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Agglomeration Economies in Developing Countries

A Meta-Analysis

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Abstract

Recent empirical work suggests that there are large agglomeration gains from working and living in developing country cities. These estimates find that doubling city size is associated with an increase in productivity by 19 percent in China, 12 percent in India, and 17 percent in Africa. These agglomeration benefits are considerably higher relative to developed country cities, which are in the range of 4 to 6 percent. However, many developing country cities are costly, crowded, and disconnected, and face slow structural transformation. To understand the true productivity advantages of cities in developing countries, this paper systematically evaluates more than 1,200 elasticity estimates from 70 studies in 33 countries. Using a frontier methodology for conducting meta-analysis, it finds that the elasticity estimates in developing countries are at most 1 percentage point higher than in advanced economies, but not significantly so. The paper provides novel estimates of the elasticity of pollution, homicide, and congestion, using a large sample of developing and developed country cities. No evidence is found for productivity gains in light of the high and increasing costs of working in developing country cities.

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Agglomeration Economies in Developing Countries: A Meta-Analysis

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1. Introduction

There is a growing body of academic literature highlighting the productivity enhancing agglomeration economies from living and working in dense cities (Ahlfedt and Pietrostefani, 2019). Duranton and Puga (2004) outline the micro-foundations of agglomeration economies based on sharing, matching, and learning mechanisms. Dense cities encourage *sharing* of indivisible public goods, production facilities, and marketplaces, a greater variety of inputs and individual specialization, and the pooling of risk; improve the quality and possibility of *matching* between firms and workers; and increase opportunities for *learning* from the generation, diffusion, and accumulation of knowledge.

Economists have used the elasticity of wages with respect to urban density as a canonical measure of agglomeration economies. A recent meta-analysis of empirical work by Ahlfedt and Pietrostefani (2019) covering 347 estimates shows a of doubling urban density is associated with a wage premium of 4 percent. In the United States, the elasticity of wages with respect to city size is 0.043; in France it is 0.03-- implying that doubling density could increase productivity by 3-4 percent. (Combes and Gobillon 2015, Melo et al. 2009, and Rosenthal and Strange 2004).

While these estimates suggest strong productivity enhancing agglomeration economies in dense urban environments, a major knowledge gap arises from the limited knowledge of agglomeration economies in developing country settings. The empirical reviews (Melo et al., 2009 and Ahlfeldt and Pietrostefani, 2019) and a recent literature survey (Duranton and Puga, 2020) primarily draw on developed country estimates. Further, there has been no attempt to systematically quantify the differences in estimates between advanced and developing countries. Filling this knowledge gap is important as most of future urban growth is expected in developing country cities (United Nations 2018) and these cities are growing in people but without the commensurate investments in human and physical capital that enhance the returns from density (Lall, Henderson and Venables 2017; Ellis and Roberts 2016).

Avner and Lall (2016) find that jobs are often located far from where people live; heavy congestion and high rates of walking and informal transportation fragment the labor market and lead to low employment rates and the misallocation of labor in Nairobi. For instance, *Matatu* (privately owned minibuses) users on average can access only 4 percent of jobs within 30 minutes, 10 percent within 45 minutes, and 20 percent within 60 minutes. In metropolitan Buenos Aires, equivalent accessibility figures using public transportation are only 7 percent, 18 percent, and 34 percent for the same time thresholds (PeraltaQuiros 2015). In Ugandan cities, 70 percent of work trips are on foot (Uganda Bureau of Statistics 2010), with only 19 percent of the city's jobs being accessible within a one hour commute (Bernard 2016). Further, many cities particularly in Sub-Saharan Africa and South Asia produce non-tradable goods and services (Lall, Henderson and Venables 2017, Venables 2017). This is consistent with what has been called "pre-mature urbanization" (see for e.g. Gollin et al., 2016), that is, people are concentrating in developing country cities but not because industrial dynamism is attracting them.

To shed light on the productivity advantages of agglomeration in developing country cities, we make the following contributions. *First*, we expand the sample size of existing meta-analyses to systematically examine 1,242 elasticity estimates, originating from 70 studies covering 21 developing and 12 advanced countries. *Second,* we construct novel estimates of density elasticity on urban costs, with respect to crime, congestion and pollution by collecting data from hundreds of cities around the world, including several in developing countries. This fills a critical knowledge gap as relative to studies measuring the benefits of agglomeration, the evidence base on urban costs is underdeveloped. *Third,* using frontier methodology for conducting meta-analysis, we control for a variety of differences across studies to provide a robust assessment. This allows us to contextualize country specific estimates showing large agglomeration economies: 0.19 in China, 0.12 in India, 0.17 in Africa, and between 0.06-0.16 in Latin America (Chauvin et al., 2017 (India, China), Combes et al. 2019 (China), Henderson et al. 2019 (six African countries: Ethiopia, Nigeria, Ghana, Malawi, Tanzania and Uganda) and Quintero and Roberts 2018 (Latin America)).

Our meta-analysis highlights that while elasticity estimates for developing countries are nearly 1 percentage point higher than that for developed countries, the estimates are not statistically different. Nonetheless, estimates using nominal wages, the canonical measure of agglomeration economies, are higher than those using TFP. This suggests that part of the wage premium is driven by higher capital intensity, perhaps a result of thicker capital markets in urban areas, rather than efficiency or spillovers per se.

Further, studies controlling for urban costs find elasticities to be 4.2 percentage points lower than studies that do not, implying a net agglomeration elasticity of 0.1 percent when using labor productivity as an outcome measure. Our novel estimates of urban dis-amenities suggest that although the elasticity of pollution and congestion in developing countries is comparable with developed countries, their levels are much higher. For the average city density in our data, 19-30 percent fewer hours are spent in traffic congestion in developed countries, pollution is 16-28 percent lower, and the homicide rate is around 4 times lower.

Our analysis confirms high wage elasticities with respect to density; however we find no evidence for efficiency gains in light of high and increasing costs of working in developing country cities. This is partly driven by bad design and lack of capital investment in cities, but also by the fact that their growth is not driven by the process of structural transformation, which would create a mass of industrial or service firms that benefit from sharing, matching, and learning. Many developing country cities are not dense and productive—they are just crowded.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes data collected for the meta-analysis. Section 4 discusses the estimation strategy, Section 5 presents the meta-analysis results on agglomeration elasticities, and Section 6 presents the results on urban costs. Section 7 concludes.

2. Density, productivity and agglomeration elasticities

There is a higher wage premium associated with working in dense cities. Meta-analysis carried out by Ahlfeldt and Pietrostefani (2019) suggests an elasticity of productivity with respect to density of 0.04, based on a citation-weighted average of 347 estimates. To set the stage for our subsequent meta-analysis, and inform our choice of study characteristics included as meta-controls, we draw on the vast literature estimating agglomeration elasticities.

Agglomeration measures

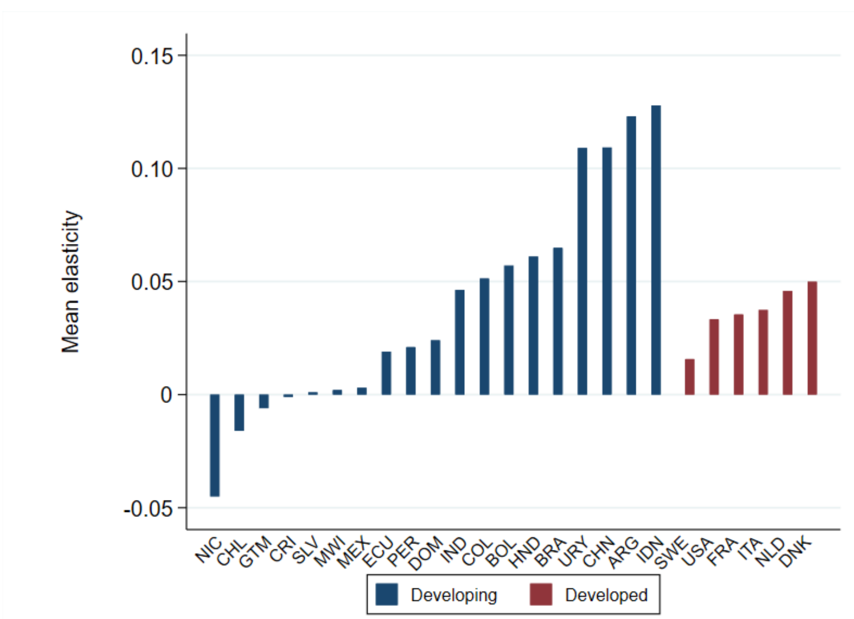
Agglomeration or city size can be measured using population, density and measures of market potential or access. The use of population or economic density is preferred relative to population mass because spatial units are often based on administrative boundaries and there is large heterogeneity in the size of these units (Ciccone and Hall, 1996). Measures of agglomeration such as market potential account for (economic or physical) distance of the region from other spatial units (Harris, 1954). Market access measures adjust market potential with local price effects to account for imperfect competition across locations (Fujita et al., 1999).

Market access is typically computed by aggregating the income of other municipalities discounted by the distance (that is, some measure of travel cost) to the municipality under consideration. Elasticity estimates with market access measure paint a rather dismal picture on the returns to agglomeration. In Colombia, for example, the elasticity of wages with respect to external market access is significantly negative, in comparison to the estimates with respect to city population, which is about 5 percent (Duranton, 2016). We do not use estimates using market access in our meta-analysis due to their limited number relative to other agglomeration measures as well as the heterogeneity in their use of travel costs in their construction.

Productivity measures

Most studies use *nominal* wages as a measure of city productivity. Figure 1 suggests that developing country cities generate huge benefits from agglomeration, measured by nominal wages (see Figure 1). These are consistent with agglomeration elasticities of 0.19 in China, 0.12 in India, 0.17 in Africa, and between 0.06-0.16 in Latin America (Chauvin et al., 2017 (India, China), Combes et al. 2019 (China), Henderson et al. 2019 (six African countries: Ethiopia, Nigeria, Ghana, Malawi, Tanzania and Uganda) and Quintero and Roberts 2018 (Latin America)).

Figure 1: Nominal wage data show significant agglomeration benefits in developing countries



Notes: The chart plots unweighted average wage elasticity estimates that focus on manufacturing or the whole economy. Developed or high-income economies and non-high income or developing countries are defined using the World Bank country-income classification at the mid-year of each study's sample period. The chart uses 433 raw elasticity estimates, 182 from developed countries and 251 from developing countries, representing two-thirds of our sample.

While r*eal* wages may be a natural indicator of city wage premia, the main challenge is the availability of price data at a local level. Even if prices are available, it is not clear whether the estimated agglomeration economies with respect to real wages represent sorting on human capital or compensation for adverse urban amenities rather than true productivity premia of cities (Chauvin et al., 2017). Wages are usually only proportional to and not equal to labor productivity by a factor that depends on the local monopsony power of the firm. Thus, the use of total factor productivity (TFP) is preferred since urban costs do not play a role and it avoids making any assumption about the relationship between the local monopsony power and agglomeration economies (Combes and Gobillon, 2015).

Melo et al. (2009) show that elasticities of TFP with respect to density are on average estimated to be larger than those obtained for wages, typically around 50 percent larger. In France, for example, the elasticity of TFP with respect to density of 0.035-0.040 whereas with the same data, the elasticity is 0.027 for wages (Combes et al., 2012). It is difficult to interpret the difference between the two types of estimates. In wage equations, all the effects are re-scaled by the share of labor in the production function. Moreover, agglomeration economies percolating through the cost of inputs other than labor, such as land and intermediate inputs affect wages, but not TFP. A further possible reason for the difference in estimates obtained from wage and TFP regressions is that most researchers have not managed to successfully control for worker skills in wage regressions.

Underlying data

Elasticity estimates vary by the underlying data used for analysis. Spatially aggregated industry- or worker-level data might yield different elasticity estimates relative to micro firm- or worker-level data because with spatial aggregation the information on industry, firm and worker attributes is lost. Even within micro data, productivity measures derived from firm level data versus those collected through household or labor force surveys vary. This may be due to the type of firms in the data set. For instance, some countries have a cut-off on employee size in their firm census data, while comparable wage elasticity using household surveys may have a different threshold or criterion. In particular, elasticity estimates using firm level data might be lower than worker level data. For instance, Chun et al. (2019) find the wage elasticity for China to be negative 0.113 using firm level data compared to other studies that find huge estimates of ranging from 0.07 to 0.29 when using worker-level data (Combes et al. 2019).

