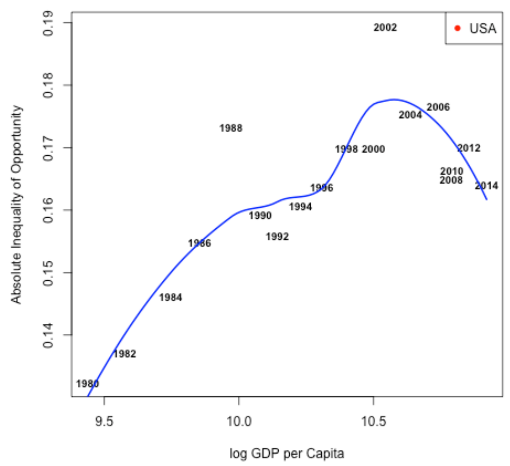
3.4 Opportunity Kuznets curves

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 11 and 12, we again use the logarithm of per capita GDP as a proxy for development. Figure 11 follows on from Figures 6 and 10 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.

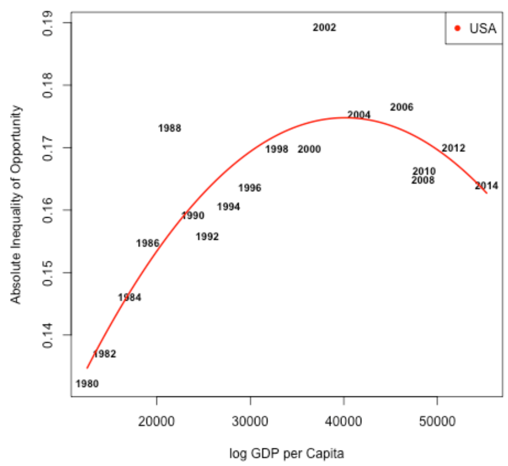
The curves for absolute IOp look similar to the income Kuznets curves in Figure 6, but the turning point around 2002 is now more marked. The downturn after that point is appreciable in the non-parametric figure and discernible even in the quadratic one. Naturally, with the numerator and denominator following reasonably similar trajectories but with a more pronounced ∩-shape for absolute IOp, the relative IOp Kuznets curve is actually quite pronounced in Figure 11.

Figure 11: Time-series 'Kuznets opportunity curves' for the USA, 1980–2014

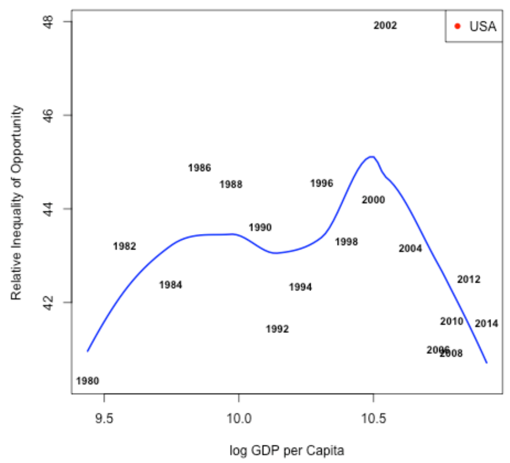
(a) Absolute IOp, non-parametric fit



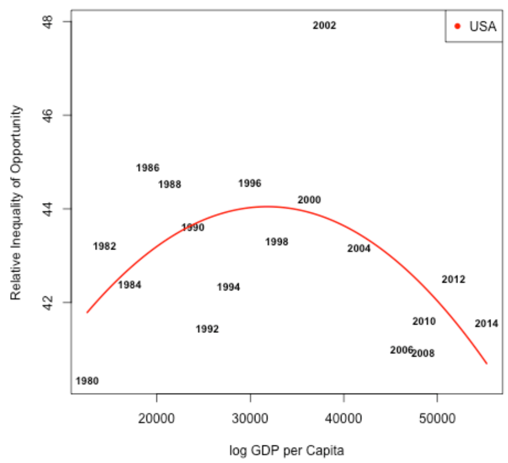
(b) Absolute IOp, parametric fit



(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.

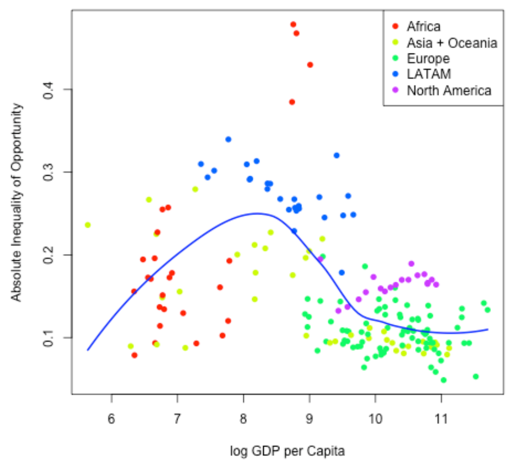
Source: elaboration on GEOM and IMF data.

Next, we present the Opportunity Kuznets relationships as observed in the GEOM pooled cross-section in graphs analogous to Figure 7. Figure 12 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.

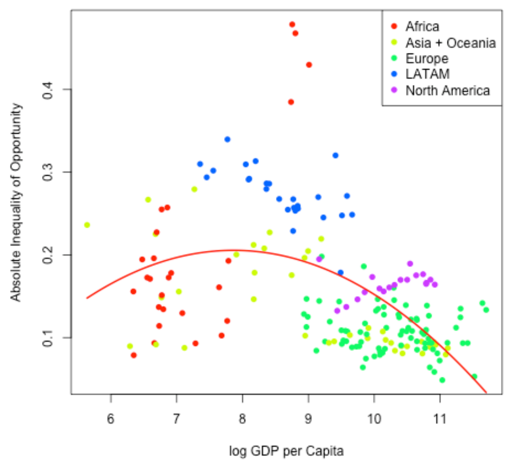
For the more flexible non-parametric fits, the opportunity Kuznets curve looks like a ∩ with an L attached, reminiscent of the pink IOp curve from our model simulation in Figure 3, from generation 3 to 12. Although we do not go so far as to claim that such a cross-sectional pattern supports our successive generation model, it is at least 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.

