GPiD Global Poverty & Inequality Dynamics Research Network

www.developersdilemma.org

Researching structural change & inclusive growth

ESRC GPID Research Network Working Paper 9

BEYOND KUZNETS:

INEQUALITY AND THE SIZE AND DISTRIBUTION OF CITIES

Author(s): David Castells-Quintana

Affiliation(s): Department of Applied Economics, Univ. Autonoma de Barcelona

Date: 3 November 2017

Email(s): David.Castells.Quintana@uab.cat

Notes: This draft relates to a presentation at the Panel on Structural change, inequality and inclusive growth, organised by the ESRC-GPiD Group, at the EADI in Bergen-August 2017. The full and revised paper is forthcoming in the Journal of Regional Science (DOI: 10.1111/jors.12368)

I want to thank Vicente Royuela, Paolo Veneri, Oriol Roca, Rosella Nicolini, Jens Suedekum and two anonymous referees for their comments. I am also grateful for comments received at the 3rd International Congress of the Spanish Network on Development Studies (REEDES) - 2016, at the AQR-IREA seminars – 2016, at the UAB-Applied Economics seminars - 2016, at the V Equalitas Workshop, at the 57th European Regional Science Association Congress – 2017, and at the EADI 2017 Conference. I also want to acknowledge the support of ECO2016-75805-R and ECO2016-76855-P

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

GCRF Global Challenges Research Fund

ABSTRACT

As countries develop the percentage of total population living in urban areas (the rate of urbanisation) tends to increase. As this happens, inequality is expected first to increase and then to decline in what is known as the Kuznets inverted-U. But the development economics literature has not paid much attention to differences in the absolute size of cities potentially affecting economy-wide inequality. Building on insights from the urban economics literature, this paper studies the relationship between the size and distribution of cities and income inequality at country level. The main contribution of the paper is to show that beyond Kuznets' hypothesis there is a U-shaped relationship between average city size and inequality; inequality is expected first to fall and then to increase with average city size. This result is found to be robust to a long list of controls, and different estimation techniques and identification strategies.

KEYWORDS

Urbanisation; agglomeration; city size; inequality; development;

About the GPID research network:

The ESRC Global Poverty and Inequality Dynamics (GPID) research network is an international network of academics, civil society organisations, and policymakers. It was launched in 2017 and is funded by the ESRC's Global Challenges Research Fund.

The objective of the ESRC GPID Research Network is to build a new research programme that focuses on the relationship between structural change and inclusive growth.

See: www.gpidnetwork.org

THE DEVELOPER'S DILEMMA

The ESRC Global Poverty and Inequality Dynamics (GPID) research network is concerned with what we have called 'the developer's dilemma'.

This dilemma is a trade-off between two objectives that developing countries are pursuing. Specifically:

1. Economic development via structural transformation and productivity growth based on the intra- and inter-sectoral reallocation of economic activity.
2. Inclusive growth which is typically defined as broad-based economic growth benefiting the poorer in society in particular.

Structural transformation, the former has been thought to push up inequality. Whereas the latter, inclusive growth implies a need for steady or even falling inequality to spread the benefits of growth widely. The 'developer's dilemma' is thus a distribution tension at the heart of economic development.

1. INTRODUCTION

One major characteristic of the process of economic development is the movement of people from rural to urban areas. As a result, the percentage of population living in urban areas (the rate of urbanisation) increases, with economic development usually going hand-to-hand with urbanisation. According to classical theories (i.e., Lewis 1954; Kuznets 1955), this process is related to economy-wide inequality in a non-linear way: inequality first increases, as countries urbanise, and then declines as urbanisation proceeds. This non-linear relationship between income (and urbanisation) and inequality is known as the Kuznets' inverted-U. But economic development is also associated with a change (usually an increase) in the number, absolute size and distribution of urban areas (cities). According to the urban economics literature, different cities and different size of cities are expected to experience different levels of mean income and of income inequality.[1] Consequently, there is no reason to expect that when the number, size and distribution of cities changes, inequality will remain unchanged. However, this is an issue that to date remains understudied.[2]

The overarching aim of this paper is to analyse the relationship between the size and distribution of cities and income inequality, using panel data for as many countries around the world as possible, looking at nation-wide inequality, controlling for several determinants of inequality, and considering non-linearities in the relationship.

Income inequality within countries has increased significantly during the last decades (see for instance Milanovic 2011 and Cairo-i-Cespedes and Castells-Quintana 2016). Understanding why and how inequalities increase is important in fairness terms, but also as the association between inequality and economic performance has been shown to depend on the factors defining inequalities (i.e., World Bank 2006; Marrero and Rodriguez 2014; Castells-

[1] The urban economics literature has shown not only the relevance of city size for city-level productivity, but also the relevance of the distribution of cities for country-level productivity (see for instance White 1981; Duranton and Puga 2004). In what refers to city-level inequality, it has been suggested that it is expected to decrease when small cities grow, but it is expected to increase when large cities grow (see for instance Nord 1980).

[2] For a fixed total population, the urbanisation rate of a given country may increase as the number of cities increase, or as the existing cities increase in size. It follows that information on the number, size and distribution of cities, can give us additional information on the evolution of inequality, *beyond* that given by the urban rate.

Quintana and Royuela 2017). As the Kuznets' hypothesis and many recent papers highlight, spatial issues, especially those associated with urban dynamics, are likely to be crucial for inequality. In the policy arena, there have been recent claims that "urbanisation can be a force for tackling inequality" (see for instance Burton and Argilagos 2016). But at the same time there have been warnings that large cities have greater income inequality (see for instance Holmes and Berube 2016). Most countries today are either highly urbanised or are experiencing a fast process of urbanisation, with the number and size of cities experiencing rapid growth, but it is not yet clear how these trends affect the evolution of country-wide inequality. In fact, how rapid urbanisation affects inequalities is still an under-researched issue (Henderson 2010). Rapid urbanisation and increasing inequalities may not only be linked but are both today major challenges for many countries around the world. Consequently, understanding the relationship between the size and distribution of cities and income inequality becomes crucial for policy makers concerned with urban life and sustainable inclusive development.

In relation to existing studies, this paper is closely linked to two main strands of the literature on inequality. On the one hand, the paper relates to works in the development economics literature studying the determinants of economy-wide inequality. Papers in this literature usually consider inequality *at the country level* (i.e., Fields 1979, for Least Developed Countries; Milanovic 1994, Li et al. 1998, Gustafsson and Johansson 1999, Barro 2000, Vanhoudt 2000, Frazer 2006, and Roine et al. 2009, for world samples; Odedokun and Round 2004, for Africa; and Castells-Quintana and Larrú 2015, for Latin America). Other papers study inequality *at the regional level* (i.e., Perugini and Martino 2008; Tselios 2008, 2014; Rodríguez-Pose and Tselios 2009; Royuela et al. 2014; Castells-Quintana et al. 2015). One key and usual issue of analysis in all of this literature is that of the relationship between development (and urbanisation) and income inequality in the spirit of the Kuznets' inverted-U. But no paper in the development economics literature considers the size and distribution of cities as a potential determinant of inequality. On the other hand, the paper is also linked to the urban economics literature. Papers in this literature study the relationship between city size and income inequality *at the city level* (i.e., Duncan and Reiss 1956; Richardson 1973; Haworth et al. 1978; Nord 1980; Long et al. 1977; Alperovich 1995; Baum-Snow and Pavan 2013; Behrens and Robert-Nicoud 2014; Glaeser et al., 2015; Sarkar et al. 2016; Ma and Tang 2016).[3] While

[3] There is mixed evidence in the urban economics literature in what refers to the city size-inequality relationship. Older papers had suggested that inequality goes down with city size. More recent papers suggest the opposite.

these papers focus on size, they look at city inequality and do not consider effects on the level of economy-wide inequality. Finally, this paper also relates to Brulhar and Sbergami (2009) and Frick and Rodriguez-Pose (2016). The first looks at urban concentration in cities of different sizes, whilst the second looks at average city size, both to analyse effects on national economic growth. To the best of my knowledge, no paper has studied the relationship between the size and distribution of cities and economy-wide income inequality. This paper aims to fill this gap.