Spatial scale

Studies evaluate the spatial extent of local spillovers ranging from the broadest administrative level (regions) to the finest administrative level (e.g. villages and neighborhood). Most studies end up somewhere in the middle – administrative level 2 or 3 (e.g. municipalities or districts). The spatial scope of agglomeration effects depends on the nature of activity. For example, while knowledge and technology intensive activities will need to be co-located, other interactions such as input–output linkages can take place at a larger scale. A common approach is to consider an individual or location defined at a fine scale and to draw rings with increasing radius around it. Agglomeration benefits dissipate with distance and are rarely significant beyond a threshold distance and hence broader spatial scales yield lower benefits (See Rosenthal and Strange, 2003; Desmet and Fafchamps, 2005 for evidence on the US and Rice et al., 2006 for the UK ; Di Addario and Patacchini, 2008 for Italy).

Manufacturing versus services

In general agglomeration benefits for services are higher because firms rely more on face-to-face contact and are more likely to co-locate at a finer spatial scale (e.g. zip-code level), while manufacturing industries that trade with each other are more likely to co-locate in the same county or state. Moreover, agglomeration economies in services decay more rapidly with distance, making it more relevant for firms to cluster. For example, evidence from the advertising services industry supports an extremely rapid spatial decay of agglomeration effects that are shown to occur primarily within 500 m (Arzaghi and Henderson, 2008). These results are broadly consistent with the findings of Graham et al. (2010) for the UK who find that the decay gradient is higher for services relative to manufacturing. Business services and consumer services have a decay gradient of 1.75 and 1.82 respectively, whereas for manufacturing the value is 1.10. Likewise, Hasan et al. (2017) find that agglomeration effects in India are stronger for services relative to manufacturing.

More broadly, the differences in elasticity estimates between developed and developing economies are smaller when the service sector is considered (Figure 2a). In fact, they are generally based on individual earnings data that compensate for the cost of urban dis-amenities in developing world cities rather than total factor productivity (TFP). The estimated gap is smaller when comparing TFP estimates (Figure 2b).

Figure 2a: Agglomeration elasticity in services

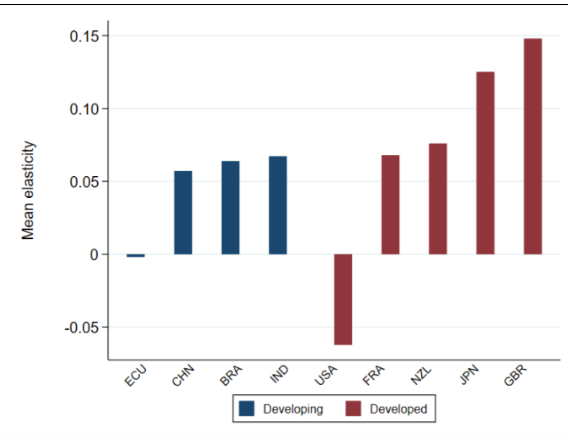
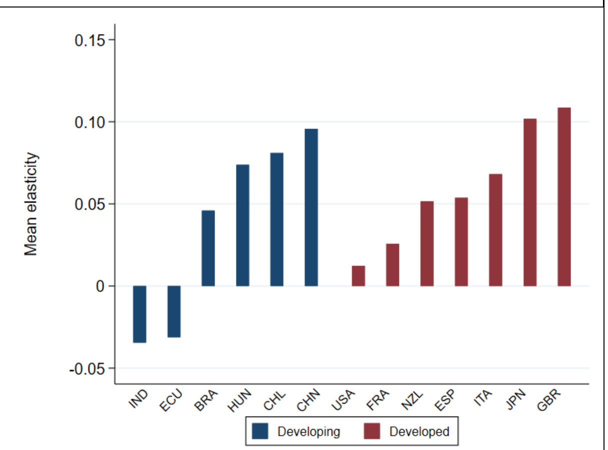


Figure 2b: Agglomeration elasticity using TFP



Notes: Panel a computes unweighted average productivity elasticity estimates for each country using services sector data – encompassing both micro and spatial data, and wages, labor productivity and TFP estimates. Developed reflects studies of high-income countries, developing reflects non-high income, with income level determined using the World Bank country-income classification at the mid-year of each study's sample period. This reflects 193 raw elasticity estimates (58 in developing countries). Panel b computes unweighted average TFP elasticity estimates for each country – encompassing both micro and spatial data and any industry. This is derived from 467 estimates (64 in developing countries).

Endogeneity concerns

Estimating agglomeration benefits requires regressing productivity measures on the size of the spatial unit (e.g. density, population or similar measures). A fundamental challenge here is that higher productivity in denser areas does not necessarily reflect a causal relationship. Instead, dense locations can attract more firms and workers due to unobserved advantages. The literature suggests two approaches to address this problem: (i) instrumental variable estimations using historical measures of density (Ciccone and Hall 1996)[1] and geological variables such as land fertility (Combes et al. 2010), land suitability for the construction of tall buildings (Rosenthal and Strange 2008; Combes et al. 2010), and (ii) including location or plant fixed effects to capture any unobserved attributes that may have attracted more establishments to a given city (Henderson 2003).

Evidence suggests that the large estimated benefits are not a reflection of exogenous shocks or reverse causality. It could have been the case that some places may be intrinsically more productive, attract more workers, and thereby causing city size or population density to rise ("quantity" effects). Estimates that use instruments to control for endogeneity due to "quantity" effects do not drastically change the elasticity magnitudes. For example, in the U.S., Brazil China, India and Brazil, the elasticity estimates remain stable when instrumenting current agglomeration with historical values. This dispels the fear that correlation between city size and productivity is caused by, for instance, in China by the post- 1980 political shocks to particular areas, like the special economic zones (Chauvin et al., 2017). Likewise, Duranton (2016) does not find significant differences in elasticity estimates in Colombia with an IV estimation that use past population density or geological variables as an instrument.

Returns to skills, worker and firm sorting

Agglomeration elasticity estimates may also be biased due to sorting of more educated workers or productive firms to large locations ("quality" effect). While education and other observable characteristics of workers and firms can be controlled, unobservable traits that affect productivity may differ systematically across cities. Glaeser and Maré (2001) and Combes, Duranton, and Gobillon (2008) suggest introducing worker fixed-effects when relating individual earnings to density. The productivity benefits of density for workers is then identified from the changes in earnings that a given worker experiences when changing work location. Plant relocations are much less frequent than worker relocations and hence firm sorting is more difficult to control for.

Several approaches have been used to measure returns to skills. Chauvin et al. (2017) estimate elasticity of real wages as returns to human capital and find that the elasticity of density is lower for the US and China, suggesting that the nominal-wage premium in dense locations does not reflect sorting of higher-ability people. By comparison, the nominal and real wage elasticities are not very different in India, which may be interpreted as large returns to human capital, given the wide heterogeneity of skills across space and low migration rates. Other studies have used observable skills and parental education and worker/individual fixed effects. Studies on the US find lower estimates of elasticity once controlling for skills (e.g. Glaeser and Mare, 2001). In Colombia, the elasticity of wages with respect to city size drops from 11 percent to 5.4 percent when individual worker characteristics such as education are included, implying that about half this relationship is explained by larger cities hosting more educated workers. This is consistent with the greater representation of more educated workers in larger cities and the view that workforce composition effects account for a sizeable fraction of spatial wage disparities (Combes and Gobillon, 2015).

In France, there is a high correlation between density and worker characteristics (0.44), and the associated elasticity of wage premium is cut by about one-half when worker fixed-effects are included (Combes et al., 2008; 2010). Worker sorting is slightly weaker in Italy, where the correlation between

[1] The validity of the instruments rely on the past populations being uncorrelated with unobserved drivers of contemporaneous wages conditional on the other controls. While a good case can be made for this (Combes et al.,2010), it is by no means decisive.

individual fixed effects and density is 0.21 (Mion and Naticchioni, 2009). There is also evidence of spatial sorting in Spain and in the United Kingdom (de la Roca and Puga, 2012; D'Costa and Overman, 2014). [2]

Urban costs

Systematic evidence about urban costs is nearly absent - most agglomeration studies use nominal wages, rather than real wages that account for local urban costs. Urban costs take a variety of forms. In larger cities, housing is more expensive, commutes are longer, and the bundle of amenities that these cities offer may differ. Residential mobility implies that urban (dis)amenities and commuting costs are reflected into land prices. The elasticity of urban costs with respect to city population is the product of three quantities: the elasticity of unit land prices at the city center with respect to population, the share of land in housing, and the share of housing in consumption expenditure. It is critical to estimate the elasticity with respect to urban cost because, *first*, city size is an outcome of a tradeoff between agglomeration economies and urban costs (Henderson, 1974; Fujita and Ogawa, 1982). The costs of agglomeration can partly explain why firms and workers do not move to larger cities. *Second*, urban policies such as barriers to labor mobility and zoning limits (e.g. Duranton, 2008) are imposed to curb population growth and costs such as housing and congestion in cities. An estimation of the association of urban cost with city size helps understand the efficacy of these policies in achieving their stated objectives.[3] The topic remains underexplored because of a lack of an integrated framework to guide empirical work and appropriate data.

Although agglomeration benefits are higher, urban costs may explain why cities do not expand further. Urban costs have been estimated for France and Colombia using land and housing price data (Combes et al., 2013; Combes et al., 2019; Duranton, 2016). In France, the elasticity of urban costs with respect to population ranges from 0.016 to 0.05, while the estimates for agglomeration effects in France range from 0.015 to 0.03 (Combes *et al.*, 2010). Similar results on the elasticity of urban costs are obtained for Colombia as well (Duranton, 2016). In both these countries, cities operate at near aggregate constant returns to scale, suggesting that the benefits of agglomeration are balanced by their costs.

The costs of density on outcomes such as pollution, crime, and congestion is significantly high, and often higher than productivity elasticities. Ahlfeldt and Pietrostefani (2019) suggest that a log- point increase in density is associated with higher rents (0.15), pollution concentration (0.13), mortality risk (0.09) and crime (0.085). Thus, to understand the true advantages of larger cities, it is critical to estimate agglomeration costs alongside benefits. Cities in developing countries face the same downsides of density, that is, congestion, crime and diseases, however, they lack the financial resources to invest in infrastructure such as transport network, clean water and air, and sewerage to mitigate these risks. They also lack the public capacity to enforce urban regulations (Glaeser and Porteba, 2020).

3. Data

We rely on two separate datasets: one for the meta-analysis of agglomeration elasticities, and another for the analysis of urban costs. First, we discuss the construction of the sample of papers used for the meta-analysis, and second, the urban cost data.

[2] For more evidence see Bacolod et al. 2009; Abel et al., 2012; Lindley and Machin, 2014 for the United States; Di Addario and Patacchini, 2008 for Italy; Groot and de Groot, 2014 for the Netherlands.

[3] In France Combes et al. (2013) find that urban costs are much lower when the physical growth of cities is not restricted.

Meta-analysis data

The primary focus of our paper is a meta-analysis of agglomeration productivity elasticities differentiating between developing and developed countries, where our paper follows the approach outlined in Stanley et al (2013) to construct the sample of studies (further details are given in the Appendix).

We build on the meta-analysis data of Melo et al. (2009) and Ahlfeldt and Pietrostefani (2019) by extending their sample on elasticity estimates for developing countries. We use a combination of keywords, such as "agglomeration" or "density" or "urban", and "elasticity" or "productivity" or "wages", applied to the academic databases EconLit, Web of Science, and Google Scholar. We supplement the keyword search by conducting an analysis of citation trees of key published and working papers by eminent researchers in the field and papers that inspired the study.[4] We also consulted with experts in academia (including the University of Pennsylvania, Johns Hopkins University, and Oxford) and practice (including the World Bank) to identify ongoing work in the field. The initial sample included peer-reviewed papers, working papers of universities, research institutes and international organizations (World Bank, NBER, CEPR, CESIfo, and IZA), chapters in books and conference proceedings.

We restrict the initial sample to papers with one of four outcome variables --- labor productivity, wages or earnings, TFP and output using a production function -- and four agglomeration measures: population size, population density, economic density and market potential. To ensure comparability, we only retain studies that either estimate unit-free agglomeration elasticities, or those that could be converted to an elasticity (e.g. semi-elasticities). Estimates reporting analysis pooled across several countries are excluded; country specific estimates are retained.

To test and correct for publication bias, we also collect standard errors of estimates either from the papers or by requesting the authors. Studies without the standard errors needed for precision-weighting are excluded from the meta-analysis. Most studies are empirical; however, studies estimating structural models are also included provided they report agglomeration elasticities and standard errors. To avoid double counting several versions of the same study, in particular for working papers, we include only the latest version.