Figure 12: Cross-sectional opportunity Kuznets curves on pooled GEOM data

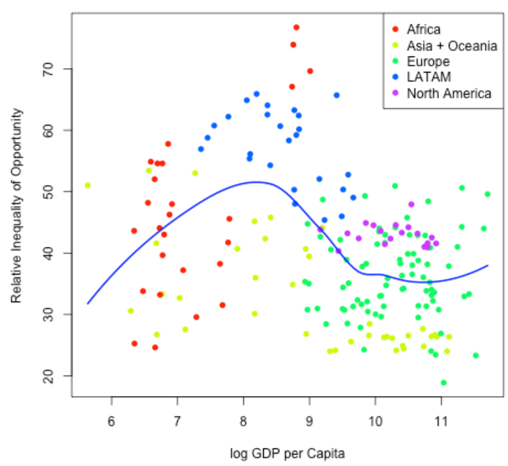
(a) Absolute IOp, non-parametric fit



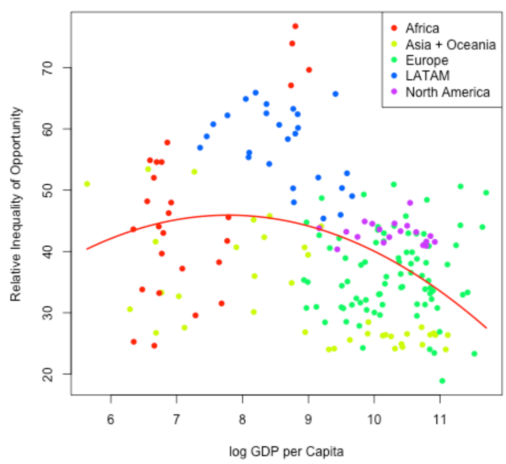
(b) Absolute IOp, parametric fit



(c) Relative IOp, non-parametric fit



(d) Relative IOp, parametric fit



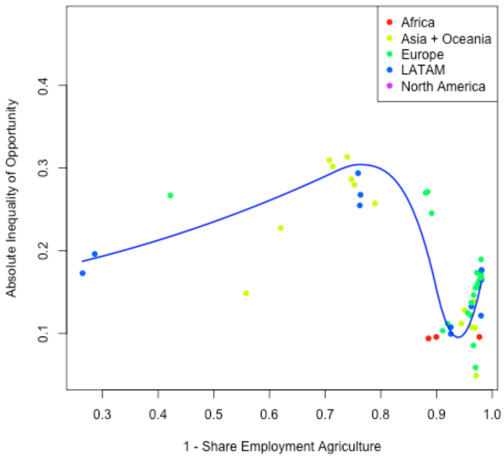
Note: pooled cross-section data.

Source: elaboration on GEOM and IMF data.

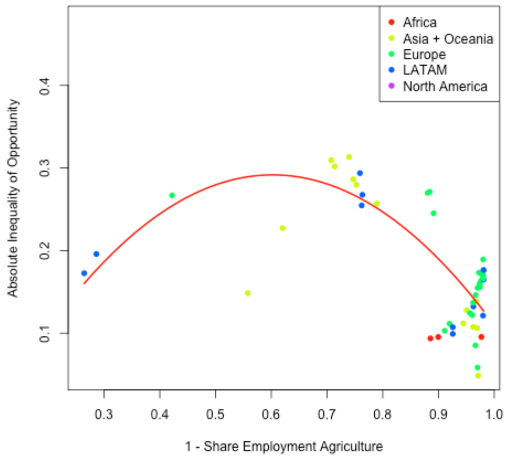
Next, just as Figure 8 did for the income Kuznets curve, Figure 13 uses the share of workers employed in the agricultural sector (top panel) or of agriculture value-added in GDP (bottom panel) as inverse proxies for development, replacing GDP per capita. Here too we see interesting patterns that suggest the existence of a Kuznets IOp curve. Figure A3 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 A2, those graphs in Figure A3 do display relatively clear inverted-U patterns, hence supporting the picture obtained from agriculture below.

Figure 13: Opportunity Kuznets curves when development is proxied by (inverse) agricultural shares: employment and valued added

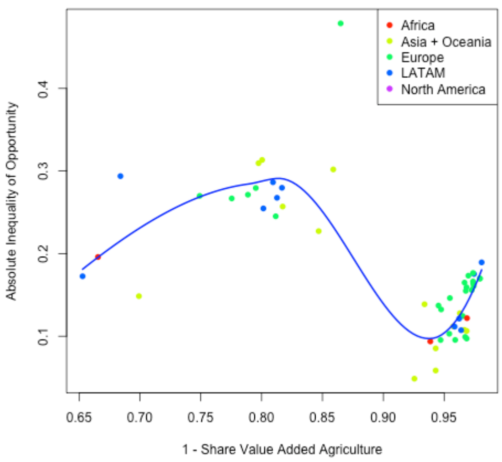
(a) Absolute IOp, non-parametric fit (employment agriculture)



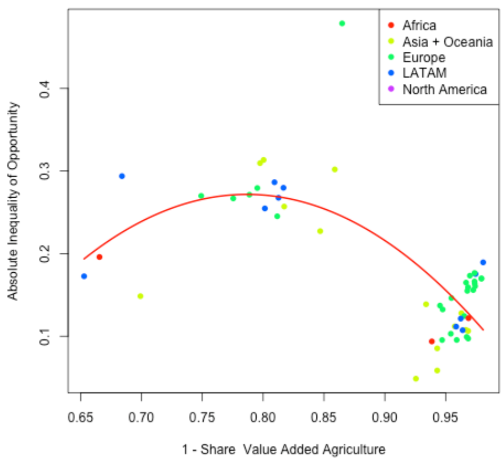
(b) Absolute IOp, parametric fit (employment agriculture)



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



(d) 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

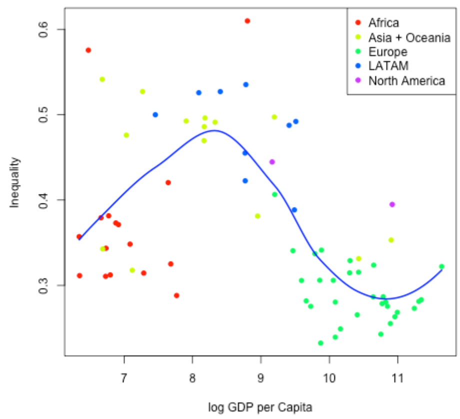
The evidence presented so far appears to be broadly supportive of the existence of an opportunity Kuznets curve, at least in the global cross-section of countries. This is consistent both with the stylized model of Section 2 and with the combination of an income Kuznets curve and a Great Gatsby curve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

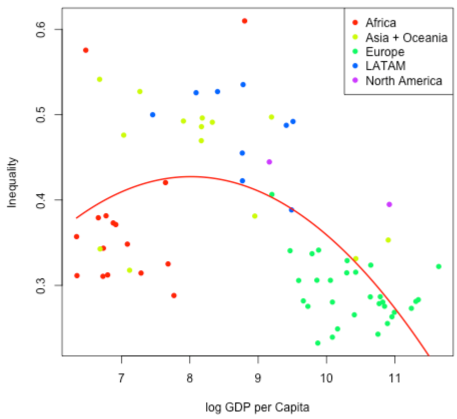
To end this empirical section by way of a brief 'robustness analysis', we look at two additional sets of figures for the three sides of the income-IOp-growth triangle. Each set contains eight graphs: non-parametric and quadratic fits for standard Kuznets curves, Great Gatsby curves, and opportunity Kuznets curves, for both absolute and relative measures. The first set, in Figure 14, 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 14: Cross-sectional Kuznets curves on latest-year GEOM data