The remainder of the paper is organised as follows. Section 2 describes the data to be used to study the relationship between inequality and the size and distribution of cities, and presents some basic stylised facts. In Section 3, main estimations and results are presented, while section 4 performs some robustness check. In Section, 5 results are discussed, delving into potential mechanisms linking what happens to cities and economy-wide inequality. Finally, section 6 concludes and derives policy implications from the results.

2. DATA AND STYLIZED FACTS

Data

To study the relationship between the size and distribution of cities and income inequality I rely on panel data for as many countries as possible depending on data availability between 1960 and 2010. Data for income inequality for several countries and for a long-time span is scarce, which has conditioned the analysis of the evolution and the determinants of inequality. To overcome this limitation, I use data from the Standardised World Income Inequality Database (SWIID) version 5.0 (Solt 2014). SWIID uses a custom missing-data multiple-imputation algorithm to standardise observations. The database combines data from several sources, including the UN-WIID Database, the OECD Income Distribution Database, Eurostat, the World Top Incomes Database, the University of Texas Inequality Project, and the Luxemburg Income Study data. The SWIID data has been homogenized to maximise the comparability of available income inequality data across countries and over time. However, following Solt (2009; 2014), multiple-imputations are performed when using the data to consider uncertainty from SWIID estimates.

To study the size and distribution of cities within countries, data from the World Urbanisation Prospects - WUP - (UN 2014) is used. The WUP gives data on agglomeration size, in terms of population, for agglomerations of more than 300 thousand inhabitants (in 1990) from 1950 onwards for as many countries in the world as possible (up to 199 countries, including more than 1690 urban agglomerations worldwide).[4] As key explanatory variable a natural starting point is to consider the average city size.[5] Urban agglomeration size, rather than city size, is considered, as the literature has shown that for both income and income inequality what matters is the size of the urban agglomeration rather than that of the city (although in the paper I may indistinctly refer to urban agglomeration or city size). To construct the variable, *AveAggSize*, I simply consider all agglomerations above 300 thousand inhabitants and calculate country-year means. In the robustness section I address the issue that average agglomeration size may be driven by one or few cities.[6]

To capture Kuznets' inverted-U, income per capita (in logs) and its square are considered, using data from the Penn World Tables (PWT). Finally, for the econometric analysis carried out in sections 3 and 4, other variables that the literature has found to potentially influence inequality at country level are considered. I start by considering economic growth (*ecogrowth*), investment shares (*ki*), government spending (*kg*), and educational levels (average years of *schooling*). As robustness, additional variables are considered, including total population, the percentage of urban population, fertility rates, coal rents, exports, and the size of the agricultural sector (these last three as percentage of GDP). Other variables that may be correlated with average agglomeration size, like the population of the largest city, the percentage of total population living in urban agglomerations of more than one million inhabitants, and the percentage of urban population living in the largest city, are also considered. All of these variables come from different sources, including the World Bank and the PWT. Historical data on population of major cities from Mitchell (2013) is also used for

[4] As many authors have highlighted, working with data on city size and urbanisation rates poses the challenge of the definition of what constitutes a city, which may vary across countries. WUP data takes this into account and aims at smoothing these differences as much as possible to ease comparability across countries.

[5] Online Supplementary Material explains in more detail why when we compare average city size across countries we are actually comparing the scale of cities for the whole city-size distribution in each country.

[6] The focus on agglomerations above 300 million inhabitants lies in three main reasons: i) data availability, ii) the fact that agglomeration economies and congestion costs have been shown to be significant only in sufficiently large cities, and iii) the fact that, according to Zipf´s law, information on cities above 300 thousand inhabitants should be enough to delineate the size of all cities. For more on Zipf's law and on the size and growth of cities, see Gabaix (1999) and Duranton and Puga (2013).

identification in cross section estimates, as explained in Section 4. Annex A lists all variables' names, definitions and sources, whilst descriptive statistics for main variables and correlations among them, as well as a list of countries included in the analysis, can be found in Online Supplementary Material.

Some Stylised Facts

Looking at the data, some clear facts emerge. The first of these facts is the rapid pace of urbanisation. The percentage of the world population living in urban areas has increased from around 30 in 1950 to around 54 in 2015, and is expected to reach 66 by 2050 (according to WUP 2014 estimates). A second fact relates to the increase in the number of urban agglomerations. Considering urban agglomerations of more than 300 thousand inhabitants, the number of urban agglomerations around the world has increased from 304 in 1950 to 1729 in 2015 (and is projected to reach 2225 in 2030). The number of urban agglomerations with more than 1 million inhabitants has also gone up dramatically, from 77 in 1950 to 501 in 2015. And the number of agglomerations with more than 10 million inhabitants has gone from 2 in 1950 (Tokyo and New York) to 29 in 2015. A third fact relates to the average agglomeration size, which also shows a rapid increase, either looking at agglomerations across the world or looking at the average agglomeration size within countries. The mean across countries in average agglomeration size has increased from 253 thousand inhabitants in 1950 to 1.268 million in 2015 (see Annex B). Annex C maps values for countries around the world in 2015. Two single-agglomeration countries, Honk-Kong and Singapore, display the highest values. Among the top 20 countries only 3 are developed (Japan, Portugal and Greece), the rest are developing countries. In terms of population, these two facts - a higher number of urban agglomerations and a higher average agglomeration size - translates into more and more people living in large cities. While in 1950 around 300 million people in the world lived in urban agglomerations of more than 300 thousand inhabitants, this figure exceeds 2.2 billion in 2015, which is almost a third of the total world population, and 57% of the world urban population. And among all urban agglomerations, the cities of more than 10 million inhabitants concentrate alone more than 12 per cent of the world urban population.

Finally, regarding inequality at country level, during the considered period, 81 out of the 174 countries in SWIID database experienced an increase in their Gini coefficients, while 55 experienced a decrease.

3. INEQUALITY AND THE SIZE AND DISTRIBUTION OF CITIES: AN EMPIRICAL ANALISIS

Bivariate Correlations

When studying the relationship between the size and distribution of cities and income inequality, we should be aware of the potential relationship between income per capita (and urbanisation) and inequality suggested by classical theories of structural change. According to these theories, the process of economic development tends to be accompanied by an increasing proportion of the population living in urban areas, affecting the overall level of inequality in a non-linear way (the Kuznets' inverted-U). We want to examine whether the relationship between the size and distribution of cities and income inequality reflects something else beyond the relationship between (economic) development and inequality. Figures 1.A to 1.F examine the correlation between income per capita and income inequality, and between average agglomeration size and income inequality. While Figures 1.A and 1.B consider all panel data, Figures 1.C and 1.D consider inequality levels in 2010 and average agglomeration size and income per capita in 1960, to capture long-run associations. Finally, Figures 1.E and 1.F consider only variation over time within countries (i.e., controlling for country fixed effects).[7] This bi-variate analysis reflects an inverted-U relationship between income and inequality levels, in line with the Kuznets hypothesis. But the analysis also reflects a different quadratic relationship beyond Kuznets', that between average city size and inequality. A U-shaped relationship emerges (not reported before in the literature): inequality first declines and then increases with average agglomeration size.