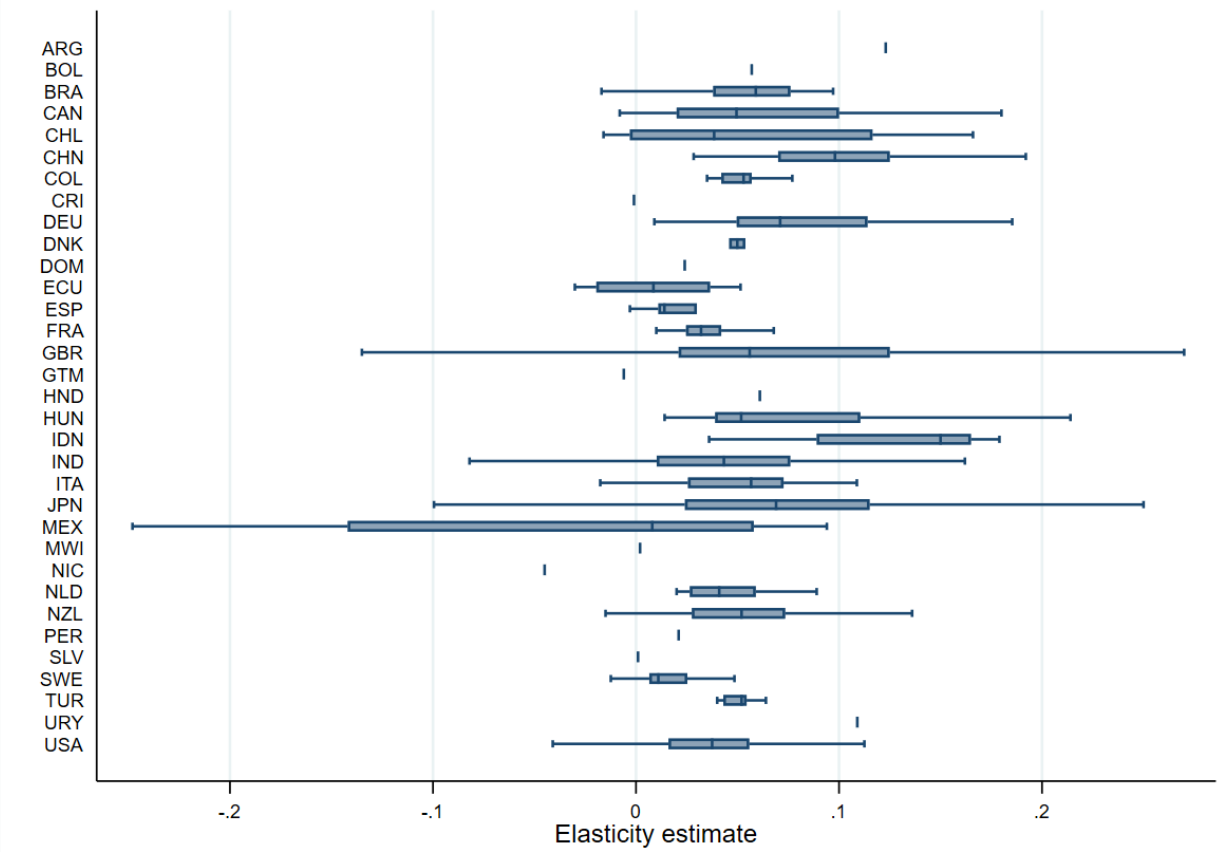
Our resulting sample comprises of 1,242 elasticity estimates sourced from 70 studies across 33 countries covering 1973 to 2020. Of the 70 studies, 29 are reported in Melo et al. (2009), 16 are drawn from Ahlfeldt and Pietrostefani (2019), with 25 additional studies included here. Table A5 in the Appendix reports the full list of 70 studies. Among the estimates, 388 are for developing countries.

Even within a single study or a single country in our data there are often a wide range of estimates, highlighting substantial heterogeneity in data and estimation methods. Figure 3 reports a forest plot of the estimated 1,242 agglomeration elasticities across the 33 countries. The figure suggests that countries show a broad range of elasticities, with some reporting both large positive and negative estimates. While some of the variation is likely a result of differences in time period, spatial scale, estimation methods and so on across papers, Appendix Figure A1 shows a similar spread in estimates within individual studies. The wide range of estimates strongly suggests key differences in underlying factors within and across studies, highlighting the importance of controlling for such distinctions

[4] Melo et al. (2009), Chauvin et al., (2017) and Ahlfeldt and Pietrostefani (2019).

through a meta-analysis. Table 1 summarizes the variables collected for each study that act as control variables in the meta-analysis, while Appendix Table A.1 summarizes the estimated agglomeration elasticities by each meta control category.

Figure 3: Elasticity estimates by Country



Notes: The box shows the 25th, median and 75th percentile elasticity for each country, with the whiskers showing the upper and lower adjacent values. Some countries reflect a single estimate, hence only the median is shown.

Table 1: Summary statistics of controls included in meta-analysis

Category	**Variable**	**Details**	**Reference Category**	**mean**	**std dev**
Country Income	Developing Country	= 1 if estimates reflect a non-high-income country, using World Bank classification at mid-point of study period	estimates reflect high-income country	0.312	0.464
Productivity Measure	Wages	= 1 if estimates reflect wage or earnings outcome	estimates reflect TFP outcomes (either TFP specifically, or outcome is an output measure in combination production function estimation)	0.453	0.498
	Labor Productivity	= 1 if estimates reflect labor productivity outcomes (output or value-added per worker)		0.171	0.376

Urban Cost	Urban Cost Control	= 1 if estimations include a local measure of urban costs, e.g. land rents, house prices, local price indices	estimations do not include an urban cost control	0.032	0.177
Industry	Manufacturing Sector	=1 if estimates reflect the manufacturing sector	estimates are not specific to manufacturing or services	0.382	0.486
	Services Sector	=1 if estimates reflect the services sector		0.155	0.362
Skill	Skilled workers	= 1 if estimates reflect skilled workers (including managers, scientists or non-routine occupations)	estimates are not specific to skilled or unskilled workers	0.021	0.143
	Unskilled workers	= 1 if estimates reflect unskilled workers (routine occupations)		0.027	0.161
Time Period	Post-1990	= 1 if mid-point of data is 1990 onwards	mid-point of data is before 1990	0.782	0.413
Study Quality	Published	= 1 if study is published in a peer-reviewed journal	study is unpublished	0.712	0.453
	Number of Citations (as of April 2020)	Log number of citations - normalized by study publication year	-	0.000	1.349
Spatial Measure	City - Level	=1 if study uses city-level spatial units	study uses regional level spatial units	0.521	0.500
	Sub City - Level	= 1 if study uses sub-city-level spatial units		0.310	0.463
Agglomeration Measure	Density Measure	= 1 if agglomeration is measured by population or employment density	agglomeration is measured by size, such as total employment or population	0.452	0.498
	Market Potential Measure	= 1 if agglomeration is measured by effective density or market potential		0.257	0.437
Localization	Localization Control	= 1 if a localization control is included (reflecting the size of own industry)	estimations do not include a localization control	0.312	0.464
Data	Panel Data	= 1 if study uses panel data	study uses cross-section data	0.590	0.492
	Firm Data	= 1 if study uses firm-level micro data	study does not use micro data	0.352	0.478
	Worker Data	= 1 if study uses worker-level micro data		0.388	0.488
Endogeneity	Panel Fixed Effects	= 1 if panel fixed effects are included or estimation is in differences	study does not use fixed effects	0.209	0.407
	IV estimation - contemporaneous	= 1 if estimates reflect IV estimation, using contemporaneous or short-lagged instruments (including GMM)	study does not use IV estimation	0.069	0.254

	IV estimation - historic	= 1 if estimates reflect IV estimation, using historic or geological instruments		0.177	0.382
Firm Heterogeneity	Industry control	= 1 if estimates include an industry dummy variable	study does include industry or firm size controls	0.275	0.446
	Firm size control	= 1 if estimates include a firm size control		0.366	0.482
Worker Sorting	Local area human capital	= 1 if study includes a local area human capital measure	study does not control for human capital	0.189	0.392
	Individual-level human capital	= 1 if study includes worker-level controls		0.261	0.439

Note: Number of observations for each variable is equal to 1,242. We normalize patents by publication year, common practice in the patent literature, by using the residual from a regression of citations on publication year[5]. We reported unweighted means and standard errors. Country-income is captured by a dummy variable reflecting whether the country is non-high-income country, using the mid-point of the study's data sample.[6]

Urban cost data

We also provide novel estimates of urban cost elasticities across developing and developed countries. While Ahlfeldt and Pietrostefani (2019) provide a good synthesis of the available literature, they focus on developed countries. We use three measures of city-level urban costs: congestion (hours lost due to traffic), pollution (PM2.5 emissions) and crime (homicide rate).

Congestion information is sourced from TomTom, which provides real time traffic statistics for over 600 million users around the world. Congestion reflects the average annual additional hours spent driving in rush hours in 2018 and is available for 337 cities, of which 69 cities are in developing countries. Pollution, measured using PM2.5 emission levels, is sourced from the World Health Organization and is available from 2008 to 2015. We use pollution data for 2014, the most recent year covering a sample of 298 cities (with 78 in developing countries). We exclude China from the pollution analysis because of potential data reporting concerns highlighted in Greenstone et al. (2020). Crime is measured using the homicide rate obtained from United Nations Office on Drugs and Crime (UNODC) global study on homicide (2019) and is available from 2003 to 2017. We utilize crime data for 2015, the latest year comprising 124 cities (with 63 in developing countries). Summary statistics of these variables are provided in Table 2. Figure 4 shows how pollution, congestion and crime vary across levels of economic development.

City-level population density is calculated as the population per square kilometer of *built up density* using 2015 data from the Global Health Settlement (GHS). Unfortunately, this data is only available at irregular intervals (1975, 1990, 2000 and 2015), which combined with limited time horizon of our urban cost measures, limits us to a cross-section analysis. We also examine robustness to population density from country census data that are available for approximately half the cities in our baseline sample.

[5] An alternative approach of demeaning citations using the mean citations of publications in that year is not possible, due to few observations in some publication years.
[6] The analysis is robust to defining country income using the first or last period of the study sample.

Table 2: Summary statistics of variables included in urban cost elasticity analysis

	n	mean	std dev
PM2.5 Pollution	298	2.563	0.614
Hours Lost to Travel Time	337	4.663	0.370
Homicide Rate	124	1.283	1.389
Population Density	337	8.638	0.660

Note: All variables are in logs and reflect city-level data. PM2.5 pollution is measured in 2014, hours lost to travel in 2018 and homicide rate in 2015. City population density is measured in 2015.

Figure 4: Urban costs by country income

Figure 4a: Pollution costs

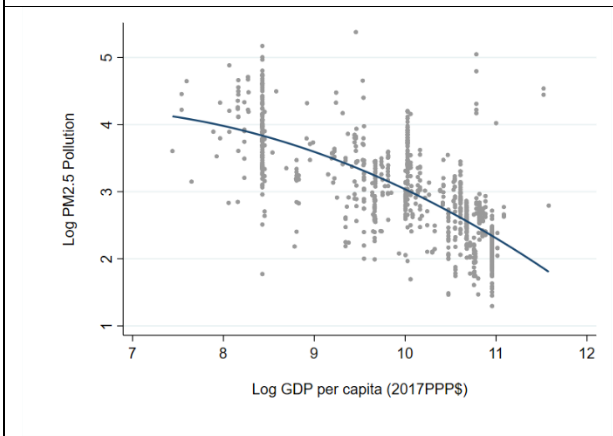


Figure 4b: Congestion costs

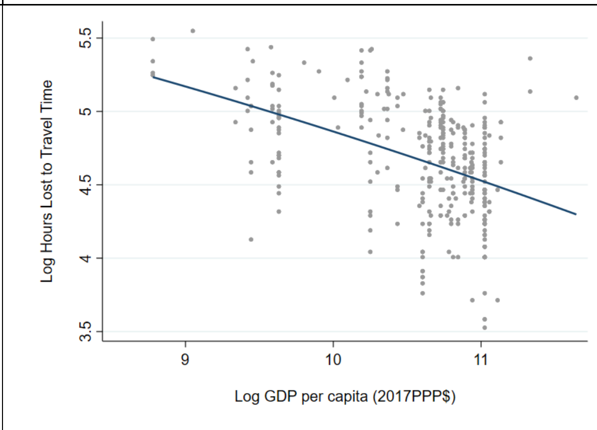
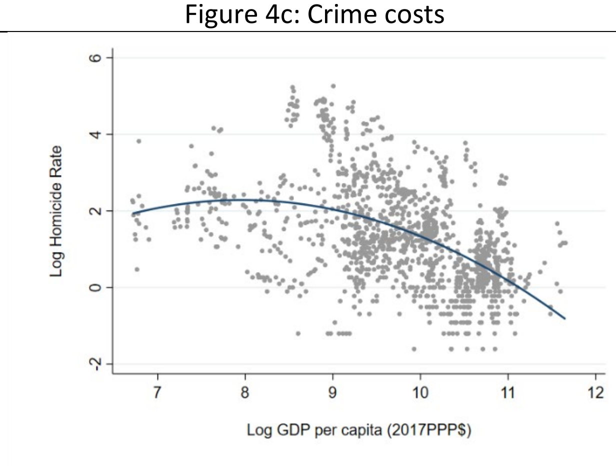


Figure 4c: Crime costs



Note: City-level pollution reflects PM2.5 data for repeated cross-sections between 2008-2015 for 1076 cities. Congestion reflects the annual additional hours spent driving in rush hours, measured in 2018, and contains data for 342 cities. Homicide rate data reflects panel data between 2003 and 2017 for 198 cities (1399 observations). Quadratic best fit lines are superimposed. Sample sizes are larger than in the urban cost analysis in section 6, due to wider availability of GDP per capita data, than city population density.