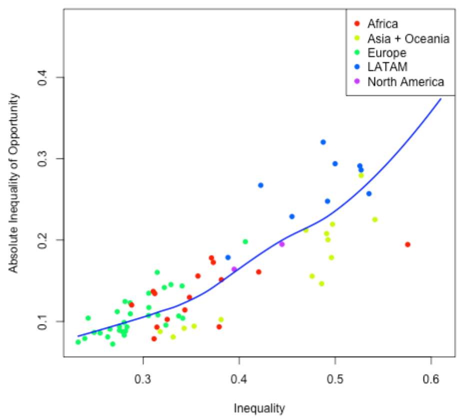
(a) Kuznets Curve, non-parametric fit



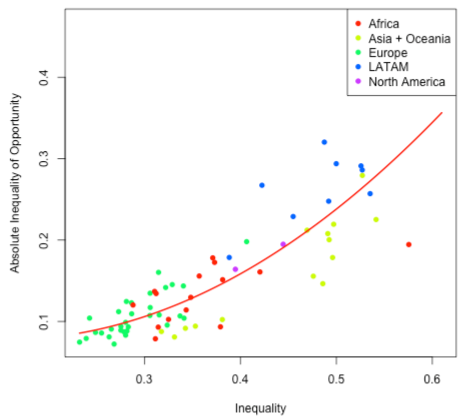
(b) Kuznets Curve, parametric fit



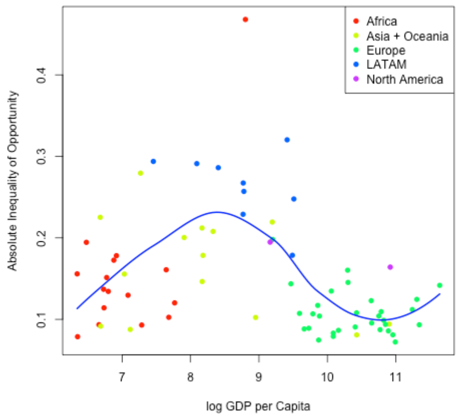
(c) Gatsby Curve, non-parametric fit



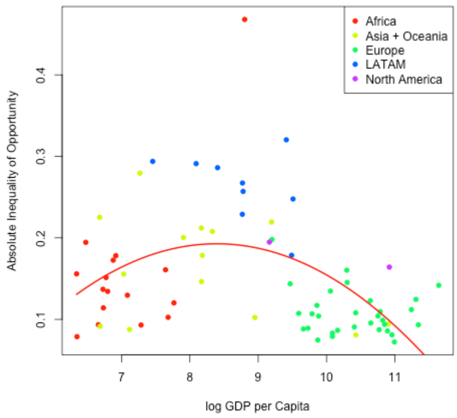
(d) Gatsby Curve, parametric fit



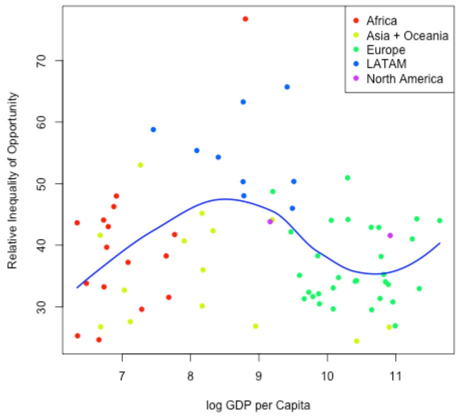
(e) Opportunity Kuznets Curve, non-parametric fit, Absolute IOp



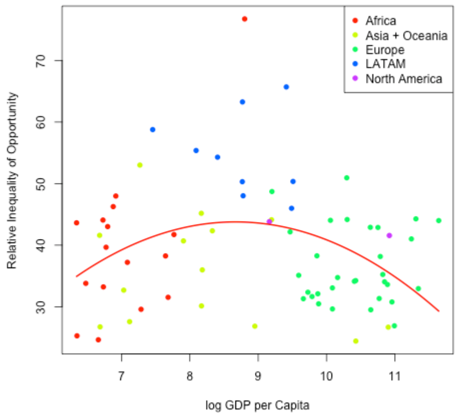
(f) Opportunity Kuznets Curve, parametric fit, Absolute IOp



(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.

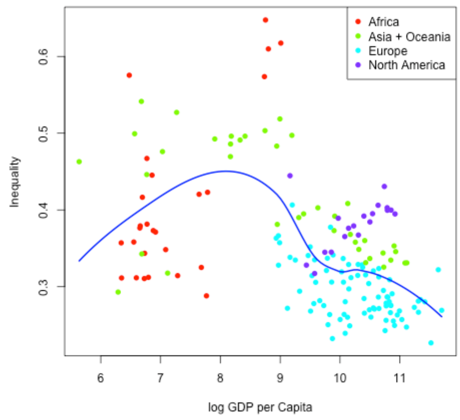
Source: elaboration on GEOM and IMF data.

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.

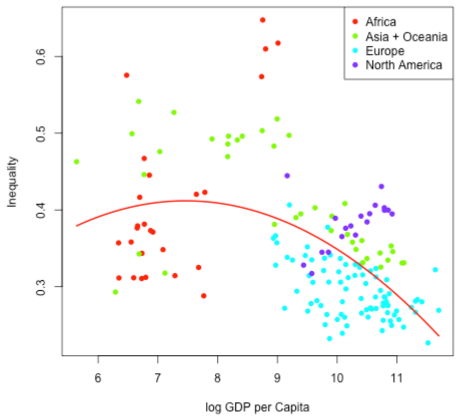
Our second set of 'robustness graphs' investigates the consequences of dropping Latin American countries from the GEOM pooled cross-section. Latin America is a particularly high-inequality region with relatively middling levels of GDP per capita—despite considerable internal heterogeneity. It is therefore possible that it drives some of the Kuznets results, and it is of some interest to see what the pictures look like when the region is excluded, as in Figure 15.