[7] For simplicity, in the scatter plots in Figure 1 I only include visual reference to observations considered in Figure 1.C and 1.D, and not in Figures 1.A, 1.B, 1.E and 1.F (as these would represent having more than 800 dots in the scatterplots, making it difficult to visualise). Also remember that inequality data comes from multiple imputations.

FIGURE 1: Income per capita and inequality, and average agglomeration size and inequality

Figure 1.A and 1.B: Pooled data

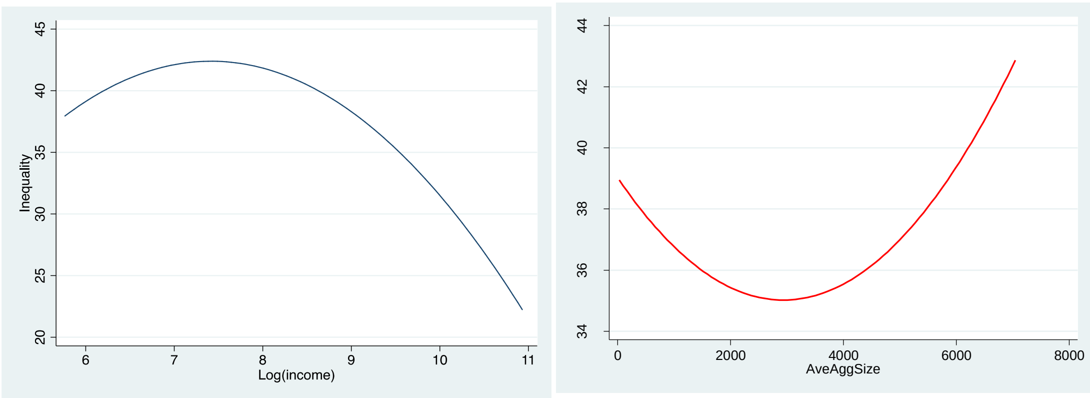


Figure 1.C and 1.D: Long-run associations

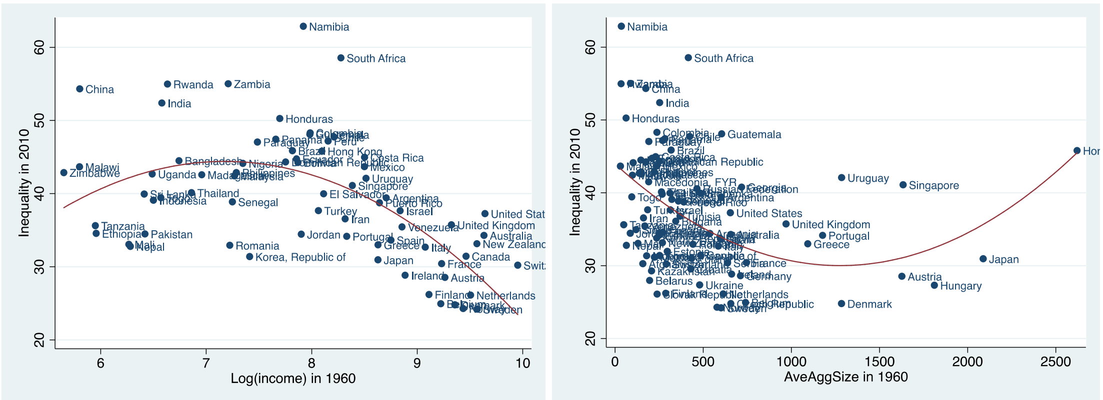
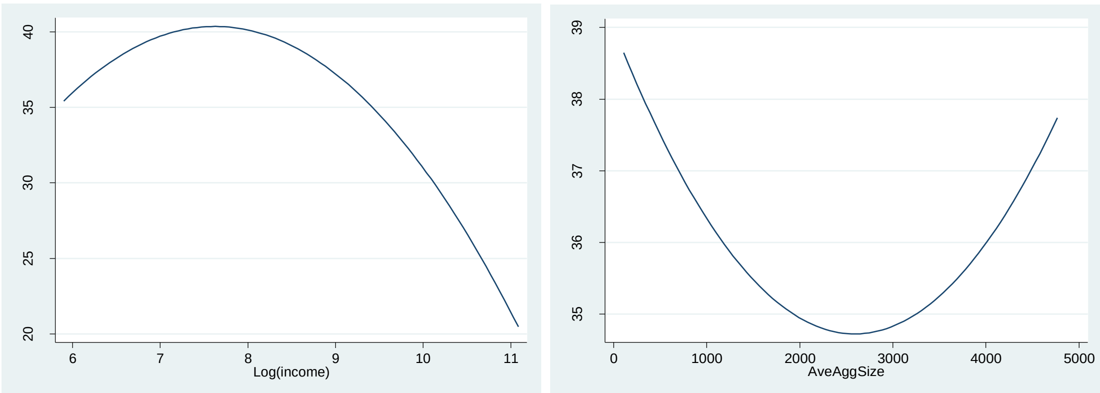


Figure 1.E and 1.F: Short-run associations (i.e., including country-fixed effects)



Note: Inequality measured by the Gini coefficient (0 to 100). AveAggSize measured in thousand inhabitants.

Econometric Analysis

Does the U-shaped relationship between average agglomeration size and income inequality survive rigorous econometric analysis? To test this, we can use the considered panel data to estimate *cross-country* regressions like the one in equation (1):

$$inequality_{it} = \alpha_1 income_{it-1} + \alpha_2 income_{it-1}^2 + \beta AveAggSize_{it-1} + \psi X_{i\,t-1} + \varepsilon_{it} \quad (1)$$

Where $inequality_{it}$ is income inequality in country i in time t, $income$ is income per capita (in logs), X potential factors influencing income inequality, and ε_{it} a country-time specific shock. Income per capita is considered in linear and quadratic form to capture the Kuznets' inverted-U.[8] The key independent variable is *AveAggSize*, average (urban) agglomeration size, for each considered country-year observation. As with income per capita, a linear as well as a quadratic term for average agglomeration size can be considered.

Equation (1) is estimated considering as many countries as possible (up to 131 in main estimations) and the longest time span depending on data availability (usually considering data from 1960 to 2010 and splitting the data into five-year periods). All right-hand-side variables are included one period before to reduce problems of reverse causality. As data to measure income inequality comes from Solt (2014), all estimations are done using multiple-imputation estimates (100 imputations), small-sample adjustment and clustering errors at the country level.[9] Time effects are included to control for global shocks. Several panel data techniques are implemented, including Ordinary Least Squares (pooled-OLS) and country-Fixed Effects (FE), in order to control for country-specific characteristics.

Table 1 presents main results. Column 1 only considers *AveAggSize* and presents pooled-OLS estimates. Results yield a negative and significant coefficient, indicating that the higher the average agglomeration size of a country the lower its level of income inequality. Column 2 considers *AveAggSize* and its square to control for non-linearities. Results yield a negative coefficient for the linear term and a positive for the quadratic, being both highly significant, and suggesting that inequality first decreases and then increases with average agglomeration size. Column 3 introduces income per capita (in logs) and its square to capture

[8] In the robustness section, other functional forms are considered.

[9] Given the uncertain nature of some estimated inequality values in SWIID data, econometric estimation are done with multiple imputations that take into account error bands in the imputed values (MI estimations in Stata).