4. Estimation

We first discuss the estimation strategy for the meta-analysis of agglomeration elasticities, followed by the methodology for estimating urban cost elasticities.

Meta-analysis estimation

There are several estimation challenges in conducting a meta-analysis (see Florax, 2001; Stanley, 2005).

First, selective reporting can lead to bias in meta analyses. Publication bias can reflect a preference among researchers and journals to selectively report statistically significant coefficients in a desirable direction, for instance, those in agreement with established theory. Such selective reporting implies that the reported estimates are truncated, that is, we primarily observe estimates that are statistically significant. This introduces a systematic relationship between reported estimate e_i for study *i* and the reported standard errors, se_i. More formally, as Stanley and Doucouliagos (2014) note, the first-order approximation of the conditional expectation of a truncated normal distribution implies the reported estimates will be a linear function of the estimates' standard errors. We follow standard practice and test for publication bias using the funnel asymmetry test (FAT) (e.g. Card and Kreuger, 1995; Egger et al., 1997; Stanley, 2008):

$$e_i = e_0 + \beta_0 . se_i + u_i \quad (1)$$

The null hypothesis of no publication bias corresponds to $\beta_0 = 0$, i.e. no relationship between the reported study effects and the reported standard errors. To test for publication bias, equation 1 can be estimated using a variety of models: unweighted OLS, meta-random effects, meta-fixed effects and precision-weighted least squares (WLS).[7] Traditional methods, including precision-weighted regressions, are particularly sensitive to publication bias (Stanley and Doucouliagos, 2014; 2019). We deploy state of the art estimators that outperform these approaches. More specifically, Precision-effect estimate with standard error (PET-PEESE) has been shown to outperform several estimators, such as unrestricted WLS or WAAP or random effects estimation under publication bias (Stanley and Doucouliagos, 2015; 2019). PET-PEESE, uses a quadratic approximation to the conditional expectation of a truncated normal distribution, to proxy publication bias. So, PET-PEESE includes the square of the estimates' standard errors, in place of a linear relationship as in equation 1. We use PET-PEESE as our preferred specification.

Our baseline specification, PET-PEESE, involves estimation the following precision-weighted regression:

$$\hat{e}_i = e_0 + \alpha_1 ldc_i + \gamma Z + \beta_0 . {se_i}^2 + \beta_1 . {se_i}^2 nonhic_i + u_i \quad (2)$$

where, ldc_i is a dummy variable for studies of developing countries and α_1 is our coefficient of interest and reflects differences in agglomeration elasticities across developing and developed countries. All regressions are weighted by the inverse of the estimates' variances (${se_i}^2$), e_0 is the constant term, and

[7] Note that we use the terms meta-random effects and meta-fixed effects to reflect "random effects" and "fixed effects" meta analyses, in order to distinguish them from the similarly named (but distinct) panel estimators.

in addition to the estimates' variance term to capture publication bias, we add interactions with ldc_i, given our interest in understanding the differences between countries in the two income groups.[8] Z is a vector of study characteristics to allow for heterogeneity across studies, outlined in Table 1. All estimations include cluster-robust standard errors, clustered within studies, to allow for correlation across estimates within a study and also mitigate potential type I errors (as suggested by Stanley and Doucouliagos, 2019).

Second, since reported estimates can vary by estimation methods, country, time period, unit of analysis, and degree of spatial aggregation among many other elements, the specification of included study characteristics can critically affect results. The vector of controls, Z are listed in Table 1. The broad set of potentially relevant study characteristics extends those included by the previous meta-analyses of Melo et al. (2009) and Ahlfeldt and Pietrostefani (2019) to encompass the recent literature as discussed in section 2. However, the choice of which sub-set of study controls to include as meta-regressors is not straight-forward.

We employ two techniques to strip-off researcher judgement and potential biases in selecting study controls. First, Bayesian Model Averaging (BMA) estimates millions of regressions consisting of subsets of the potential explanatory variables and weights them by model fit and model complexity (following Havranek et al., 2017; Steel, 2020). BMA reports an average of these many underlying regressions. The only covariates required to be included in each regression are the variance terms (to control for publication bias) and the non-interacted developing country dummy and post-1990 terms – we estimate nearly 17 million regressions for every combination of other covariates. We use as a robustness of our variable selection, since BMA does not report clustered standard errors – which can help control for type I errors (De Luca and Magnus, 2011; Havranek et al., 2017). Second, we run all 17 million combinations of covariates, with standard errors clustered at the study-level, and choose the parsimonious models that minimize the Bayesian Information Criteria or the Akaike Information Criteria. Both BIC and BMA are consistent, meaning that they converge to the true model, and BIC provides a good approximation of many linear models (van Erven et al., 2012, Fragoso et al., 2018). Cluster-robust estimation using BIC model selection is our preferred specification.

Third, meta-analyses that take a single "preferred" estimate per study have the risk of overweighting smaller studies that contribute to only a small number of estimates (and underweighting larger studies that produce multiple estimates). This also raises complications in choosing a single "best" estimate from each study, particularly when even within a single study there can be a range of estimation methods or data sample restrictions employed (e.g. manufacturing vs services, worker skill). Selecting a single estimate also requires researcher judgement, which may inadvertently introduce bias in the meta-analysis.

Instead, for our focal analysis, we follow the most common practice and retain multiple estimates per study and include an exhaustive set of potential covariates to explain heterogeneity across estimates and address issues of within-study autocorrelation by clustering at the paper-level. Our sample of 1,242 elasticity estimates are drawn from 70 studies and range from a single estimate in some papers to up to 80 estimates in a given study. To ensure our results are not driven by a few studies with a large number of estimates, we do a robustness check by taking a single estimate per combination of

[8] In section 5a, we also add interactions between the estimates' variances and other data characteristics, to test for heterogeneous publication bias across data samples.

meta controls. To avoid introducing researcher biases in choosing this estimate, the single estimate is the mean elasticity reported in the study.

Urban cost estimation

We estimate urban cost elasticities across developed and developing countries using city-level OLS regressions of (log) urban cost against (log) population density (equation 3). We use three measures of city-level urban costs: congestion (hours lost due to traffic), pollution (PM2.5 emissions) and crime (homicide rate).

A developing country dummy is included to reflect difference in urban costs in *levels*, and interact the dummy with population density to estimate the difference in urban cost *elasticities* across income groups. We normalize density relative to the mean value, such that constant terms can be interpreted as the levels at the mean city density.

Specifically, we estimate:

$$cost_i = \delta_o + \delta_1 . nonhic_i + \delta_2 . density_i + \delta_3 . ldc_i * density_i + u_i \quad (3)$$

where $cost_i$ is the log urban cost for city i, urban costs reflect either the log average annual additional hours spent driving in rush hours in 2018, log PM2.5 emissions for 2014 or log homicide rates in 2015. ldc_i is a dummy variable reflecting cities in developing countries, $density_i$ is the log population density for city i in 2015. Developing countries reflects non-high-income status as defined in 2015, using the World Bank classification.

5. Meta-analysis: Estimation of Agglomeration Benefits

This section presents the results of the meta-analysis of agglomeration elasticities. We first examine potential publication bias, present overall meta-estimates and then examine the role of heterogeneity by study characteristics.

a) Publication Bias

The results from Funnel Asymmetry Test (FAT) for publication bias, are presented in Table 3. For all estimation methods we find robust evidence of a highly significant positive relationship between the estimated agglomeration elasticity and the corresponding standard error, suggestive of publication bias.

Table 3: Funnel Asymmetry Test for Publication Bias

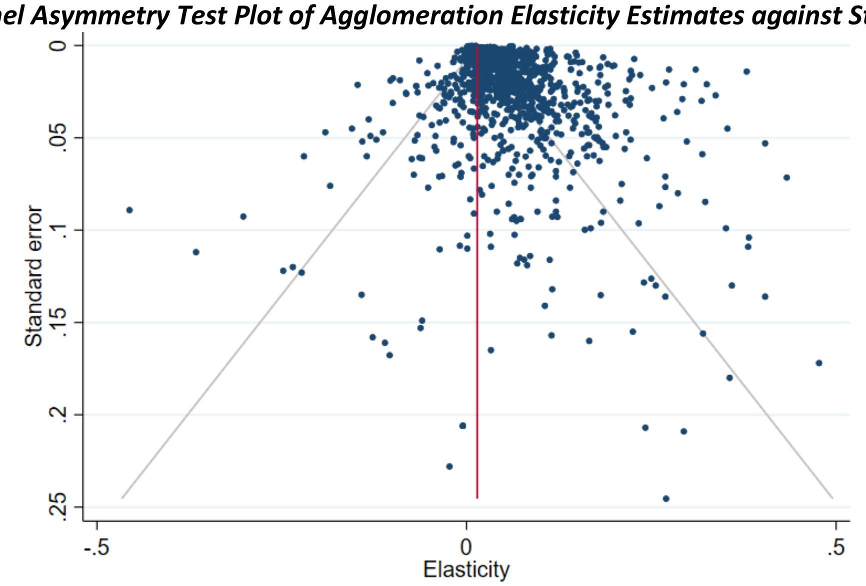
	(1)	**(2)**	**(3)**
Estimation Method:	Meta RE	Meta FE	WLS
Standard error (publication bias)	1.225***	3.824***	3.824***
	(0.087)	(0.030)	(0.566)

Constant	0.039***	0.012***	0.012***
	(0.002)	(0.000)	(0.004)
Observations	1,242	1,242	1,242

Notes: Estimation of equation 1. Meta FE denotes meta-analysis fixed effects estimation, Meta RE reflects meta-analysis random effects estimation, WLS are precision-weighted least squares estimates, using the inverse of the reported estimate's variances as weights. Outcome is the reported agglomeration elasticity expressed as absolute values. We do not exclude outliers from our baseline analysis, but rather include an extensive set of controls to explain study heterogeneity.[9] Robust standard errors are presented in parentheses and clustered at the study level for OLS and WLS, clustering is not possible under the Meta RE and Meta FE commands. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

Publication bias can be visualized with a funnel plot of all the reported elasticities against their standard errors (Stanley and Doucouliagos, 2010). The funnel plot in Figure 5 illustrates that the estimates do not appear to be randomly distributed. In the absence of publication bias, one would expect 95 percent of elasticity estimates to lie within the grey funnel (triangle) and to be evenly distributed. There is no systematic relationship between reported estimates and their standard errors. Instead reported elasticities are disproportionately in the top right, outside the funnel, suggesting positive bias towards selection of statistically significant positive agglomeration elasticities.

Figure 5: Funnel Asymmetry Test Plot of Agglomeration Elasticity Estimates against Standard Errors



Notes: Elasticity estimates are plotted against standard errors. The red line represents the constant and grey funnels represent 95percent confidence intervals of a t-test of publication bias, from a meta-random effects estimation (as in column 2 of Table 2). In the absence of publication bias, one would expect 95percent of elasticity estimates to lie within the funnel and to be evenly distributed.

We explore a variety of study characteristics to examine whether evidence of publication bias is constrained to a sub-sample of studies, or is more pervasive (following Havranek, 2015). Table 4 presents estimation results of an augmented equation 1, where standard errors are interacted with the study characteristic. Results suggest that publication bias is more severe in developed country than in developing country studies and higher in studies with a mid-year of data after 1990 (columns 1 and 2).

[9] Our results are robust to winsorizing the top and bottom 1percent of estimates by country.