Figure 15: Cross-sectional Kuznets curves on GEOM data excluding Latin America

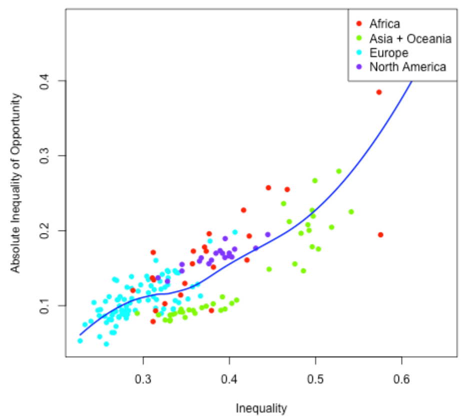
(a) Kuznets Curve, non-parametric fit



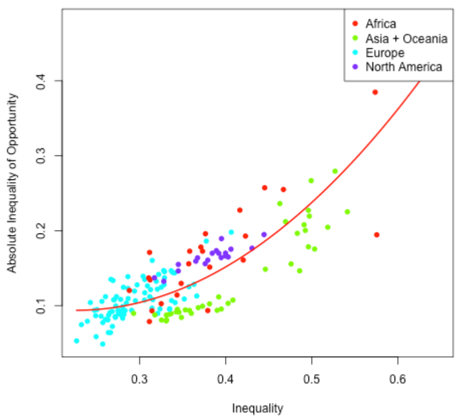
(b) Kuznets Curve, parametric fit



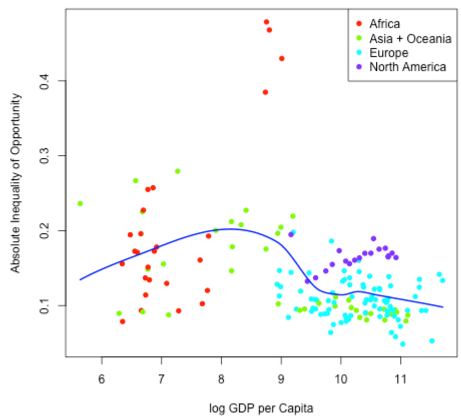
(c) Gatsby Curve, non-parametric fit



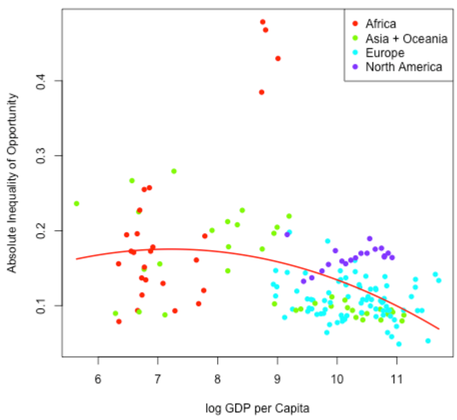
(d) Gatsby Curve, parametric fit



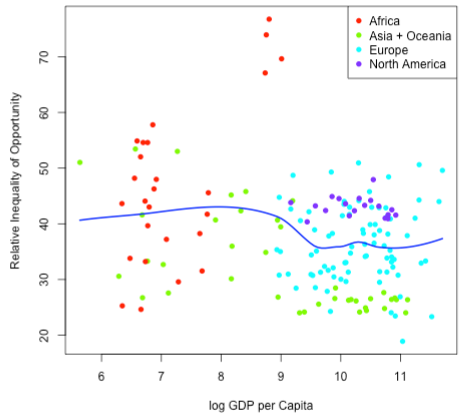
(e) Opportunity Kuznets Curve, non-parametric fit, Absolute IOp



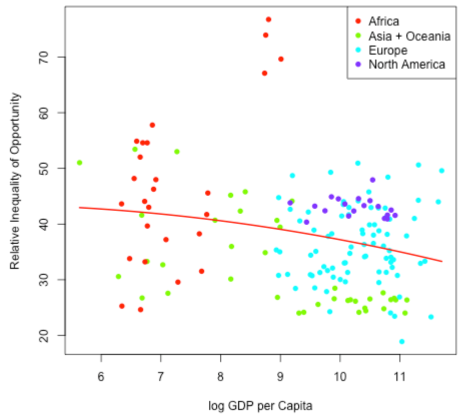
(f) Opportunity Kuznets Curve, parametric fit, Absolute IOp



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



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



Note: pooled cross-section data.

Source: elaboration on GEOM and IMF data.

The outcome of this last 'test' is considerably more mixed. The Great Gatsby curves survive the exclusion of Latin America completely unscathed. Interestingly, the income Kuznets curves are not very much affected either and the inverted-U pattern is still clearly visible in both those panels, although perhaps slightly less marked than when Latin American countries are included. There are enough high-inequality, middle-income African and Asian countries in that space to preserve the curves. But the exact pattern of the data is such that the opportunity Kuznets curves are substantially reduced. The inverted-U pattern is still visible in the absolute IOp graphs, but they disappear almost completely in the non-parametric relative IOp diagram and are absent altogether in the corresponding quadratic fit.

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.

Through a simple, stylized model of wealth distribution dynamics with capital and labour market imperfections, we identified two separate—but potentially reinforcing—economic mechanisms capable of generating opportunity Kuznets curves. First, if capital markets are imperfect, inherited wealth plays a role in determining the level of investment in physical or human capital that members of the new generation can make. So long as there are positive returns to capital, differences in inherited wealth will translate into future income inequality. And if development involves a migration of capital and labour to a sector where the returns to capital are even higher, for a while the gap between those moving earlier and those moving later will exacerbate the effect of inherited wealth on income inequality.

This 'baseline' effect is further amplified if, as appears plausible, the *selection* of those who move first into the more-productive sector is itself affected by inherited wealth. This would be the case, as we show, if the new, more-productive technology required some minimum level of investment, not available to all in the traditional sector. Together, these two effects were shown to generate marked income and opportunity Kuznets curves in simple simulations of the model.

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, 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. However, we find that the opportunity Kuznets curve is less robust to the exclusion of Latin American countries from the pooled cross-sectional GEOM data. While it does not disappear completely for absolute IOp, it is basically absent for relative IOp.

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). The economic mechanisms highlighted by our simple model also suggest that wealth can play a determinant role in allocating new opportunities arising from technological progress and economic development, so that 'success' in these new sectors may well draw upon earlier family privilege.

We would be cautious, however, in inferring from either the model or the data any notion 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.