Kuznets' inverted-U. All coefficients are highly significant and have the expected signs, reflecting an inverted-U relationship between income and inequality (Kuznets), but also a U-shaped relationship between average agglomeration size and inequality (our hypothesis). Column 4 introduces country fixed effects. Results hold for *AveAggSize* and its square, but the coefficients for income are no longer significant. Finally, columns 5 and 6 introduce further controls (at the expense of losing observations). Controls have the expected sign (although coefficients are not always significant) and seem to affect the coefficient for income and its square. However, *AveAggSize* and its square still display significant coefficients, negative the first and positive the second.[10]

Estimates confirm a U-shaped relationship between average agglomeration size and inequality. This relationship between the two variables suggests an optimal level of average agglomeration size. This level changes depending on the estimation, falling between 2 and 3 million inhabitants. In other words, everything else equal, an average agglomeration size between 2 and 3 million inhabitants minimizes the overall level of national inequality. An average agglomeration size of 3 million inhabitants turns out to be a relatively high value. Most countries in our sample have levels of average agglomeration size below 3 and even 2 million. But countries differ greatly in what refers to the functional characteristics of their urban agglomerations (see for instance Castells-Quintana 2017), which is likely to influence the relationship between average agglomeration size and inequality. Consequently, we can expect each country to have its optimal level of average agglomeration size (something that arises as interesting for further research).

[10] Regressing economic growth on average agglomeration size and its square yields significant coefficients: economic growth increases and then declines with average agglomeration size (results available upon request). This result is expected according to the urban economics literature, given agglomeration benefits and congestion costs that come with city size, and are in line with Frick and Rodriguez-Pose (2016).

TABLE 1: Main results

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: *Inequality* (Gini Coefficient)						
AveAggSize	-0.0012**	-0.0060***	-0.0025**	-0.0039*	-0.0052**	-0.0054
	(0.0005)	(0.0013)	(0.0010)	(0.0023)	(0.0026)	(0.0046)
$AveAggSize^2$		0.0001***	0.0001***	0.0001***	0.0001***	0.0001**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log*(income)*			31.6839***	11.5567	10.799	24.7052**
			(3.4654)	(8.3669)	(8.8662)	(10.9818)
$\text{Log}(income)^2$			-2.0863***	-0.5605	-0.4389	-1.4248**
			(0.2108)	(0.4457)	(0.4728)	(0.6251)
Ecogrowth					0.0789	0.0300
					(0.0940)	(0.0792)
Investment (*ki*)					-0.0407	-0.0246
					(0.0526)	(0.0634)
Gov spend (*kg*)					-0.1569	-0.2704
					(0.1739)	(0.2189)
Education (*schooling*)					-1.2582*	-0.6577
					(0.6623)	(1.0041)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES	YES
Additional controls	NO	NO	NO	NO	NO	YES
Observations	828	828	752	752	690	524
No. of countries	131	131	131	131	111	107

Note: All right-hand-side variables are lagged one period. *Econ growth*, *ki* and *kg* are calculated as averages over 5 years. All remaining variables are measured at the beginning of the period. Additional controls include: *poptotal*, *urbrate*, *fertility*, *coal*, *exports*, and *agriculture*. The time span goes from 1970 to 2010. All estimations are done with multiple-estimation regressions (100 imputations) and small-sample correction. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4. ROBUSTNESS CHECKS

An N-Shaped Relationship between Income and Inequality

It has been suggested that growth patterns of recent decades are leading to increasing inequalities in already industrialised countries –where inequality should be decreasing according to the traditional Kuznets' hypothesis (see Alderson and Doran 2013). In fact, non-significant results for the Kuznets hypothesis in columns 4 and 5 of Table 1 could mask a different functional form for the relationship between income and inequality. Furthermore, our U-shaped relationship between average agglomeration size and inequality may be capturing the recent increasing inequalities in developed countries. Column 1 of Table 2 allows for a more flexible functional form in the income-inequality relationship; including income per capita (in logs) in linear, quadratic and cubic form.[11] Results are highly significant and suggest that the inverted-U relationship between economic development and inequality may now have an N shape: first increasing, then declining, and finally rising again. Similar results have recently been found for European regions (Castells-Quintana et al. 2015). To the best of my knowledge this result has not been documented before in a cross-country framework. The inclusion of this N-shaped relationship between income and inequality indeed affects the coefficients for *AveAggSize*, and its square. This means that part of the association between average agglomeration size and inequality may be explained by the association between city-size and economic performance.[12] However, even controlling for income levels, we still find a significant quadratic relationship between average agglomeration size and income inequality.[13]

[11] Non-parametric estimations support this cubic relationship between income per capita and inequality.

[12] Recent research in urban economics for developed countries shows that i) productivity increases with city size, and ii) that the largest cities are also the most unequal (i.e., Baum-Snow and Pavan 2013; Behrens and Robert-Nicoud 2014). Consequently, the high and increasing inequality of the largest cities may help explain why the inverted-U now has an N shape.

[13] I also checked that results are not driven by i) potential outliers, or ii) specific regions of the world, and iii) that they hold when excluding countries for which we have information on only one urban agglomeration (but at the expense of losing observations).

Confounding Factors

As further robustness checks we can consider potential "confounding factors"; variables potentially correlated with average agglomeration size that may influence income inequality also in a non-linear way. In column 2 of Table 2 I introduce *poplargest*, the population of the largest city (urban agglomeration) of the country, and its square. Our key variable, *AveAggSize*, is highly influenced by the size of the largest urban agglomeration of each country. Also, concentrating a big fraction of the population and economic activity of the country, the largest city can have a potential effect on both economy-wide economic performance and income inequality. Thus, by controlling for *poplargest*, we can check whether results are only driven by what happens to the largest agglomeration or indeed reflect something related to the average agglomeration size of the entire country. In a similar fashion, it would be interesting to control for what happens to the largest cities. In column 3 I introduce *urb1m*, the percentage of total population living in cities of more than 1 million inhabitants, and its square. Finally, in column 4 I introduce *primacy*, the percentage of urban population living in the largest city. Primacy captures how concentrated urban population is in a country, which may be interesting to control for, to disentangle the effect of average agglomeration size from that of the urban structure of the country.[14] In all cases the coefficients for *AveAggSize* and its square remain significant, negative the first and positive the second.[15]

[14] Primacy has also been shown to be relevant for economic growth (i.e., Henderson 2003; Castells-Quintana 2016). It can be interesting to also examine its role in income inequality (something not done before in the literature). Results suggest that if we control for average agglomeration size primacy plays no significant role in income inequality. Results in Table 2 hold regardless of the model used - in terms of i) whether we include base controls or also additional controls, and ii) whether we include Log*(income)*^{3} or not.

[15] The dispersion in the size of cities does seem to be relevant: higher dispersion is associated with lower inequality when dispersion is low, but it is associated with higher inequality when dispersion is already high.