However, publication quality, as measured by the number of citations or publication in a journal, is not significant (columns 3 and 4). At first glance it appears publication bias is more severe for studies using micro-data (column 5), but more recent studies are more likely to use micro-data and study developing countries. A full specification model with the characteristics together suggests that differences in publication bias are driven by the time period of study and the country's income level (column 6).[10]

Table 4: Funnel Asymmetry Test for Heterogeneity in Publication Bias across Study Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method:	WLS					
Standard error	4.386***	-0.349	3.540***	4.118***	1.968***	0.618
	(0.719)	(1.066)	(0.981)	(0.536)	(0.520)	(1.521)
Standard error * Developing Country	-2.437***					-2.563***
	(0.883)					(0.900)
Standard error * Post-1990		4.980***				5.782***
		(1.216)				(1.580)
Standard error * Published			-0.576			0.333
			(1.052)			(1.072)
Standard error * Number of Citations				-0.796		-0.391
				(0.666)		(0.360)
Standard error * Micro Data					2.593***	-2.211
					(0.836)	(1.853)
Constant	0.011***	0.038***	0.029***	0.006**	0.010*	0.039**
	(0.004)	(0.014)	(0.008)	(0.003)	(0.006)	(0.017)
Observations	1,242	1,242	1,242	1,242	1,242	1,242

Notes: Outcome is the reported agglomeration elasticity. WLS is precision-weighted least squares estimates, using the inverse of the reported estimate's variances as weights. WLS estimation of equation 1, but interacting the estimates' standard errors with different study characteristics to allow for heterogeneous publication bias across studies. Non-interacted study characteristics are included in the estimation, but not reported for parsimony. Study characteristics are defined in Table 1. Reported agglomeration elasticity expressed as absolute values. Robust standard errors clustered at the study level are in parentheses. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

b) Homogenous meta-estimates

In this section, we present meta-estimates examining agglomeration elasticities across developed and developing economies. To this end, Table 5 presents results from estimating equation (2), with country level income as the only source of heterogeneity in elasticity estimate. Traditional meta-analysis techniques that do not control for publication bias (columns 1 to 3) suggest significant positive agglomeration elasticities for developed countries ranging from 1.4 percent to 5.1 percent, as

[10] Interacting the standard error with study characteristics allows testing of significant differences in publication bias. In Table A2 in the Appendix we estimate FAT using different sub-samples of studies, and find evidence of publication bias in both high and non-high-income subsamples, across published and un-published studies and across studies using both micro and macro-data. Only for the pre-1990 studies do we fail to find evidence of publication bias.

reflected in the constant term. For developing countries, agglomeration elasticities appear to be significantly higher than developed countries – of the range 1.1 to 2.3 percentage points.

The pervasive evidence of publication bias suggests that the raw meta-estimates cannot be taken at their face value. The state of the art methodology, PET-PEESE, that outperforms other estimations under publication bias is presented in columns 4 and 5 of Table 5. We start with PET-PEESE estimation in column 4. Given that the publication bias is stronger for studies post-1990, we augment our estimating equation (2) to allows for publication bias that differs across studies based on these variables (column 5).[11] We find that controlling for publication bias in PET-PEESE does not substantially change the results relative to estimates that do not control for the bias. Agglomeration elasticities appear to be significantly higher than developed countries by around 2.1 to 2.2 percentage points (column 4 and 5). [12]

Table 5: Homogeneous meta-estimates – agglomeration elasticities across developed and developing countries

	(1)	(2)	(3)	(4)	(5)
Estimation Method:	Meta RE	Meta FE	WLS	PET-PEESE	
Publication Bias Correction:		N		Y	
Developing Country	0.011***	0.023***	0.023**	0.022**	0.021**
	(0.004)	(0.001)	(0.009)	(0.009)	(0.010)
Post-1990s					-0.025*
					(0.013)
Constant	0.051***	0.014***	0.014***	0.014***	0.037***
	(0.002)	(0.000)	(0.004)	(0.004)	(0.013)
Observations	1,242	1,242	1,242	1,242	1,242

Notes: Outcome is the reported agglomeration elasticity. Meta RE reflects meta-analysis random effects estimation, Meta FE reflects meta-analysis fixed effects estimation, WLS are precision weighted least squares estimates, using the inverse of the reported estimate's variance as the weight. PET-PEESE are "precision-effect estimates with standard errors" following Stanley and Doucouliagos (2019), which to correct for publication bias includes a squared standard error term in column 6, and its interaction with a developing country dummy, and with a post-1990s dummy in column 7. The standard error terms are omitted for parsimony. PET-PEESE and WLS are precision-weighted, using the inverse of the reported estimate's variance as the weight. Robust standard errors are presented in parentheses, these are clustered at the study level for all except Meta RE and FE estimation. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

[11] Our results are robust, although somewhat less precisely estimated, when not allowing for heterogeneous publication bias.

[12] A robustness check using Andrews and Kasy (2019) estimator finds similarly meta estimates are around 2 percentage points higher in non-high income countries. Depending on the choice of cutoff for probability of publication, the estimator finds a mean high-income true elasticity of 1.6 percent to 2.0 percent, compared to 3.8 percent to 4.8 percent for non-high income. The estimator is available at https://maxkasy.github.io/home/metastudy/ . We employ PET-PEESE as our preferred estimator it is readily adaptable to heterogeneity by study characteristics.

c) Heterogeneity by study characteristics

Considering the wide range of differences within and across studies on characteristics pertaining to estimation methods, sector of study, skills of workers spatial scale, underlying data and so on, we augment our meta-analysis by controlling for a broad set of study characteristics outlined in Table 1.

Table 6 presents our preferred PET-PEESE specification where we deploy a variety of model selection methods to objectively arrive at the sub-set of controls included as meta-regressors. In addition to the general model including all controls, we experiment with Bayesian Model Averaging (BMA) to examine robustness of our variable selection (Steel, 2020). We report the posterior inclusion probability (PIP) for each variable under BMA in square brackets (see column 2). Our preferred specification, in column 4, involves estimating all 17 million combinations of covariates to choose the models that minimizes the Bayesian Information Criteria (BIC). The variables included in our preferred BIC specification, is broadly similar to that proposed by BMA, excluding all variables with a PIP of less than 50 percent and including all those with a PIP of more than 80 percent. We also examine robustness to using the Akaike Information Criteria (AIC) in column 3.

Table 6 suggests that the agglomeration premia in developing countries is about 1 percentage point higher than developed countries, after controlling for not only publication bias, but also differences in time period, agglomeration or productivity measures, estimation methods and underlying data (columns 1 to 4). Across all specifications, the difference between elasticities in developed and developing countries ranges from 0.8 to 1.0 percentage points across all specifications. However, in all specifications except BMA, the difference in agglomeration premia is not statistically significant. The significance in BMA may be driven by the fact that we are not able to cluster BMA standard errors within papers. To examine if the small overall differences between agglomeration premia in developing and developed countries is driven by a few outlier countries, we re-estimate the specification in column 4 (BIC) replacing income level dummy with indicator variables for each country. The estimated country coefficients, with the United States as the reference category, are presented in the Appendix Figure A2. While there are differences across individual countries, as expected, we find that most developed and developing countries are clustered around the reference category. The small differences between agglomeration premia across developed and developing countries broadly holds across the countries in our sample, and is not driven by one or two outlier countries.

Table 6 suggests that while the agglomeration elasticities may be comparable across country income groups, many other differences in data or estimation methods across studies matter much more. More specifically, we make the following observations. *First*, the productivity measure matters when it comes to measuring agglomeration premia. Estimated nominal wages or labor productivity premia are much higher than studies using TFP – by 6.5 and 4.3 percentage points respectively. *Two*, one possible reason for the difference is urban costs. Urban costs increase local prices and the cost of inputs, which feed through into higher nominal wages or labor productivity, however, TFP elasticities are theoretically independent of urban costs (Combes and Gobillon, 2015).[13] Studies that estimate *real* wages or labor productivity – controlling for urban costs – have 4.2 percentage point lower estimates

[13] Note also that TFP estimates need to be scaled up by the labor share to be comparable with wages or labor productivity.

than those that use nominal values.[14] Accounting for urban costs and labor share explains the majority of the difference we find between nominal wage and labor productivity estimates and TFP.

Three, agglomeration premia differ substantially across industries. The agglomeration premia in services is on average much higher, around 3.5 percentage points higher than estimates encompassing all industries (column 4). *Four,* controlling for heterogeneity in firm or worker traits and underlying data also yields interesting results. Studies that control for firm size tends to reduce agglomeration premia, likely because larger firms tend to be more productive and hire more skilled workers. More spatially disaggregated studies tend to find around 1.1 percentage point smaller agglomeration benefits, perhaps because of spillovers on surrounding areas. Skilled workers disproportionately benefit from density, although the strength of the statistical significance depends on the model selection. Skilled workers have between 1.1 to 1.7 percentage point higher productivity than workers as a whole. *Five*, controlling for sorting of skilled workers in cities either at the local level or using individual's education reduces agglomeration premia by 1.0 and 1.3 percentage points respectively (column 4). Similarly, more productive firms may choose to locate in cities and agglomeration premia may reflect local characteristics that are hard to measure. Employing panel fixed effects leads to lower estimates of around 1.8 percentage points (column 4). *Six,* controlling for the so-called endogeneity via instrumental variable estimation typically does not materially impact the results.

Lastly, there are no robust differences for agglomeration premia estimated in higher and lower quality publications, or across different agglomeration measures (although there is some evidence localization controls matter).

In the Appendix Table A3 we examine robustness of our main results to alternative estimation approaches and sample restrictions. The main findings shown in Table 6 remain intact, that is, the differences in agglomeration premia across developed and developing countries are small, once publication bias and other study differences are considered. It becomes clearer that underlying data or estimation choices matter far more that country-income. In Appendix Table A3, we decompose the panel fixed effects, industry, firm size and local area human capital controls into those separately reflecting spatial, worker and firm data (column 1). In general, we fail to find that these controls matter differentially across data sources. In column 2, we mitigate any residual risk that our results are driven by a few papers with a large number of estimates (although note we cluster standard errors at the study-level in the baseline estimation). To do so we take a single mean estimate per combination of meta controls in each paper, which reduces the sample substantially to only 310 observations. We now find there is weak evidence that agglomeration premia are somewhat *higher* in developed countries. This confirms the message of our baseline results that differences across country income groups are small, and other data or estimation choices matter far more. Finally, columns 3 to 6 repeat our preferred specification (from Table 6 column 4) but exclude two developed and developing countries with the largest number of estimates, Brazil, China, UK, USA. The results are unchanged.

[14] This is broadly in line with differences between real wage and nominal wage elasticities within the same papers, e.g. Chauvin et al. (2017) or Faberman and Freedman (2016).

Table 6: Heterogeneous meta-estimates by study characteristics

		(1)	(2)		(3)	(4)
	Estimation Method:		PET-PEESE			
	Model Selection:	General	BMA		AIC	BIC
Country Income	Developing Country	0.009	0.009***		0.008	0.010
		(0.007)	(0.003)	[1.00]	(0.007)	(0.008)
Productivity Measure	Wages	0.067***	0.065***		0.065***	0.063***
		(0.013)	(0.005)	[1.00]	(0.014)	(0.012)
	Labor Productivity	0.045***	0.043***		0.045***	0.042***
		(0.010)	(0.004)	[1.00]	(0.010)	(0.012)
Urban Cost	Urban Cost Control	-0.039***	-0.042***		-0.041***	-0.045***
		(0.013)	(0.005)	[1.00]	(0.013)	(0.012)
Industry	Manufacturing Sector	0.012*	0.011***		0.012	0.011
		(0.007)	(0.003)	[1.00]	(0.007)	(0.008)
	Services Sector	0.035***	0.034***		0.035***	0.035***
		(0.010)	(0.004)	[1.00]	(0.011)	(0.011)
Skill	Skilled workers	0.014***	0.011		0.015***	0.017***
		(0.004)	(0.009)	[0.66]	(0.004)	(0.004)
	Unskilled workers	-0.002***	-0.001		-0.002***	
		(0.001)	(0.001)	[0.31]	(0.001)	
Time Period	Post-1990s	-0.001	-0.004		-0.001	-0.007
		(0.008)	(0.003)	[1.00]	(0.008)	(0.007)
Study Quality	Published	-0.005	-0.003		-0.005	-0.005
		(0.005)	(0.003)	[0.54]	(0.005)	(0.005)
	Number of Citations	0.001	0.000		0.001	
		(0.002)	(0.000)	[0.04]	(0.003)	
Spatial Measure	City - Level	0.002	0.000			
		(0.002)	(0.001)	[0.09]		
	Sub City - Level	-0.008	-0.011***		-0.009*	-0.011***
		(0.006)	(0.002)	[1.00]	(0.005)	(0.003)
Agglomeration Measure	Density Measure	-0.007	-0.001		-0.010	
		(0.009)	(0.002)	[0.08]	(0.009)	
	Market Potential Measure	-0.007	-0.001		-0.010	
		(0.007)	(0.003)	[0.10]	(0.007)	
Localization	Localization Control	0.009	0.010***		0.009	0.009***
		(0.007)	(0.002)	[1.00]	(0.006)	(0.003)
Data	Panel Data	-0.005	-0.006			
		(0.006)	(0.004)	[0.77]		
	Firm Data	0.047***	0.049***		0.046***	0.046***
		(0.012)	(0.005)	[1.00]	(0.013)	(0.012)
	Worker Data	-0.021**	-0.021***		-0.022**	-0.021***
		(0.009)	(0.003)	[1.00]	(0.009)	(0.008)