References

Acemoglu, D., and J.A. Robinson (2002). 'The Political Economy of the Kuznets Curve'. *Review of Development Economics*, 6(2): 183–203. **https://doi.org/10.1111/1467-9361.00149**

Anand, S., and S.M.R. Kanbur (1993). 'Inequality and Development: A Critique'. *Journal of Development Economics*, 41(1):19–43. **https://doi.org/10.1016/0304-3878(93)90035-L**

Andreoni, J. (1989). 'Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence'. *Journal of Political Economy*, 97(6): 1447–58. **https://doi.org/10.1086/261662**

Banerjee, A.V., and A.F. Newman (1993). 'Occupational Choice and the Process of Development'. *Journal of Political Economy*, 101(2): 274–98. **https://doi.org/10.1086/261876**

Bourguignon, F., F.H.G. Ferreira, and M. Menendez (2007). 'Inequality of Opportunity in Brazil'. *Review of Income and Wealth*, 53(4): 585–618. **https://doi.org/10.1111/j.1475-4991.2007.00247.x**

Brunori, P., F.H. Ferreira, and V. Peragine (2013). 'Inequality of Opportunity, Income Inequality, and Economic Mobility: Some International Comparisons'. In E. Paus (ed.), *Getting Development Right: Structural Transformation, Inclusion, and Sustainability in the Post-crisis Era.* New York, NY: Palgrave Macmillan US. Available at: **https://link.springer.com/chapter/10.1057/9781137333117_5** (accessed 18 March 2025).

Brunori, P., F.H.G. Ferreira, and P. Salas-Rojo (2023). 'Inherited Inequality: A General Framework and an Application to South Africa'. International Inequalities Institute Working Paper 107. London: London School of Economics. **https://doi.org/10.31235/osf.io/rgq7t**

Brunori, P., P. Hufe, and D, Mahler (2023). 'The Roots of Inequality: Estimating Inequality of Opportunity from Regression Trees and Forests'. *Scandinavian Journal of Economics*, 125(4): 900–32. **https://doi.org/10.1111/sjoe.12530**

Checchi, D., and V. Peragine (2010). 'Inequality of Opportunity in Italy'. *Journal of Economic Inequality*, 8(4): 429–50. **https://doi.org/10.1007/s10888-009-9118-3**

Corak, M. (2013). 'Income Inequality, Equality of Opportunity, and Intergenerational Mobility'. *Journal of Economic Perspectives*, 27(3): 79–102. Available at: **https://www.aeaweb.org/articles?id=10.1257/jep.27.3.79** (accessed 18 March 2025).

Deininger, K., and L. Squire (1998). 'New Ways of Looking at Old Issues: Inequality and Growth'. *Journal of Development Economics*, 57(2): 259–87. **https://doi.org/10.1016/S0304-3878(98)00099-6**

Ferreira, F.H.G. (2022). 'Not All Inequalities Are Alike'. *Nature*, 606: 646–49. **https://doi.org/10.1038/d41586-022-01682-3**

Ferreira, F.H.G., and J. Gignoux (2011). 'The Measurement of Inequality of Opportunity: Theory and an Application to Latin America'. *Review of Income and Wealth*, 57(4): 622–57. **https://doi.org/10.1111/j.1475-4991.2011.00467.x**

Ferreira, F.H.G., and V. Peragine (2016). 'Individual Responsibility and Equality of Opportunity'. In M.D. Adler and M. Fleurbaey (eds), *Oxford Handbook of Well-being and Public Policy*. Oxford: Oxford University Press. **https://doi.org/10.1093/oxfordhb/9780199325818.013.24**

Ferreira, F.H., C. Lakner, M.A. Lugo, and B. Özler (2018). 'Inequality of Opportunity and Economic Growth: How Much Can Cross-Country Regressions Really Tell Us?'. *Review of Income and Wealth*, 64(4): 800–27. **https://doi.org/10.1111/roiw.12311**

Fleurbaey, M. (1994). 'On Fair Compensation'. *Theory and Decision*, 36: 277–307. **https://doi.org/10.1007/BF01079932**

Gallup, J.L. (2012). 'Is There a Kuznets Curve?'. Unpublished Manuscript. Portland, OR: Portland State University.

Galor, O., and J. Zeira (1993). 'Income Distribution and Macroeconomics'. *Review of Economic Studies*, 60(1): 35–52. **https://doi.org/10.2307/2297811**

GEOM (2024). 'Global Estimates of Opportunity and Mobility Database'. Available at: **https://geom.ecineq.org/** (accessed: 20 December 2024).

Hothorn, T., K. Hornik, and A. Zeileis (2006). 'Unbiased Recursive Partitioning: A Conditional Inference Framework'. *Journal of Computational and Graphical Statistics*, 15(3): 651–74. **https://doi.org/10.1198/106186006X133933**

Hothorn, T., and A. Zeileis (2021). 'Predictive Distribution Modeling Using Transformation Forests'. *Journal of Computational and Graphical Statistics*, 30(4): 1181–96. **https://doi.org/10.1080/10618600.2021.1872581**

Huang, H.-C., and S.-C. Lin (2007). 'Semiparametric Bayesian Inference of the Kuznets Hypothesis'. *Journal of Development Economics*, 83(2):491–505. **https://doi.org/10.1016/j.jdeveco.2006.03.008**

International Monetary Fund (2024). 'World Economic Outlook (October 2024): GDP Per Capita, Current Prices'. Available at: **https://www.imf.org/external/datamapper/NGDPDPC@WEO/OEMDC/ADVEC/WEOWORLD** (accessed 12 March 2025).

Jovanovic, B. (2018). 'When is There a Kuznets Curve? Some Evidence Form the Ex-socialist Countries'. *Economic Systems*, 42(2): 248–68. **https://doi.org/10.1016/j.ecosys.2017.06.004**

Kuznets, S. (1955). 'Economic Growth and Income Inequality'. *American Economic Review*, XLV(1): 1–26.

Lewis, A. (1954). 'Economic Development with Unlimited Supplies of Labour'. *The Manchester School*, 22(2): 139–91. **https://doi.org/10.1111/j.1467-9957.1954.tb00021.x**

Marrero, G.A., and J.G. Rodríguez (2013). 'Inequality of Opportunity and Growth'. *Journal of Development Economics*, 104: 107–22. **https://doi.org/10.1016/j.jdeveco.2013.05.004**

Marrero, G.A., and J.G. Rodríguez (2023). 'Unfair Inequality and Growth'. *The Scandinavian Journal of Economics*, 125(4): 1056–92. **https://doi.org/10.1111/sjoe.12531**

Milanovic, B. (2016). *Global Inequality: A New Approach for the Age of Globalization*. Cambridge, MA: Harvard University Press. **https://doi.org/10.4159/9780674969797**

Peragine, V. (2002). 'Opportunity Egalitarianism and Income Inequality'. *Mathematical Social Sciences*, 44(1): 45–64. **https://doi.org/10.1016/S0165-4896(02)00006-9**

Roemer, J. (1993). 'A Pragmatic Theory of Responsibility for the Egalitarian Planner'. *Philosophy & Public Affairs*, 10: 146-166.