TABLE 2: Robustness checks

	(1)	(2)	(3)	(4)
Dependent variable: *Inequality* (Gini Coefficient)				
AveAggSize	-0.0035	-0.0048*	-0.0071**	-0.0041*
	(0.0026)	(0.0028)	(0.0035)	(0.0024)
AveAggSize^2	0.0001**	0.0001**	0.0001**	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(*income*)	130.124***	128.1552***	155.7610***	135.1993***
	(40.1534)	(40.7313)	(39.5491)	(40.7030)
Log(*income*)^2	-14.9421***	- 14..8199***	-18.1386***	-15.4686***
	(4.7874)	(4.9016)	(4.7442)	(4.8645)
Log(*income*)^3	0.5758***	0.5748***	0.7037***	0.5920***
	(0.1888)	(0.1950)	(0.1878)	(0.1920)
Pop largest city		0.0002		
		(0.0004)		
Pop largest city^2		0.0001		
		(0.0001)		
Urb 1m			0.4799	
			(0.3307)	
Urb 1m^2			-0.0028	
			(0.0037)	
Primacy				0.3039
				(0.2012)
Primacy^2				-0.0029
				(0.0028)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES

Controls	YES	YES	YES	YES
Observations	690	690	690	688
No. of countries	111	111	111	110

Note: *Pop largest city* is the size of the largest city, *Urb 1m* is the total population in cities of more than one million inhabitants (as percentage of total population), and *Primacy* is the percentage of urban population living in the largest city. All right-hand-side variables are lagged one period. Controls include: *econ growth*, *ki*, *kg* and *schooling*. The time span goes from 1970 to 2010. All estimations are done with multiple-estimation regressions (100 imputations) and small-sample correction. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sorting and Endogeneity

So far results point towards a U-shaped relationship between average agglomeration size and income inequality at country level, robust to a long list of controls. A relationship that is interesting in itself, and so far overlooked in the literature. Does this relationship imply a causal effect of average agglomeration size on income inequality? Papers working with income (or income inequality) at city level face a problem of sorting across cities: these papers need to disentangle the *true* effect of city size on income (or income inequality) from the one produced by the fact that larger cities attract people with different abilities and skills. With much less mobility across countries (and most probably not driven by cross-country differences in average city size), this problem is much lower when we work with income inequality at country level. But we can still face endogeneity concerns. First, due to reverse causality: it could be that higher inequality at country level leads to higher average agglomeration size, for instance if more unequal places grow at a faster rate - higher inequality has usually been associated with higher fertility rates (i.e., Barro 2000). Second, we may suffer from endogeneity due to relevant omitted variables. These concerns have already been partially considered: estimations in Tables 1 and 2 introduced *AveAggSize*, and its square, lagged 5 years with respect to income inequality, to reduce reverse causality. Estimations in Table 2 also considered several additional controls potentially correlated with both average agglomeration size and income inequality. However, to further check for endogeneity we can perform alternative estimation techniques. Furthermore, income inequality at country level has been shown to be very persistent over time, implying that our FE results could be inconsistent – and calling for a different estimation strategy if we want to get closer to a causal relationship.[16] In this line two things are done. One is to first difference equation (1), to remove unobserved time-invariant country-specific characteristics that may be correlated with both average agglomeration size and income inequality. Column 1 of Table 3 shows first-differences (FD) estimates. Results are very similar to those in column 6 of Table 1.[17] A first-differences specification then allows us to use lags of *AveAggSize*, and its square, to predict first-differences and perform Instrumental Variables (FD-IV) estimations.[18] Consistency of IV estimates depends on the validity of the instruments. For lags of *AveAggSize* to be valid instruments they should not only be relevant (that is, explain first-differences in *AveAggSize*) but also exogenous and affect inequality only through first-differences in *AveAggSize* (the exclusion restriction). First-stage results (available as Online Supplementary Material) show second and third lagged levels of *AveAggSize* displaying significant power to predict first-differences. To test for the exclusion restriction, we can estimate residuals from the first and second stage and then run residuals of the second stage on those from the first stage. Results are not significant, indicating that the two residuals are not correlated, and providing evidence to support the exclusion restriction. Table 3 reports additional tests that support the validity of the instruments. Column 2 uses second and third lagged levels of *AveAggSize*, and its square, as instruments. Column 3 uses third and fourth lagged levels. In both cases, FD-IV estimates yield significant coefficients for *AveAggSize* and its square.[19]

---

[16] I have estimated dynamic models using different techniques (including GMM estimations), in which inequality in time t depends on inequality in $t-1$. The coefficient for the lagged dependent variable is positive and highly significant, confirming the persistence of inequality, but this does not affect our main results.

[17] In static models first differencing (FD) is almost equivalent to introducing fixed effect (see Wooldridge 2010). However, if strict exogeneity fails, FD is preferred over FE: FD removes long-run trends, which is important given the nature of our variables (something that is not done with FE).

[18] Gonzalez-Navarro and Turner (2016) also work with panel data on city-level population across the world, and use a similar identification strategy building on Olley and Pakes (1991) and Arellano and Bond (1991).

[19] Online Supplementary Material provides a table with main results using different specifications for average agglomeration size: i) considering average agglomeration divided by total population, and ii) considering average agglomeration size in logs. Main results hold.

TABLE 3: First Differences and Instrumental Variables estimations

	(1) FD	(2) FD-IV	(3) FD-IV
Dependent variable: Δ*Inequality* (Gini Coefficient)			
ΔAveAggSize	-0.0051**	-0.0099***	-0.0105**
	(0.0025)	(0.0036)	(0.0044)
ΔAveAggSize^2	0.0001**	0.0001***	0.0001**
	(0.0000)	(0.0000)	(0.0000)
ΔLog(*income*)	1.3838	1.4862	1.5374
	(2.9273)	(2.0995)	(2.1015)
ΔLog(*income*)^2	-4.0014	-4.3714	-4.3821
	(4.2466)	(4.1762)	(4.1755)
ΔLog(*income*)^3	21.0575***	22.5732***	22.8786***
	(6.2468)	(6.3318)	(6.3807)
Year FE	YES	YES	YES
Controls	YES	YES	YES
Observations	477	477	477
No. of countries	111	111	111
AP first-stage F-stats p-value		0.000; 0.000	0.000; 0.013
Kleibergen-Paap F-stat		38.09	7.171
Kleibergen-Paap LM-stat		36.06***	23.01***
Hansen J stat p-value		0.325	0.254

Note: Controls include: *Δecon growth*, *Δki*, *Δkg* and *Δschooling*. Instruments in column 2 are second and third lags of *AveAggSize*, and its square. Instruments in column 3 are third and fourth lags of *AveAggSize*, and its square. Angrist-Pischke (AP) F tests the significance of excluded instruments. Kleibergen-Paap F-stat tests for weak instruments. Kleibergen-Paap LM-stat tests the null hypothesis that the equation is underidentified. Hansen J tests that the excluded instruments are uncorrelated with the error term. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Estimates in Table 3 allow for a better identification of a causal effect of average agglomeration size on income inequality at country level. This effect is non-negligible. According to estimates, a standard deviation from the optimum level of average agglomeration size can represent a Gini coefficient approximately one point higher, and up to 5 points higher in the case of those countries with the highest average agglomeration size. Nevertheless, these results should be taken with caution and could invite further research.

Cross-Section Specification and External Instruments

Finally, there are questions as to whether panel methods are the most appropriate when working with variables that are fairly stable over time, as is the case with inequality (see for instance Easterly 2007). An alternative approach is to estimate equation (1) using a simple 'deep' cross-section, regressing inequality measured in 2010 on right-hand-side variables measured in 1960. This is another strategy to further reduce problems of reverse causality and consider a long-run association (50 years) between average agglomeration size and income inequality.[20] Columns 1 and 2 in Table 4 show estimates by OLS. Column 1 controls for the Kuznets' hypothesis, while column 2 includes further controls as well as dummies for Latin America and the Caribbean and Sub-Saharan African countries, which tend to display significantly higher levels of inequality. Columns 3 and 4 show IV estimates: in column 3 levels of average agglomeration size in 2010 are instrumented with levels in 1960, while in column 4 levels of average agglomeration size in 1960 are instrumented with average agglomeration size *circa* 1870, constructed with historical data from Mitchell (2013), but at the expense of losing observations.[21] Recent papers have used historical data to instrument for current population

[20] Panel FE, or panel FD, estimates consider variation within countries over time, so results relate to the association between *changes* in average agglomeration size and *changes* in income inequality. Our cross section setting considers variation between countries, so results relate to the association between *levels* in average agglomeration size in the past (1960) and *levels* in income inequality today (2010).