Endogeneity	Panel Fixed Effects	-0.019***	-0.018***		-0.020***	-0.018**
		(0.007)	(0.002)	*[1.00]*	(0.007)	(0.008)
	IV estimation - contemporaneous	-0.002	-0.000			
		(0.005)	(0.001)	*[0.05]*		
	IV estimation - historic	-0.001	-0.000			
		(0.007)	(0.000)	*[0.03]*		
Firm Heterogeneity	Industry control	0.012**	0.012***		0.011***	0.010***
		(0.005)	(0.002)	*[1.00]*	(0.004)	(0.004)
	Firm size control	-0.004*	-0.004***		-0.004*	-0.004*
		(0.002)	(0.001)	*[0.99]*	(0.002)	(0.002)
Worker Sorting	Local area human capital	-0.012***	-0.010***		-0.012***	-0.010**
		(0.004)	(0.002)	*[1.00]*	(0.004)	(0.004)
	Individual-level human capital	-0.014**	-0.013***		-0.014**	-0.011*
		(0.006)	(0.003)	*[1.00]*	(0.006)	(0.006)
	Constant	-0.002	-0.005		0.000	-0.004
		(0.010)	(0.005)	*[1.00]*	(0.010)	(0.009)
	Observations	1,242	1,242		1,242	1,242

Notes: Outcome is the reported agglomeration elasticity. All models are estimated under PET-PEESE, "precision-effect estimates with standard errors" following Stanley and Doucouliagos (2019), which to correct for publication bias includes a squared standard error term, and its interaction with a developing country dummy, and with a post-1990 dummy. The standard error terms are not reported for parsimony. PET-PEESE estimates are precision-weighted, using the inverse of the reported estimate's variance as the weight. Robust standard errors are presented in parentheses, these are clustered at the study level for all model selection methods except Bayesian Model Averaging (BMA). The square brackets reflect the probability of each variable's model inclusion under BMA. The General model includes all control variables. BIC and AIC are the specifications (from all 17million combinations of controls) that minimize the Bayesian and Akaike Information Criteria respectively. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

6. Estimating urban costs

Our meta-analysis in section 5 suggests that urban costs play a major role in explaining differences in agglomeration benefits across studies. Most studies measure "gross" agglomeration benefits of density rather than advantages of locating in crowded, congested and crime prone places that "net" out these benefits. In sum, the evidence base for urban costs is underdeveloped. Using novel data on crime, congestion and pollution from hundreds of cities around the world, including those in developing countries, we present estimates of density elasticity of urban costs in Table 7. The table makes the following points:

First, urban costs are significantly higher in *levels* in developing countries, and this is true across our measures of congestion and crime, and depending on the specification, pollution, suggested by the positive developing country dummy (and mirroring Figure 4). In levels, for the average city density in our data, pollution is on average 16-28 percent higher (although not significantly different from zero in column 1), 19-30 percent more hours are lost hours to congestion and homicides are 4 times as likely.

Second, although developing countries have higher urban cost levels, their cost *elasticities* may not be different than that observed in developed countries. Relative to developed countries, the elasticity of urban dis-amenities in developing countries are similar for pollution and congestion. Our results point to an elasticity of pollution and congestion with respect to city density to be 45 percent and 16 percent respectively in developing countries (compared to 48 percent and 18 percent for developed countries).[15] By contrast, the elasticity of crime, measured by the homicide rate, with respect to city built-up density is significantly higher at +24 percent in developing countries compared with -56 percent in developed countries. The latter suggests that if crime is accounted for in measuring the advantages of locating agglomerations, the net benefits in developing countries would be much smaller.

As a robustness exercise we use city population density from census data (instead of build-up density) for each country.[16]. The results are presented in the Appendix Table A4. Although we find somewhat lower urban cost elasticities for pollution (18 percent overall) and higher for congestion (26 percent), the key messages do not change. We find that the levels of congestion, crime and pollution are larger in developing economies, but the urban cost elasticities are not discernibly different between developing and developed countries.

Table 7: Urban cost elasticities and cost levels - across developed and developing countries

Outcome:	**Log PM2.5 Pollution**		**Log Hours Lost to Travel Time**		**Log Homicide Rate**	
	(1)	(2)	(3)	(4)	(5)	(6)
Developing Country	0.150	0.252**	0.176***	0.264***	1.578***	1.686***
	(0.097)	(0.118)	(0.060)	(0.073)	(0.212)	(0.201)
Log Population Density	0.453***	0.481***	0.158***	0.177***	0.006	-0.566**
	(0.052)	(0.056)	(0.039)	(0.043)	(0.166)	(0.259)
Log Population Density * Developing Country		-0.145		-0.140		0.807**
		(0.136)		(0.094)		(0.331)
Constant	2.525***	2.534***	4.627***	4.631***	0.428***	0.220*
	(0.040)	(0.042)	(0.023)	(0.024)	(0.122)	(0.125)
Observations	298	298	337	337	188	188

Note: City-level pollution reflects PM2.5 data for 2014 for 298 cities (78 in developing countries). Congestion reflects the annual additional hours spent driving in rush hours, measured in 2018, and contains data for 337 cities (69 in developing countries). Homicide rate data reflects 124 cities (63 in developing countries) in 2015. Population density reflects population per square km of built up area in 2015. The top and bottom 1 percent of population density observations are excluded. Non-HIC reflects a dummy variable for developing countries using World Bank country classifications in 2015. Log population density is demeaned such that the constant terms are interpreted at the mean city density. Robust standard errors in parentheses, ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

7. Conclusions

[15] Our estimate is somewhat higher than Ahlfeldt and Pietrostefani (2019) who report the pollution elasticity to be +22 percent, using OLS estimation and OECD data. They also find a congestion elasticity of +8 percent, using a different measure of congestion to our paper, average travel speeds using OECD data. Their meta-analysis of 13 high income country studies of crime elasticities (not focusing on homicides as we do) finds a mean elasticity of -24 percent.

[16] Census data is available for only about half the cities in our sample.

We examine more than 1,200 estimates of agglomeration elasticities from 70 studies covering 33 countries over the period 1973 to 2020. While raw agglomeration elasticities are positive and high in China, India and countries in Africa, countries such as Chile have negative elasticity estimates. Overall, raw estimates tend to suggest that developing countries reap huge benefits from urban density, nearly 5 points higher than developed countries. Further, these estimates are not driven by reverse causality.

These aggregate estimates, however, hide substantial heterogeneity. The differences in estimates can be attributed to estimation set-up (outcome and agglomeration measure), consideration of urban costs in estimating net benefits, and the variation in pay-off across sectors and skills. Studies using wages as an outcome variable have higher estimated elasticities compared to those using TFP measures, while studies using population size or density have larger estimates relative to market access measures. Service sector estimates are on average higher than manufacturing, while skilled workers disproportionately benefit from density relative to others. These findings are broadly consistent with the literature.

Our most important finding is that nominal wages, the canonical measure of agglomeration economies, seldom capture the costs of working and living in cities. These costs include higher housing costs, time lost in commuting as well as dis-amenities such as pollution or crime. Our meta-analysis shows that studies controlling for urban costs find elasticities to be 4.2 percentage points lower than studies that do not, implying a net agglomeration elasticity of 0.1 percent for developed countries, when using labor productivity as an outcome measure. Although our analysis confirms the relatively higher "gross" wage elasticities with respect to density; we find no evidence for "net" gains in light of high and increasing costs of working in developing country cities.

Further, rather than developing country agglomeration estimates being much higher than advanced countries as noted in country studies using wage data from China and India (e.g. Chauvin et al., 2017), there is no statistically significant difference between developing country and developed country estimates. Our novel estimates of urban dis-amenities suggest that although the elasticity of pollution and congestion in developing countries is comparable with developed countries, their levels are much higher. Higher costs in developing country cities are partly due to bad design and lack of capital investment, but also the fact that their growth is not driven by the process of structural transformation, which would create a critical mass of more productive firms that benefit from sharing, matching, and learning. Many developing country cities are not dense and productive—they are just crowded.

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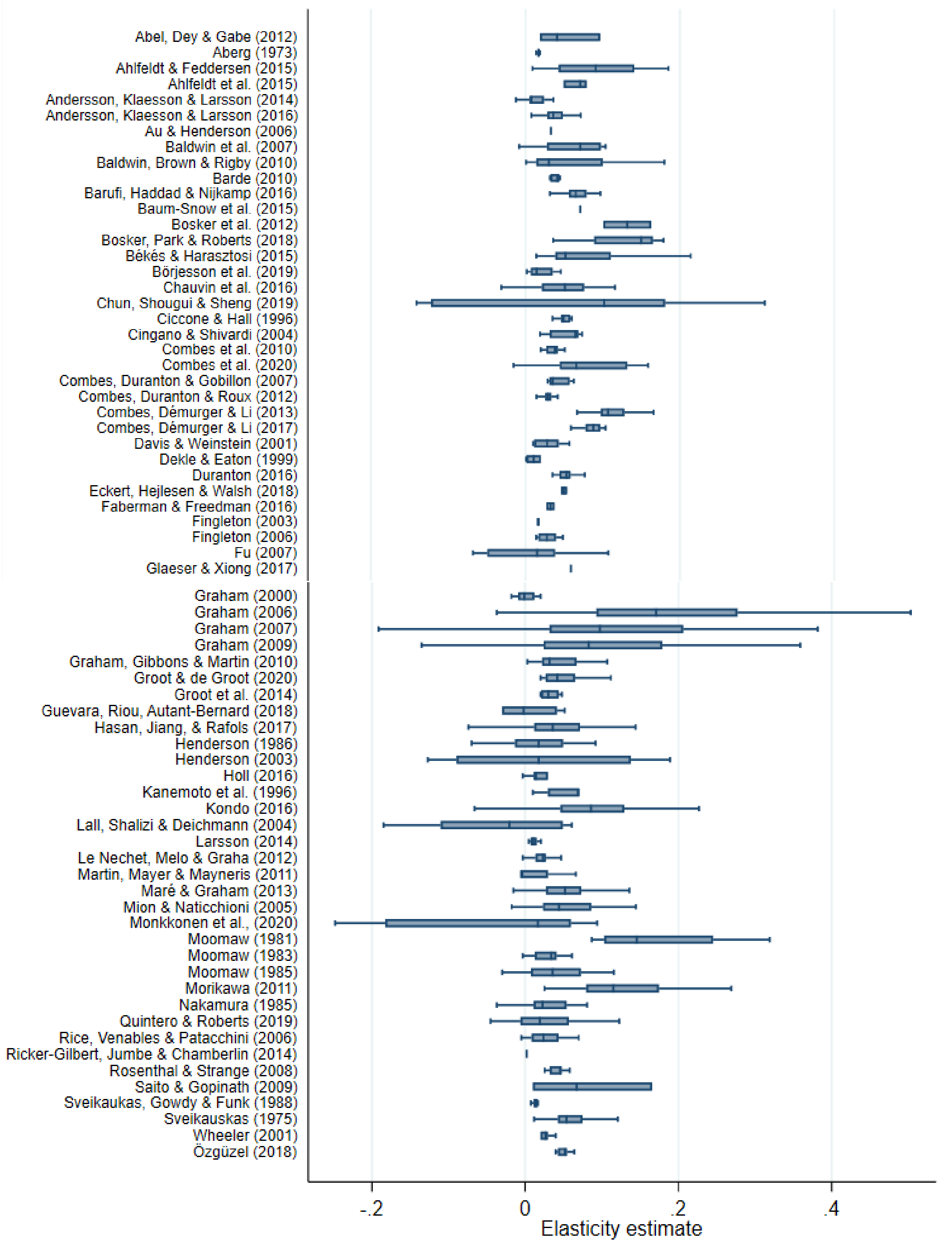
Appendix