Roemer, J.E., and A. Trannoy (2015). 'Equality of Opportunity'. In A.B. Atkinson and F. Bourguignon (eds), *Handbook of Income Distribution, Vol. 2*. Amsterdam: Elsevier. **https://doi.org/10.1016/B978-0-444-59428-0.00005-9**

Stokey, N.L., and R.E. Lucas (1989). *Recursive Methods in Economic Dynamics*. Cambridge, MA: Harvard University Press. **https://doi.org/10.2307/j.ctvjnrt76**

Timmer, M.P., de Vries, G.J., and de Vries, K. (2015). 'Patterns of Structural Change in Developing Countries'. In J. Weiss and M. Tribe (eds), *Routledge Handbook of Industry and Development*. London: Routledge.

van de Gaer, D. (1993). 'Equality of opportunity and investment in human capital'. Unpublished Ph.D. Dissertation. Leuven: Katholieke Universiteit Leuven.

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	0.470	45.2
Australia	8	2019	54,391	0.353	26.7
Austria	3	2019	50,192	0.280	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	0.500	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	0.280	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	0.491	42.3
Germany	3	2019	47,629	0.279	31.3
Ghana	2	2017	2,087	0.420	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	0.486	30.1
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	0.381	26.8
Kyrgyzstan	1	2016	1,132	0.476	32.7
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

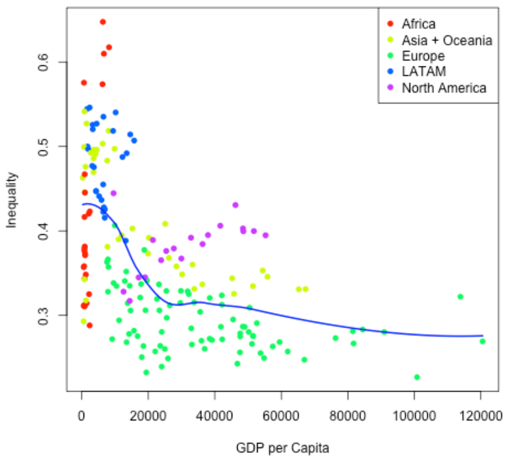
Malta	2	2019	33,106	0.266	34.1
Mexico	1	2017	9,543	0.445	43.8
Mongolia	1	2016	3,575	0.496	36.0
Nepal	2	2011	795	0.541	41.6
Netherlands	3	2019	53,755	0.255	33.6
Niger	1	2018	571	0.311	25.3
Nigeria	1	2019	2,361	0.288	41.7
Norway	3	2019	76,304	0.273	41.0
Panama	1	2003	4,470	0.527	54.3
Peru	11	2015	6,436	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	0.610	76.7
South Korea	11	2019	33,827	0.331	24.4
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	0.343	26.7
Tanzania	3	2013	970	0.373	46.3
Timor Leste	2	2014	1,234	0.318	27.6
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	0.492	40.7

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

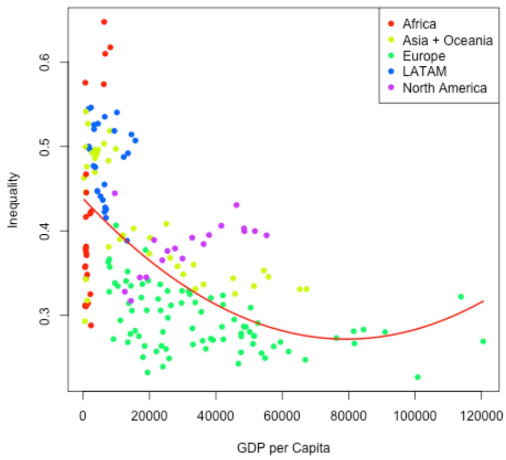
Source: income Gini and relative IOp from GEOM data.

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

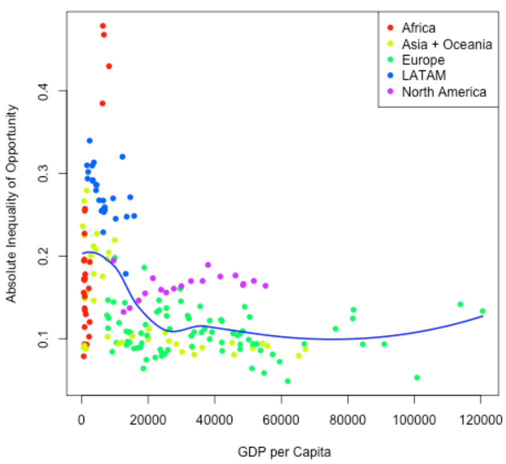
(a) Kuznets Curve, non-parametric fit



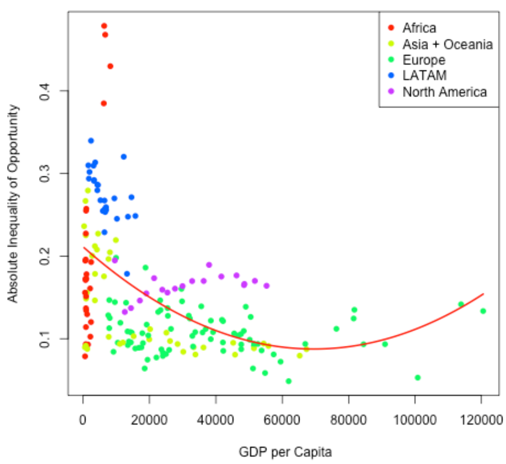
(b) Kuznets Curve, parametric fit



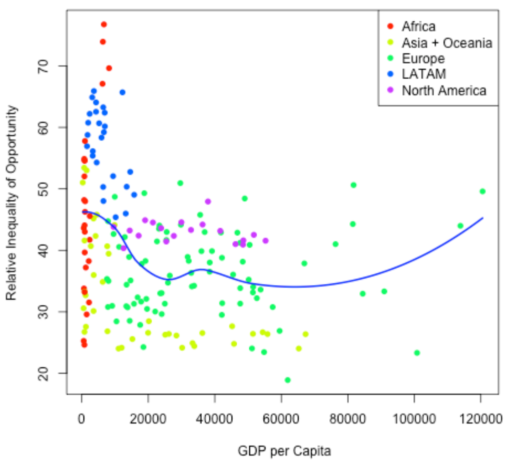
(c) Opportunity Kuznets Curve, non-parametric fit, absolute IOp