[21] Online Supplementary Material describes how average agglomeration size *circa* 1870 is constructed, and shows results from first stage of column 4-Table 4. IV estimations using historical data, although in line with the rest of our results, should be taken with caution according to standard instrument tests (there is risk of underidentification probably due to small sample).

(see for instance Duranton 2015). In all four columns of Table 4 the coefficients for *AveAggSize* and its square remain significant and in line with our panel results.[22]

TABLE 4: Cross-section results

	(1) OLS	(2) OLS	(3) IV	(4) IV
Dependent variable: *Inequality* (Gini Coefficient in 2010)				
AveAggSize	-0.0118**	-0.0091**	-0.0113***	-0.0243**
	(0.0053)	(0.0044)	(0.0035)	(0.0123)
AveAggSize^2	0.0001*	0.0001*	0.0001***	0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(*income*)$_{1960}$	37.1296***	35.7961***	62.7216***	45.7037***
	(11.0606)	(13.2371)	(11.7061)	(13.9785)
Log(*income*)$^2{}_{1960}$	-2.5164***	-2.4826***	-4.3020***	-2.9784***
	(0.6878)	(0.8176)	(0.7482)	(0.8998)
Controls	NO	YES	YES	YES
Observations	70	66	66	56
F test of excluded instruments			59.76***; 39.01***	11.24***: 9.86***
Kleibergen-Paap F-stat			14.20	5.58
Kleibergen-Paap LM-stat			14.08***	1.998

Note: Controls include e*con growth*, *ki*, *kg* and *schooling*. In columns 1, 2 and 4 *AveAggSize* and its square are measured in 1960. In column 3 *AveAggSize* and its square are measured in 2010 and instrumented with 1960 values. In column 4 *AveAggSize* and its square are measured in 1960 and instrumented with *circa* 1870 values. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[22] These cross-section regressions can also be estimated using data from the World Bank, rather than using Solt (2014) data. Results are very similar, which reassures us about the robustness of the results to using alternative data for inequality. Results are available upon request.

5. DISCUSSION

Results so far suggest a U-shaped relationship between average agglomeration size and inequality; inequality first declines and then increases with average agglomeration size. FD-IV estimates using internal instruments and cross-section IV estimates using historical data suggest that this U-shaped relationship may reflect a causal effect of average agglomeration size on income inequality (although causality should be taken with caution).

This U-shaped relationship is in line with insights from urban economics and recent papers analysing the association between different types of urbanisation and inequality. These papers suggest that while urbanisation biased towards small and medium-sized cities is associated with decreasing inequality, urbanisation in large cities is expected to increase inequality (Behrens and Robert-Nicoud 2014 and Castells-Quintana and Royuela 2015). A decrease in inequality from larger urban agglomerations when average agglomeration size is still low may be associated with the fact that larger cities provide more opportunities, which may more strongly benefit low-income workers (see for instance Todaro 1969, 1976; North 1980). By contrast, the increase in inequality from larger urban agglomerations when average agglomeration size is already high may reflect agglomeration economies, which benefit more the high-skilled workers (as the urban economics literature suggests).

To delve deeper into potential mechanisms linking what happens to the system of cities and economy-wide inequality, we can explore the relationship between average agglomeration size and different factors related to inequality that may be affected by average agglomeration size.[23] I focus on four of these: access to basic services, human capital accumulation, fertility, and industrial specialisation.[24] Table 5 shows regressions (by OLS and FD) for proxies for these factors on average agglomeration size and its square (and several controls).

[23] In any case, this "exploratory" analysis should be interpreted with caution, as suggesting potential mechanisms and opening lines for further research. I do not pretend to identify these as strictly causal mechanisms (as this is not the aim of the paper).

[24] I focus on these specific factors as they may help explain why inequality falls as average agglomeration size increases, for low initial levels of this second variable. Factors explaining why inequality increases in large metropolitan areas –

TABLE 5: Average agglomeration size and variables associated with inequality

	(1) OLS	(2) FD	(3) OLS	(4) FD	(5) OLS	(6) FD	(7) OLS	(8) FD
Dep. variable:	sanitation	sanitation	enrolment	enrolment	fertility	fertility	agriculture	agriculture
AveAggSize	0.0116***	0.0039*	0.0049***	0.0165*	-0.0011***	-0.0005**	-0.0027***	-0.0016
	(0.0031)	(0.0021)	(0.0015)	(0.0090)	(0.0001)	(0.0003)	(0.0009)	(0.0051)
AveAggSize^2	-3.09e-06***	-6.71e-06	-1.05e-06***	-8.87E-06	1.80e-07***	-1.58E-07	6.56e-07***	5.77E-06
	(6.71e-07)	(5.98e-06)	(2.66e-07)	(0.00001)	(2.54e-08)	(5.72e-07)	(1.67e-07)	(0.0001)
Log(*income*)	13.4912***	4.6221**	4.9637***	0.4133	-0.7159***	-0.0748	-5.3133***	-11.5984**
	(1.1330)	(1.8424)	(0.4780)	(4.6754)	(0.0501)	(0.0974)	(0.5544)	(1.9511)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	433	330	477	243	1065	942	805	621

Note: Controls include: *econ growth*, *ki*, *kg*, *schooling*, *poptotal* and *urbrate*. *Sanitation* is the percentage of urban population with access, *enrolment* is primary enrolment rate, *fertility* is the national fertility rate, and *agriculture* is the share of agriculture in GDP. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

One potential mechanism relates to access to basic services, which appears as significantly associated with inequality. For instance, the correlation between access to sanitation facilities and inequality is -0.42. A higher average agglomeration size may allow for more efficient provision of basic services (and therefore a higher coverage). As columns 1 and 2 in Table 5 show, regressions of access to basic services (i.e., sanitation) on average agglomeration size and it square yield significant coefficients for our key variables: positive

for instance higher returns to high skills – have already been analysed in other papers (i.e., Baum-Snow and Pavan 2013; Behrens and Robert-Nicoud 2014).

for average agglomeration size and negative for its square. This suggests that, for low levels of average agglomeration size, an increase in this variable is associated with increases in access to basic services (in turn associated with lower inequality). And this happens in a non-linear way: an “excessive” average agglomeration size can lead to *lower* access to basic services. Another potential mechanism relates to human capital accumulation, proxied by primary enrolment rates. The literature has shown the relevance of primary education in reducing inequality (see for instance Psacharopoulos 1994). Starting from low values, a higher average agglomeration size may allow for higher enrolment rates. As with services, results (in columns 3 and 4) suggest a non-linear association between average agglomeration size and (primary) human capital accumulation. A third potential mechanism is demographic. Several authors have highlighted the connection between fertility and inequality, and how fertility usually falls with income and urbanisation (see for instance Barro 2000). Columns 5 and 6 in Table 5 show that fertility rates fall as average agglomeration size increases. Finally, we can look at the industrial composition of the economy. One of the main arguments behind the idea of urbanisation being a force to tackle inequality is that cities offer a wide range of opportunities for the low- and medium-skilled (Todaro 1976; Burton and Argilagos 2016). Columns 7 and 8 show regressions for agriculture-to-GDP ratio on average agglomeration size and its square, yielding a negative coefficient for the first and a positive for the second (both significant under OLS but not under FD). This means that when average agglomeration size is low, larger agglomerations are associated with a lower share of agriculture in GDP, which is associated with lower inequality. And this happens controlling for the expected association between lower shares of agriculture and higher income levels and urbanisation (central to structural change models).