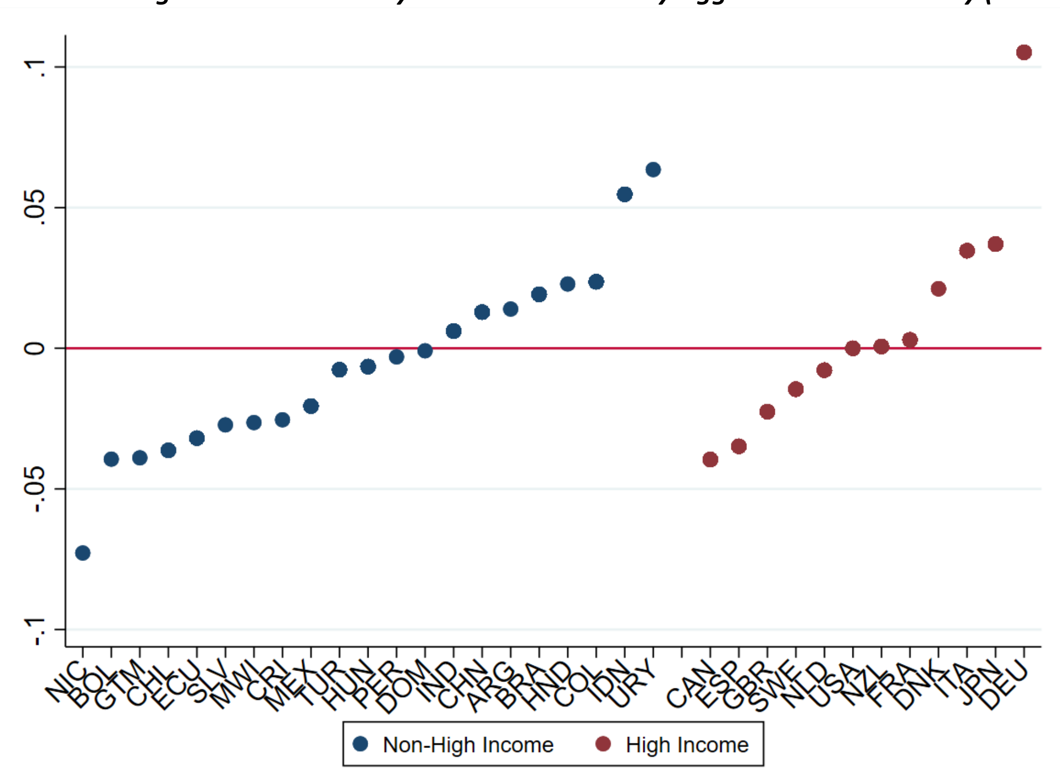
Figures

Figure A1: Elasticity estimates by Study



Notes: The box shows the 25th, median and 75th percentile elasticity for each paper, with the whiskers showing the upper and lower adjacent values. Some papers contain a single estimate, hence only the median is shown.

Figure A2: Meta-Analysis Estimated Country Agglomeration Elasticity (vs USA)



Notes: Estimated under PET-PEESE, "precision-effect estimates with standard errors" following Stanley and Doucouliagos (2019), which to correct for publication bias includes a squared standard error term, and its interaction with a developing country dummy, and with a post-1990 dummy. Model selection under Bayesian Information Criterion, equivalent of column 4 in Table 6, but allowing for separate country dummies in place of a developing country dummy. USA is the omitted reference category, represented by the horizontal line at zero. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

Tables

Table A1: Mean agglomeration elasticities by meta variable category

Category	Variable	Estimated Elasticity: Mean if dummy = 1	Estimated Elasticity: Mean of reference category (dummy = 0)
Country Income	Developing Country	0.063	0.056
Productivity Measure	Wages	0.055	0.061
	Labor Productivity	0.044	0.061
Urban Cost	Urban Cost Control	0.034	0.059
Industry	Manufacturing Sector	0.049	0.064
	Services Sector	0.109	0.049
Skill	Skilled workers	0.059	0.058
	Unskilled workers	0.027	0.059
Time Period	Post-1990s	0.064	0.037
Study Quality	Published	0.050	0.077
Spatial Measure	City - Level	0.045	0.072
	Sub City - Level	0.071	0.052
Agglomeration Measure	Density Measure	0.062	0.055
	Market Potential Measure	0.073	0.053
Localization	Localization Control	0.047	0.063
Data	Panel Data	0.064	0.049
	Firm Data	0.077	0.048
	Worker Data	0.057	0.059
Endogeneity	Panel Fixed Effects	0.047	0.061
	IV estimation - contemporaneous	0.012	0.061
	IV estimation - historic	0.059	0.058
Firm Heterogeneity	Industy control	0.058	0.058
	Firm size control	0.065	0.054
Worker Sorting	Local area human capital	0.033	0.064
	Individual-level human capital	0.064	0.056

Note: Number of observations for each variable is equal to 1,242. Table shows the mean agglomeration elasticity for each of the dummy variable categories listed in Table 1.

Table A2: Funnel Asymmetry Test for Publication Bias Across Data Subsamples

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Estimation Method:				WLS				
Sub Sample:	Developing Countries	Developing Countries	Post-1990	Pre-1990	Published	Unpublished	Micro Data	Macro Data
Standard error	1.949***	4.386***	4.631***	-0.349	2.964***	3.540***	4.561***	1.968***
	(0.532)	(0.721)	(0.585)	(1.090)	(0.384)	(1.004)	(0.657)	(0.527)
Constant	0.026**	0.011***	0.009***	0.038**	0.011***	0.029***	0.011***	0.010
	(0.010)	(0.004)	(0.002)	(0.014)	(0.004)	(0.008)	(0.004)	(0.006)
Observations	388	854	971	271	884	358	919	323
R-squared	0.188	0.169	0.316	0.002	0.126	0.127	0.196	0.209

Notes: Estimation of equation 1. WLS are precision-weighted least squares estimates, using the inverse of the reported estimate's variances as weights. Robust standard errors are presented in parentheses. Reported agglomeration elasticity expressed as absolute values. Standard errors are clustered at the study level. The estimation is conducted over different subsamples of the data. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

Table A3: Meta results robustness to alternative estimation approaches and sample restrictions

		(1)	(2)	(3)	(4)	(5)	(6)
	Sample Restrictions	Full Sample – Additional FEs	Single Estimate	Exclude GBR	Exclude USA	Exclude BRA	Exclude CHN
Country Income	Developing	0.011	-0.007	0.006	0.011	0.001	0.010
		(0.008)	(0.005)	(0.008)	(0.008)	(0.009)	(0.008)
Productivity Measure	Wages	0.034***	0.043***	0.063***	0.069***	0.069***	0.065***
		(0.008)	(0.008)	(0.012)	(0.016)	(0.013)	(0.012)
	Labor Productivity	0.026***	0.026***	0.038***	0.044***	0.044***	0.044***
		(0.008)	(0.009)	(0.013)	(0.013)	(0.011)	(0.012)
Urban Cost	Urban Cost Control	-0.036***	-0.014	-0.046***	-0.046***	-0.046***	-0.045***
		(0.008)	(0.009)	(0.013)	(0.015)	(0.012)	(0.012)
Industry	Manufacturing Sector	0.007	-0.013*	0.013	0.012	0.009	0.012
		(0.005)	(0.007)	(0.010)	(0.008)	(0.007)	(0.008)
	Services Sector	0.035***	0.058***	0.057***	0.035***	0.033***	0.033***
		(0.011)	(0.008)	(0.012)	(0.011)	(0.011)	(0.010)
Skill	Skilled workers	0.017***	0.012***	0.011**	0.018***	0.018***	0.018***
		(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Time Period	Post-1990s	0.005	-0.005	-0.012*	-0.006	-0.005	-0.006
		(0.008)	(0.006)	(0.007)	(0.011)	(0.007)	(0.007)
Study Quality	Published	-0.006	-0.009*	-0.016***	-0.005	-0.005	-0.005
		(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Spatial Measure	Sub City - Level	-0.011***	-0.008**	-0.005*	-0.010***	-0.013***	-0.011***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Localization	Localization Control	0.003	0.002	0.003	0.011***	0.009***	0.010***
		(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Data	Firm Data	0.037***	0.033***	0.050***	0.051***	0.049***	0.048***
		(0.010)	(0.007)	(0.013)	(0.017)	(0.012)	(0.012)
	Worker Data	0.004	-0.015***	-0.015**	-0.022***	-0.026***	-0.021**
		(0.008)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
Endogeneity	Panel Fixed Effects	-0.001	-0.029***	-0.023***	-0.018**	-0.019**	-0.018**
		(0.004)	(0.006)	(0.007)	(0.009)	(0.008)	(0.007)
	Panel Fixed Effects * Firm Data	0.009					
		(0.015)					
	Panel Fixed Effects * Worker Data	-0.034***					
		(0.009)					
Firm Heterogeneity	Industy control	0.004	0.015***	0.005*	0.010**	0.012***	0.010***
		(0.010)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
	Industy control * Firm Data	-0.007					
		(0.011)					
	Industy control * Worker Data	0.010					
		(0.009)					
	Firm size control	0.005	-0.002***	-0.003**	-0.004*	-0.005*	-0.004*
		(0.011)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
	Firm size control * Firm Data	-0.020					
		(0.012)					
	Firm size control * Worker Data	-0.008					
		(0.011)					
Worker Sorting	Local area human capital	-0.007	-0.016**	-0.008	-0.010**	-0.013***	-0.009**
		(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)

	Local area human capital * Firm Data	-0.005					
		(0.008)					
	Local area human capital * Worker Data	-0.014					
		(0.011)					
	Individual-level human capital	-0.022***	-0.016***	-0.017***	-0.013	-0.009	-0.011*
		(0.006)	(0.005)	(0.005)	(0.009)	(0.006)	(0.006)
	Constant	0.006	0.023***	0.011	-0.010	-0.006	-0.006
		(0.008)	(0.008)	(0.009)	(0.014)	(0.010)	(0.010)
	Observations	1,242	310	1,067	1,037	1,129	1,157

Notes: Outcome is the reported agglomeration elasticity. Columns 1 to 6 are estimated under PET-PEESE, "precision-effect estimates with standard errors" following Stanley and Doucouliagos (2019), which to correct for publication bias includes a squared standard error term, and its interaction with a developing country dummy, and with a post-1990 dummy. The standard error terms are not reported for parsimony. All estimates are precision-weighted, using the inverse of the reported estimate's variance as the weight. All models are variations of the baseline BIC estimation of column 4 of Table 6 (model selection by Bayesian Information Criterion). Full Sample – Additional FEs decomposes the panel fixed effects, industry, firm size and local area human capital controls into those separately reflecting spatial, worker and firm data. Single Estimate uses a single mean estimate per combination of meta controls in each paper. Columns 3 to 6 repeat the baseline estimation but exclude the two developed and developing countries with the largest number of estimates – UK, US, Brazil and China respectively. Standard errors are clustered at the study-level. ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

Table A4: Using census population data, there urban cost elasticities are not statistically different between developed and developing countries

	Log PM2.5 Pollution		Log Hours Lost to Travel Time		Log Homicide Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Developing Country	0.746***	0.746***	0.338***	0.341***	1.213***	1.211***
	(0.063)	(0.064)	(0.042)	(0.043)	(0.315)	(0.316)
Log Population Density	0.182***	0.158***	0.258***	0.274***	0.071	0.114
	(0.033)	(0.041)	(0.021)	(0.029)	(0.240)	(0.306)
Log Population Density * Developing Country		0.037		-0.042		-0.065
		(0.062)		(0.039)		(0.451)
Constant	2.275***	2.272***	4.588***	4.589***	0.522***	0.528***
	(0.030)	(0.032)	(0.027)	(0.027)	(0.177)	(0.170)
Observations	163	163	177	177	60	60

Note: City-level pollution reflects PM2.5 data for 2014 for 163 cities (65 in developing countries). Congestion reflects the annual additional hours spent driving in rush hours, measured in 2018, and contains data for 177 cities (50 in developing countries). Homicide rate data reflects 60 cities (30 in developing countries) in 2015. Population density reflects population per square km from census data. The top and bottom 1percent of population density observations are excluded. Non-HIC reflects a dummy variable for developing countries using World Bank country classifications in 2015. Robust standard errors in parentheses, ***, ** and * reflect significance at the 1, 5 and 10 percent levels respectively.

Meta-Analysis Methodology

Meta-Analysis Paper Selection

The selection of papers is driven by different search approaches. Several combinations of keywords were used to find papers in EconLit, ScienceDirect and Google Scholar. The search was completed on April 13, 2020.