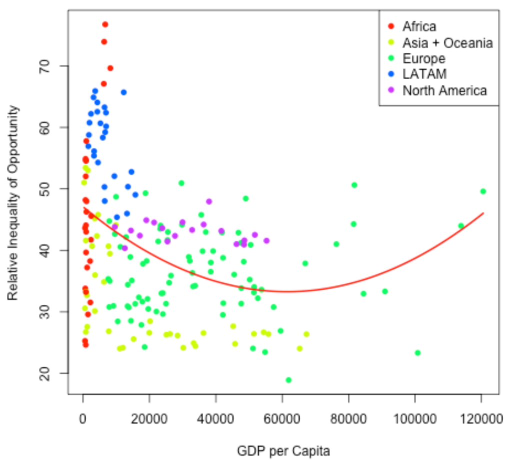
(d) Opportunity Kuznets Curve, parametric fit, absolute IOp



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



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

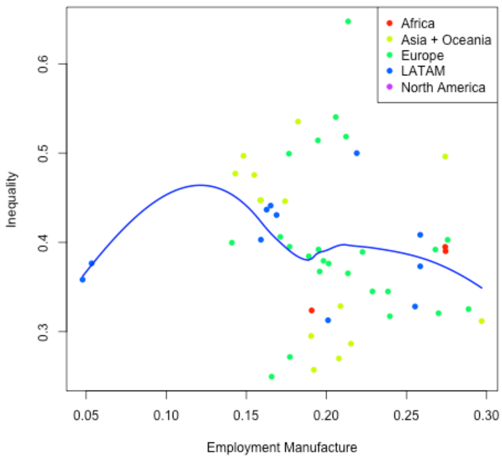


Note: pooled cross-section data.

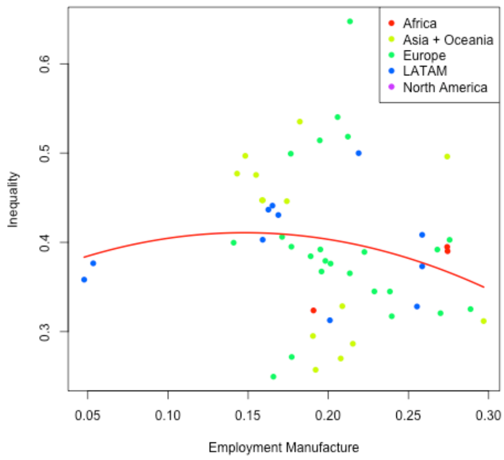
Source: elaboration on GEOM and IMF data.

Figure A2: ‘Kuznets curves’ when development is proxied by employment and valued-added shares in manufacturing and the service sectors

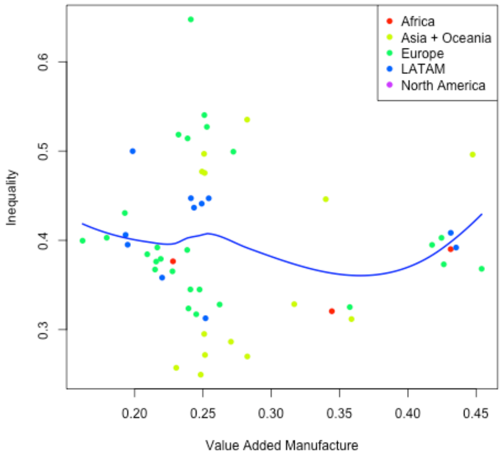
(a) Non-parametric fit (employment manufacture)



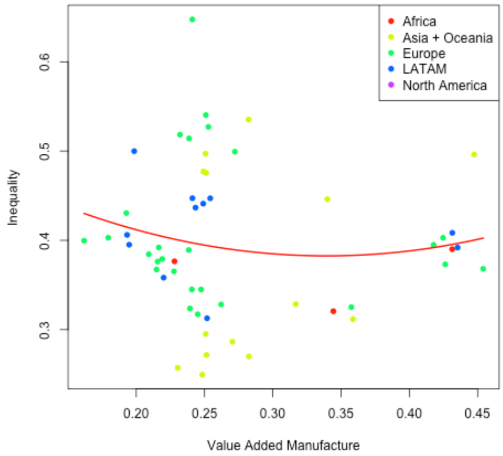
(b) Parametric fit (employment manufacture)



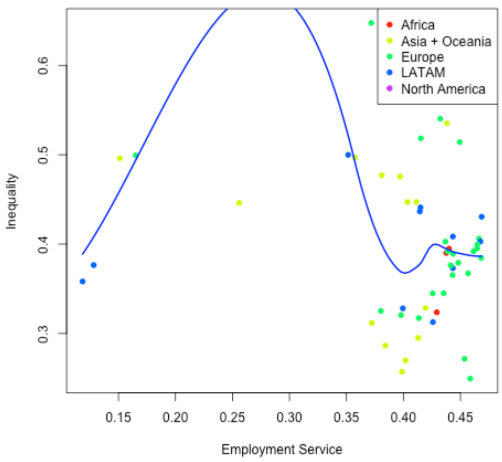
(c) Non-parametric fit (value-added manufacture)



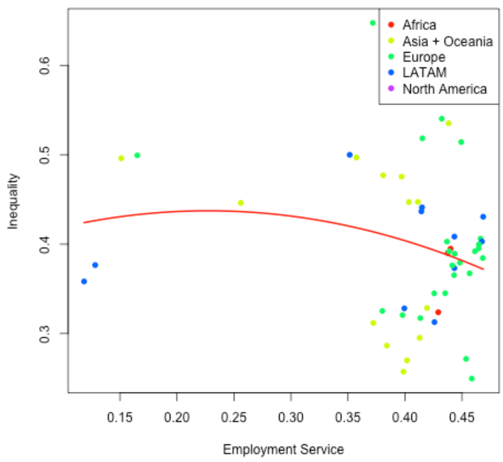
(d) Parametric fit (value-added manufacture)



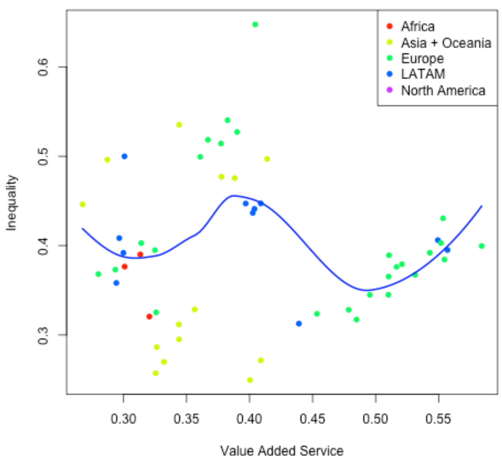
(e) Non-parametric fit (employment services)