Results in Table 5 simply suggest potential mechanisms explaining the U-shaped relationship between average agglomeration size and inequality. More insights into the issue, maybe formalising a structural model, arise as interesting further research.

6. CONCLUSION AND POLICY IMPLICATIONS

This paper has studied a relationship so far neglected in the literature; that between average agglomeration size and income inequality. While the literature has emphasized the relationship between economic development (and urbanisation) and income inequality, it has not paid much attention to the potential role of differences across economies and over time in the size and distribution of cities. To address this issue, this paper has combined the literature on the determinants of income inequality at country level with the literature focusing on the relationship between city size and inequality.

Using cross-country panel data for as many countries and for the longest time span as possible, results support the original inverted-U relationship between economic development and inequality (the Kuznets' hypothesis). Additionally, results are also in line with the idea that the inverted-U may now have an N shape; inequality first increases with income, then declines, and finally rises again. But, beyond Kuznets' relationship between income and inequality, results also suggest a U-shaped relationship between average agglomeration size and inequality; inequality first declines and then increases with average agglomeration size. This relationship, so far overlooked in the empirical literature, has been found to be robust to several estimation techniques and a long list of controls and robustness checks. Furthermore, these findings can also help us reconcile the seemingly opposing claims on the inequality-reducing effect of urbanisation, on the one hand, and the risks of large cities increasing inequality, on the other.

Put together, results evidence that current patterns of economic growth and increasing size of cities bring with them a worrying risk of increasing inequalities. And the policy implications are straightforward. Larger average agglomeration size may be desirable when cities are small. In this case, larger cities are likely to lead to better economic performance, as cities benefit from agglomeration economies. Also, income inequality is expected to fall. However, a very high average agglomeration size is undesirable. On the one hand, continuous growth of very large cities has been argued to reduce overall economic performance, mostly due to increasing congestion costs. On the other hand, as results in this paper show, excessive average agglomeration size is associated with increases in inequality. High inequality has been found to be detrimental for long-run economic growth, but also to hinder the benefits from agglomeration (Castells-Quintana and Royuela 2014). Consequently, results reinforce the idea that medium-sized cities may be more desirable for economic development: they may be associated with stronger long-run economic performance and to more cohesive societies. Nevertheless, as the urban economics literature has emphasized, to properly study the desirability of larger or smaller cities it is important to consider further characteristics of cities beyond size. In this line, further research is needed to better understand the mechanisms behind the relationship between the size and distribution of cities (and what happens in cities) and the overall level of inequality.

REFERENCES

Alderson, A. & Doran, K. (2013). How has income inequality grown? The reshaping of the income distribution in LIS countries. In J. Gornick, & M. Janti (Eds.), *Income Inequality: Economic Disparities and the Middle Class in Affluent Countries* (pp. 51-74). Stanford, CA: Stanford University Press.

Alperovich, G. (1995). The relationship between income inequality and city size: a general equilibrium model of an open system of cities approach. *Urban Studies*, 32(6), 853-862.

Arellano, M. & Bond, S. (1991). Some test of specification for panel data: Monte Carlo evidence and an application to employment. *Review of Economic Studies*, 58(2), 277-297.

Barro, R. J. (2000). Inequality and growth in a panel of countries. *Journal of Economic Growth*, 5, 5-32.

Baum-Snow, N., & Pavan, R. (2013). Inequality and city size. *The Review of Economics and Statistics*, 95(5), 1535-1548.

Behrens, K., & Robert-Nicoud, F. (2014). Survival of the fittest in cities: Urbanization and inequality. *The Economic Journal*, 124(581), 1371-1400.

Brulhart, M., & Sbergami, F. (2009). Agglomeration and growth: Cross-country evidence. *Journal of Urban Economics*, 65(1), 48-63.

Burton, J, & Argilagos, A. (2016). Habitat III: Urbanization can be a force for tackling inequality. In FordFoundation website: https://www.fordfoundation.org/ideas/equals-change-blog/posts/habitat-iii-urbanization-can-be-a-force-for-tackling-inequality/

Cairo-Cespedes, G. & Castells-Quintana, D. (2016). Dimensions of the current systemic crisis. *Progress in Development Studies*, 16(1), 1-23.

Castells-Quintana, D. (2017). Malthus living in a slum: urban concentration, infrastructure and economic growth. *Journal of Urban Economics*, 98, 158-173.

Castells-Quintana, D. & Larrú, J.M. (2015). Does aid reduce inequality? Evidence for Latin America. *European Journal of Development Research*, 27, 826-849.

Castells-Quintana, D., Ramos, R. & Royuela, V. (2015). Inequality in European Regions: recent trends and determinants. *Review of Regional Research*, 35, 123-146.

Castells-Quintana, D. & Royuela, V. (2014). Agglomeration, inequality and economic growth. *Annals of Regional Science*, 52(2), 343-366.

Castells-Quintana, D. & Royuela, V. (2015). Are increasing urbanization and inequalities symptoms of growth? *Applied Spatial Analysis and Policy*, 8(3), 291-308.

Castells-Quintana, D. & Royuela, V. (2017). Tracking positive and negative effects of inequality on long-run growth. *Empirical Economics*. Advance online publication. DOI:10.1007/s00181-016-1197-y

Duncan, O., & Reiss, A. (1956). *Social Characteristics of Urban and Rural Communities, 1950*. John Wiley and Sons, New York.

Duranton, G. (2015). Agglomeration effects in Colombia. *Journal of Regional Science,* 56(2), 210-238.

Duranton, G. & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In Henderson, V. and J. Thisse (eds.) *Handbook of Regional and Urban Economics*, vol. 4. Amsterdam: North-Holland. pp. 2063-2117.

Duranton, G. & Puga, D. (2013). The growth of cities. In V. Henderson, & W. Strange (Eds.), *Handbook of Economic Growth*, vol. 2A (pp. 781-853). Amsterdam: North-Holland.

Easterly, W. (2007). Inequality does cause underdevelopment: Insights from a new instrument. *Journal of Development Economics,* 84, 755-776.

Fields, G.S. (1979). A Welfare Economic Approach to Growth and Distribution in the Dual Economy. *Quarterly Journal of Economics*, 93, 325-353.

Frazer, G. (2006). Inequality and development across and within countries. *World Development*, 34(9), 1459-1481.

Frick, S. & Rodriguez-Pose, A. (2016). Average city size and economic growth. *Cambridge Journal of Regions, Economy and Society*. Advance online publication. DOI: 10.1093/cjres/rsw013

Gabaix, X. (1999). Zipf's law for cities: an explanation. *Quarterly Journal of Economics*, 114(3), 739-767.

Glaeser, E., Resseger, M., & Tobio, K. (2015). Inequality in cities. *Journal of Regional Science*, 49(4), 617-646.

Gonzalez-Navarro, M. & Turner, M. (2016). *Subways and Urban Growth: Evidence from Earth*. Unpublished manuscript.

Gustafsson, B. & Johansson, M. (1999). In search of smoking guns: What makes income inequality vary over time in different countries? *American Sociological Review*, 64(4), 585-605.

Haworth, C., Long, J., & Rasmussen, D. (1978). Income distribution, city size, and urban growth. *Urban Studies*, 15(1), 1-7.

Henderson, J.*V*. (2003). The *urbanization process* and *economic growth*: The *so*-what *question. Journal of Economic Growth*, 8, 47-71.