The keywords were used to reflect agglomeration measures, productivity measures and country income. All of the following keywords were used individually: agglomeration, elasticity, density, urban, cost, developing countries, developed countries, productivity, urban, wages, output. In addition, the following keyword combinations were employed:

- Agglomeration, elasticity, density
- Agglomeration, elasticity, urban
- Agglomeration, density, cost
- Agglomeration, density, urban
- Agglomeration, elasticity, productivity
- Agglomeration, elasticity, output
- Urban, cost, density
- Urban, wages, density
- Agglomeration, elasticity, developing country
- Agglomeration, elasticity, developed country
- Density, elasticity, developing country
- Density, elasticity, developed country

Given the vast results on EconLit, ScienceDirect and Google Scholar, we limited our search to the first 15 pages, where the pages are sorted based on the relevance of the studies for the keyword combination. Since the focus of our work is on developing countries where estimations of agglomeration elasticity are quite recent, we only focused on studies that were published after 2002. For prior works, we rely on the underlying data for meta-analysis provided in Melo et al. (2009).

We complemented this approach with analysis of citation trees for the papers that inspired the study (Melo et al. (2009), Chauvin et al., (2017) and Ahlfeldt and Pietrostefani (2019)), as well as publications and working papers noted on the websites of the most cited authors (Pierre-Philippe Combes, Gilles Duranton, Edward Glaesar, Laurent Gobillon, Stephen Redding, Esteban-Rossi Hansberg, Daniel J. Graham). Lastly, we consulted with colleagues at the World Bank and academic institutions to identify any ongoing work in the field.

The initial sample included peer-reviewed papers, working papers of universities or specialist research institutes (World Bank, NBER, CEPR, CESIfo, and IZA), chapters in books and conference proceedings.

Estimates were excluded that did not report standard errors (due to our correction for publication bias), those with economic scale outcomes rather than productivity (note we include production function approaches), or those not reporting estimates by individual countries (e.g. by European region).

Some papers report semi-elasticities (from a log-linear model) that we convert to an elasticity. Two papers (Combes et al., 2012 and Kondo, 2016) report estimated agglomeration premia at above and below average densities. These have been converted to an elasticity by taking the difference in agglomeration premia divided by the difference in densities at these two points, similar to the meta-analysis of Ahlfeldt and Pietrostefani (2019). Studies are excluded that cannot be represented as an elasticity.

The list of variables collected for each study is given by Table 1. The literature review was conducted by Somya Bajaj, and reviewed by Jonathan Timmis. The resulting sample is 1,242 estimates from 70 papers from 1973 to 2020.

Table A5: Full List of Studies

#	Authors	Journal	Volume, Page No.	Paper Name
1	Abel, Dey & Gabe (2012)	Journal of Regional Science	52 (4), pp. 562-586	Productivity and the density of human capital
2	Aberg (1973)	Regional and Urban Economics	3 (2), pp. 131-155	Regional productivity differences in Swedish manufacturing
3	Ahlfeldt & Feddersen (2015)	Journal of Economic Geography	111, pp. 93-107	From periphery to core - Measuring agglomeration effects using high-speed
4	Ahlfeldt et al. (2015)	Econometrica	83 (6), pp. 2127-2189	The economics of density - evidence from the Berlin wall
5	Andersson, Klaesson & Larsson (2014)	Regional Science	93 (4), pp. 727-747	The sources of the urban wage premium by worker skills - spatial sorting or agglomeration economies?
6	Andersson, Klaesson & Larsson (2016)	Regional Studies	50 (6), pp. 1082-1095	How local are spatial density externalities? Neighbourhood effects in agglomeration economies
7	Au & Henderson (2006)	The Review of Economic Studies	73 (3), pp. 549-576	Are Chinese cities too small?
8	Baldwin et al. (2007)	Economic Analysis (EA) Research Paper Series	No. 2007045	Urban economies and productivity
9	Baldwin, Brown & Rigby (2010)	Journal of Regional Science	50 (5), pp. 915-934	Agglomeration economies - Microdata panel estimates from Canadian manufacturing
10	Barde (2010)	Spatial Economic Analysis	5 (1), pp. 73-91	Increasing returns and the spatial structure of French wages
11	Barufi, Haddad & Nijkamp (2016)	Annals of Regional Science	56, pp. 707-755	Industrial scope of agglomeration economies in Brazil
12	Baum-Snow et al. (2015)	European Regional Science Association	ersa15p1177	Transport infrastructure, urban growth and market access in China
13	Békés & Harasztosi (2013)	Regional Science and Urban Economics	43 (1), pp. 51-64	Agglomeration premium and trading activity of firms
14	Börjesson et al. (2019)	Economics of Transportation	18, pp. 27-39	Agglomeration, productivity and the role of transport system improvements
15	Bosker et al. (2012)	Journal of Urban Economics	72 (2-3), pp. 252-266	Relaxing Hukou - Increased labor mobility and China's economic geography
16	Bosker, Park & Roberts (2018)	World Bank Policy Research Paper	No. 8641	Definition matters - metropolitan areas and agglomeration economies in a la developing country
17	Chauvin et al. (2016)	Journal of Urban Economics	98, pp. 17-49	What is different about urbanization in rich and poor countries? Cities in Bra China, India and US

18	Chun, Shougui & Sheng (2019)	Regional Science and Urban Economics	77, pp. 141-154	Agglomeration economies in creative industries
19	Ciccone & Hall (1996)	The American Economic Review	86 (1), pp. 141-154.	Productivity and the density of economic activity
20	Cingano & Shivardi (2004)	Journal of the European Economic Association	2(4), pp. 720-744.	Identifying the sources of local productivity growth
21	Combes et al. (2020)	Journal of Development Economics	142	Unequal migration and urbanisation gains in China
22	Combes et al. (2010)	National Bureau of Economic Research Chapter	In Agglomeration Economics, pp. 15-66	Estimating agglomeration economies with history, geology, and worker effec
23	Combes, Démurger & Li (2013)	CEPR Discussion Paper	No. 9352	Urbanisation and Migration Externalities in China
24	Combes, Démurger & Li (2017)	Universite de Lyon Working Paper	Working Papers 1709	Productivity gains from agglomeration and migration in Chinese cities over 2 2013
25	Combes, Duranton & Gobillon (2008)	Journal of Urban Economics	63 (2), pp. 723-742	Spatial wage disparities - sorting matters
26	Combes, Duranton & Roux (2012)	Econometrica	80, pp. 2543-2594	The productivity advantages of large city: distinguishing agglomeration from selection
27	Davis & Weinstein (2001)	NBER Working paper	No. 8518	Market size, linkages, and productivity - a study of Japanese regions.
28	Dekle & Eaton (1999)	Journal of Urban Economics	46 (2), pp. 200-214	Agglomeration and land rents - evidence from the prefectures
29	Duranton (2016)	Journal of Regional Science	56 (2), pp. 210-38	Agglomeration effects in Colombia
30	Eckert, Hejlesen & Walsh (2018)	Opportunity and Inclusive Growth Institute Working Paper	No. 24	The return to big city experience - evidence from danish refugees
31	Faberman & Freedman (2016)	Journal of Urban Economics	93, pp. 71-84	The urban density premium across establishments
32	Fingleton (2003)	Oxford Economic Papers	55 (4), pp. 716-739	Increasing returns - evidence from local wage rates in Great Britain
33	Fingleton (2006)	Oxford Economic Papers	58 (3), pp. 501-530	The new economic geography versus urban economics - an evaluation using wage rates in Great Britain
34	Fu (2007)	Journal of Urban Economics	61 (1), pp. 86-111	Smart café city- testing human capital externalities in the Boston metropolit area
35	Glaeser & Xiong (2017)	Oxford Review of Economic Policy	33 (3), pp. 373-404	Urban productivity in the developing world
36	Graham (2000)	International Review of Applied Economics	14 (3), pp. 323-341	Spatial variation in labor productivity in British manufacturing

37	Graham (2006)	Transportation Research Board 85th Annual Meeting	06-0531	Transport investment, agglomeration and urban productivity
38	Graham (2007)	Journal of Transport Economics And Policy	41 (3), pp. 317-343	Agglomeration, productivity and transport investment
39	Graham (2009)	Papers in Regional Science	88 (1), pp. 63-84	Identifying urbanization and localization externalities in manufacturing and s industries
40	Graham, Gibbons & Martin (2010)	LSE Working Paper	October 2010	The spatial decay of agglomeration economies - estimates for use in transpo appraisal
41	Groot & de Groot (2020)	De Economist	168 (1), pp. 53-78	Estimating the skill bias in agglomeration externalities and social returns to education - evidence from Dutch matched worker-firm micro-data
42	Groot et al. (2014)	Journal of regional science	54 (3), pp. 503-523	Regional wage differences in the Netherlands - micro evidence on agglomera externalities
43	Guevara, Riou, Autant-Bernard (2018)	University of Lyon Working Paper	No. 1818	Agglomeration externalities in Ecuador - do urbanisation and tertiarisation matter?
44	Hasan, Jiang, & Rafols (2017)	Asian Development Review	34 (2), pp. 201-228	Urban agglomeration effects in India: evidence from town-level data
45	Henderson (1986)	Journal of Urban Economics	19 (1), pp. 47-70	Efficiency of resource usage and city size
46	Henderson (2003)	Journal of Urban Economics	53 (1), pp. 1-28	Marshall's scale economies
47	Holl (2016)	Journal of Urban Economics	93, pp. 131-151	Highways and productivity in manufacturing firms
48	Kanemoto et al. (1996)	Journal of the Japanese and International Economies	10 (4), pp. 379-398	Agglomeration economies and a test for optimal city sizes in Japan
49	Kondo (2016)	REITI Discussion Paper	No. 16098	Testing for agglomeration economies and firm selection in spatial productivi differences: the case of Japan
50	Lall, Shalizi & Deichmann (2004)	Journal of Development Economics	73 (2), pp. 643-673	Agglomeration economies and productivity in Indian industry
51	Larsson (2014)	The Annals of Regional Science	52, pp. 367-384	The neighborhood or the region? reassessing the density-wage relationship geocoded data
52	Le Nechet, Melo & Graha (2012)	Transportation Research Record	2307 (1), pp. 21-30	Transportation-induced agglomeration effects and productivity of firms in megacity region of Paris basin
53	Maré & Graham (2013)	Journal of Urban Economics	75, pp. 44-56	Agglomeration elasticity and firm heterogeneity
54	Martin, Mayer & Mayneris (2011)	Journal of Urban Economics	69 (2), pp. 182-195	Spatial concentration and plant-level productivity in France

55	Mion & Naticchioni (2005)	CEPR Discussion Papers	No. 5172	Urbanization externalities, market potential and spatial sorting of skills and f
56	Monkkonen et al., (2020)	Urban studies	57 (10), pp. 2080-2097	Compact city and economic productivity in Mexico
57	Moomaw (1981)	The Quarterly Journal of Economics	96 (4), pp. 675-688	Productivity and city size - a critique of the evidence
58	Moomaw (1983)	Regional Science and Urban Economics	13, pp. 525 – 545	Is population scale a worthless surrogate for business agglomeration econon
59	Moomaw (1985)	Journal of Urban Economics	17 (1), pp. 73-89	Firm location and city size - reduced productivity advantages as a factor in th decline of manufacturing in urban areas
60	Morikawa (2011)	The Review of Economics and Statistics	93 (1), pp. 179-192	Economies of density and productivity in service industries - an analysis of personal service industries based on establishment-level data
61	Nakamura (1985)	Journal of Urban Economics	17 (1), pp. 108-124	Agglomeration economies in urban manufacturing industries - a case of Japa cities
62	Özgüzel (2018)	Economic Research Forum Working Papers	No. 1341	Agglomeration effects in a developing economy - evidence from Turkey
63	Quintero & Roberts (2018)	World Bank Policy Research Paper	No. 8560	Evidence from 16 Latin American and Caribbean countries
64	Rice, Venables & Patacchini (2006)	Regional Science and Urban Economics	36 (6), pp. 727-752	Spatial determinants of productivity - analysis for the regions of Great Britai
65	Ricker-Gilbert, Jumbe & Chamberlin (2014)	Food Policy	48, pp. 114-128	How does population density influence agricultural intensification and productivity? evidence from Malawi
66	Rosenthal & Strange (2008)	Journal of Urban Economics	64 (2), pp. 373-389	The attenuation of human capital spillovers
67	Saito & Gopinath (2009)	Journal of Economic Geography	9 (4), pp. 539-558	Plants self-selection, agglomeration economies and regional productivity in
68	Sveikaukas, Gowdy & Funk (1988)	Economics of Transportation,	28 (2), pp. 185-202	Urban productivity- city size or industry size

69	Sveikauskas (1975)	The Quarterly Journal of Economics	89 (3), pp. 393-413	The productivity of cities
70	Wheeler (2001)	Journal of Labor Economics	19 (4), pp. 879 - 899	Search, sorting, and urban agglomeration