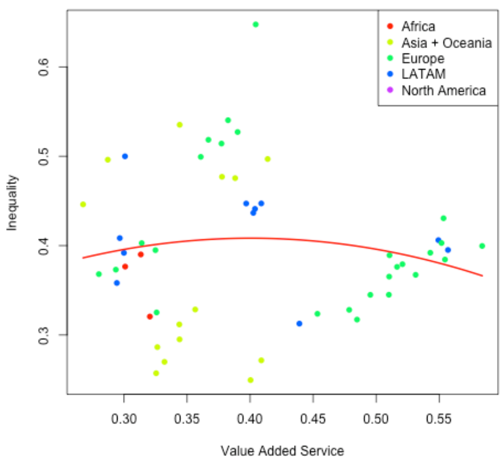
(f) Parametric fit (employment services)



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



(h) Parametric fit (value-added services)

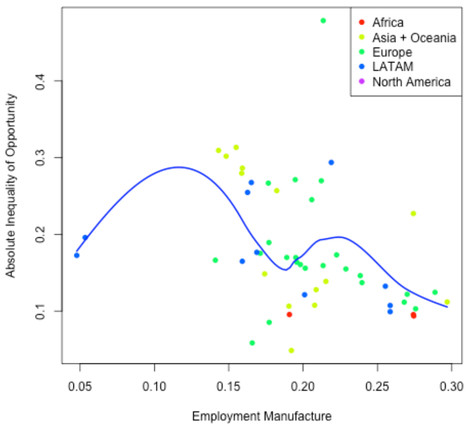


Note: pooled cross-section data.

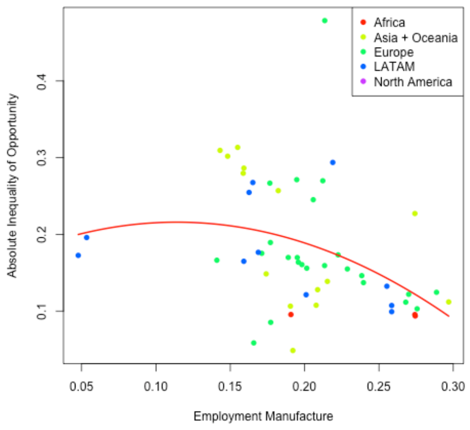
Source: elaboration on GEOM and ten-sector (Timmer et al. 2015) data.

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

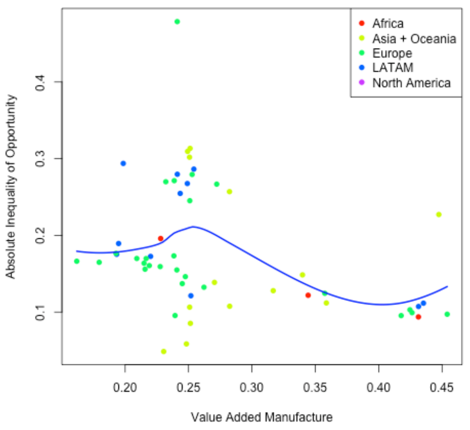
(a) Non-parametric fit (employment manufacture)



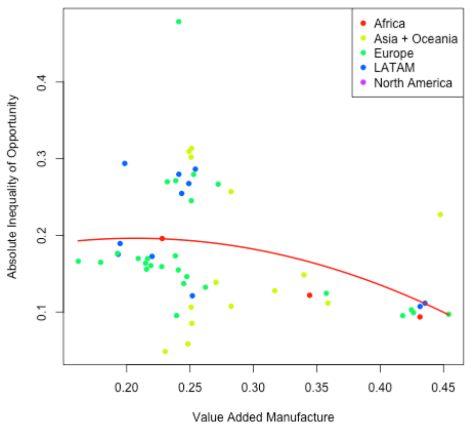
(b) Parametric fit (employment manufacture)



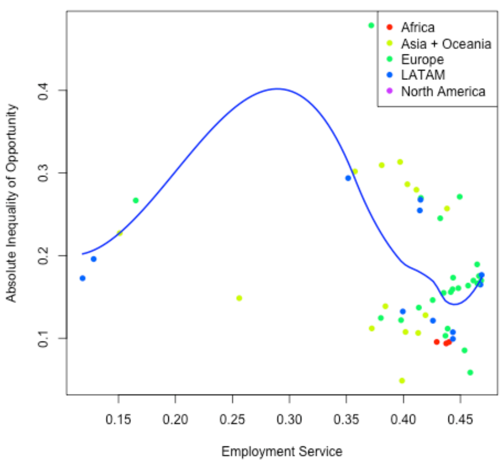
(c) Non-parametric fit (value-added manufacture)



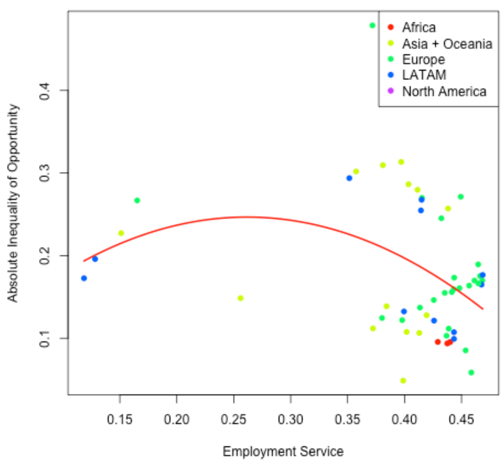
(d) Parametric fit (value-added manufacture)



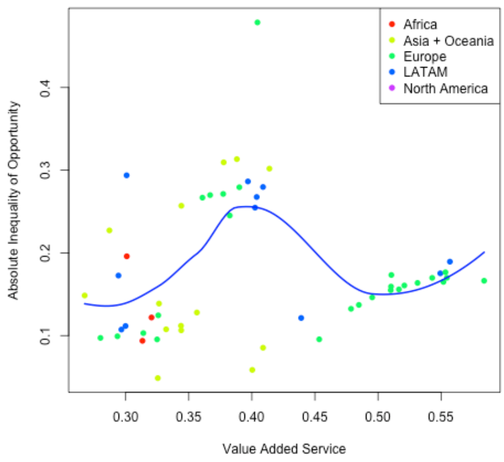
(e) Non-parametric fit (employment services)



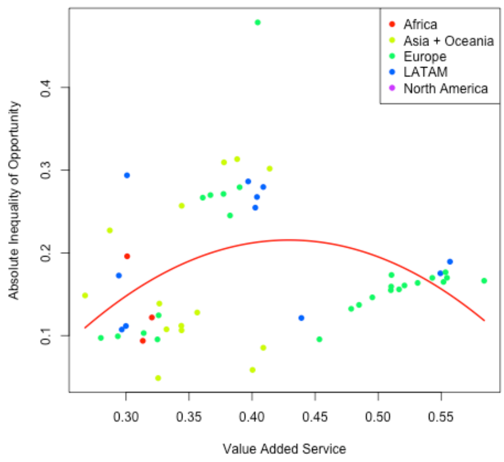
(f) Parametric fit (employment services)



(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.