Henderson, J.V. (2010). Cities and Development. *Journal of Regional Science*, 50(1), 515-540.

Heston, A., Summers, R., & Aten, B. (2012). Penn World Table Version 7.1, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Holmes, N., & Berube, A. (2016). City and metropolitan inequality on the rise, driven by declining incomes. In Brookings website: https://www.brookings.edu/research/city-and-metropolitan-inequality-on-the-rise-driven-by-declining-incomes/

Kuznets, S. (1955). Economic Growth and Income Inequality. *American Economic Review*, 45, 1–28.

Lewis, A. (1954). Economic development with unlimited supplies of labor. *Manchester School of Economics and Social Studies,* 22, 139-191.

Li, H., Squire, L. & Zou, H. (1998). Explaining international and intertemporal variations in income inequality. *The Economic Journal*, 108(446), 26-43.

Long, J.E., Rasmussen, D.W., & Haworth, C.T. (1977). Income inequality and city size. *The Review of Economics and Statistics*, 59(2), 244-246.

Ma, L., & Tang, Y. (2016). A tale of two tails: wage inequality and city size. Unpublished manuscript.

Marrero, G. & Rodríguez, J.G. (2014). Inequality of opportunity and growth. *Journal of Development Economics*, 104, 107-122.

Mitchell, B. (2013). International Historical Statistics. Edited by Palgrave Macmillan Ltd.

Milanovic, B. (1994). Determinant of cross-country income inequality. *World Bank Policy Research Working Paper* 1246. World Bank.

Milanovic, B. (2011). Global Income Inequality by the Numbers: in History and Now - An Overview. *World Bank Policy Research Working Paper* No. 6259.

Nord, S. (1980). An Empirical Analysis of Income inequality and city size. *Southern Economic Journal*, 46(3), 863-872.

Olley, G. & Pakes, A. (1991). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263-1297.

Odedokun, M.O. & Round, J. (2004). Determinants of income inequality and its effects on economic growth: Evidence from African countries. *African Development Review*, 16(2), 287-327.

Psacharopoulos, G. (1994). Returns to investment in education: a global update. *World Development,* 22(9), 1325-1343.

Perugini, C. & Martino, G. (2008). Income inequality within European regions: Determinants and effects on growth. *Review of Income and Wealth*, 54(3), 373-406.

Richardson, H. (1973). *The Economics of Urban Size*. Saxon House: Westmead.

Rodriguez-Pose, A., & Tselios, V. (2009). Education and income inequality in the regions of the European Union. *Journal of Regional Science*, 49, 411-437.

Roine, J., Vlachos, J. & Waldenstrom, D. (2009). The long-run determinants of inequality: what can we learn from top income data? *Journal of Public Economics*, 93, 974-988.

Royuela, V., Veneri, P., & Ramos, R. (2014). Income inequality, urban size and economic growth in OECD regions. OECD Regional Development Working Papers.

Sarkar, S., Phibbs, P., Simpson, R., & Wasnik, S. (2016). The scaling of income distribution in Australia: possible relationships between urban allometry, city size, and economic inequality. *Urban Studies*. Advance online publication. DOI: 10.1177/0265813516676488

Solt, F. (2009). Standardizing the World Income Inequality Database. *Social Science Quarterly*, 90(2), 231-242.

Solt, F. (2014). The Standardized World Income Inequality Database. Working Paper. SWIID Version 5.0, October 2014.

Todaro, M. (1969). A model of labor migration and urban unemployment in less developed countries. *American Economic Review*, 59, 138-148.

Todaro, M. (1976). Urban job creation, induced migration and rising unemployment: A formula and simplified empirical test for LDCs. *Journal of Development Economics*, 3, 211-226.

Tselios, V. (2008). Income and educational inequalities in the regions of the European Union: geographical spillovers under welfare state restrictions. *Papers in Regional Science*, 87, 403-430.

Tselios, V. (2014). The Granger-causality between income and educational inequality: a spatial cross-regressive VAR framework. *Annals of Regional Science*, 53, 221-243.

United Nations, Department of Economic and Social Affairs, Population Division. (2015). World Urbanization Prospects: The 2014 Revision. UN DESA Press.

Vanhoudt, P. (2000). An assessment of the macroeconomic determinants of inequality, *Applied Economics*, 32(7), 877-883.

White, M. (1981). Optimal inequality in a system of cities or regions. *Journal of Regional Science*, 21(3), 375-387.

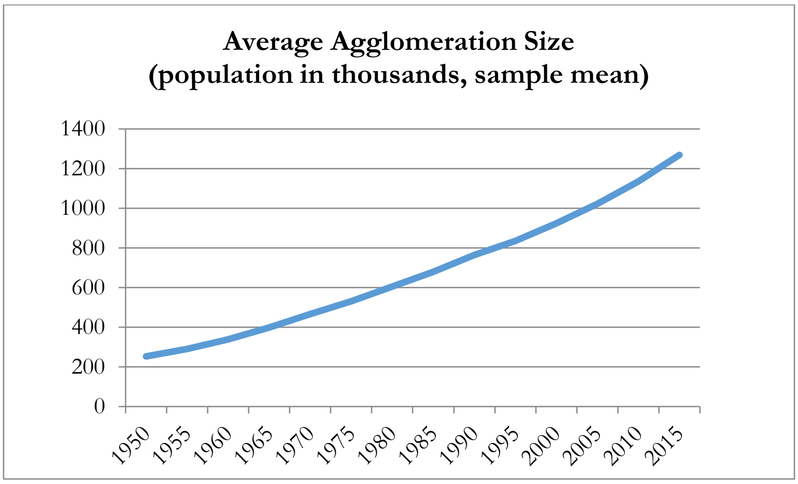
Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*, second ed. MIT Press. Cambridge. MA.

World Bank. (2006). World Development Report 2006: Equity and development. The World Bank, Washington.

ANNEX A: Variable names, definitions and sources

Main variables:	Description	Source
inequality	Income inequality measured by the Gini coefficient (Estimate in equivalised household net income)	SWIID v5.0 (Solt 2014)
AveAggSize	Average agglomeration size, in terms of population (thousand inhabitants)	Constructed with data from World Urbanisation Prospects 2014.
income	Per capita GDP (in logs)	Constructed with data from PWT 7.1 (Heston et al. 2012), using real GDP chain data (rgdpch)
growth	Cumulative annual average per capita GDP growth rate	Constructed with data from PWT 7.1 (Heston et al. 2012), using real GDP chain data (rgdpch)
ki	Investment share (% of GDP)	PWT 7.1. (Heston et al. 2012)
kg	Government consumption (% of GDP)	PWT 7.1. (Heston et al. 2012)
schooling	Average years of secondary and tertiary schooling of adult population	Barro and Lee dataset
poplargest	Total population living in the largest city	World Urbanisation Prospects 2014
urb1m	Total population living in cities of more than 1 million inhabitants, as percentage of total population	World Bank - World Development Indicators
primacy	Population living in the largest city, as percentage of total urban population	World Bank - World Development Indicators
Additional controls:	**Description**	**Source**
poptotal	Total population, in thousands	World Bank - World Development Indicators
urbrate	Population living in urban areas, as percentage of total population	World Urbanisation Prospects 2014
fertility	Fertility rate	World Bank - World Development Indicators
Coal	Coal rents, as percentage of GDP	World Bank - World Development Indicators
exports	Total exports, as percentage of GDP	World Bank - World Development Indicators
agriculture	Value added in agriculture, as percentage of GDP	World Bank - World Development Indicators

Annex B: increasing trend in average agglomeration size



ANNEX C: average agglomeration size around the world in 2015