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**Working Paper**

## Unravelling urban advantages - A meta-analysis of agglomeration economies

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# Unravelling urban advantages - A meta-analysis of agglomeration economies

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# Unravelling urban advantages—A meta-analysis of agglomeration economies

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## Abstract

A large body of literature considers the productive advantages of cities, or “agglomeration economies”. Most empirical studies report positive agglomeration economies, although large variation exists in the magnitude of estimates. We use a meta-analysis to explore this variation, drawing on 6,684 estimates from 295 studies that cover 54 countries and span six decades. Using rich data and robust methods, we unify and extend earlier reviews. For our preferred combination of study attributes, we find agglomeration elasticities are likely to lie in the range 2.7–6.4%. Our findings confirm the controls enabled by detailed data give rise to smaller estimates. We also document several trends, with overall estimates rising from 1980–2000 and then falling. Estimates for manufacturing sectors, in contrast, fell for the entire six decades covered by our data. We speculate on possible causes of these trends, such as urban congestion, technological shocks, freight costs, and regulatory settings.

**Keywords:** agglomeration, meta-analysis, urbanisation, cities, productivity

**JEL-classification:** C11, R11, R12.

# 1. Introduction

The productive advantages of cities have long fascinated economists. Writing over one century ago, Alfred Marshall argued that proximity benefitted firms by enhancing the transmission and adoption of ideas, famously writing “The mysteries of the trade become no mysteries; but are as it were in the air . . .” (Marshall, 1890, p. 198). Today, a large body of literature considers the productive advantages of cities, or “agglomeration economies”. Whereas most empirical studies report positive effects—that is, agglomeration enhances productivity—large variation exists in the magnitude of estimates. In their review of the literature, for example, Rosenthal and Strange (2004) observe “. . . doubling city size seems to increase productivity by an amount that ranges from roughly 3–8%” (p. 2133). Notably, the bounds of this range vary by more than a factor of two.

In this study, we use a meta-analysis to explore variation in estimates of agglomeration economies.<sup>1</sup> Meta-analysis involves both the systematic review and the quantitative synthesis of a body of empirical literature (Stanley, 2001; Havránek et al., 2020). We build on the earlier review by Rosenthal and Strange (2004) as well as several recent meta-analyses. Perhaps the closest study to ours is Melo et al. (2009), who analyse approximately 700 estimates of agglomeration economies drawn from 34 studies—finding meaningful effects for several contextual and methodological attributes. Similar attributes are highlighted in the meta-analysis by de Groot et al. (2009), which explains the direction and significance of estimates. Recently, Ahlfeldt and Pietrostefani (2019) present a meta-analysis of agglomeration economies arising from urban density.

To unify and extend earlier reviews, we combine rich data with robust methods. In doing so, we stand gratefully on the shoulders of a percussion of giants: Our benchmark data consists of 6,684 estimates drawn from 295 studies that cover 54 countries and span six decades.<sup>2</sup> With almost ten-times more observations than Melo et al. (2009), we can examine a wider range of contextual and methodological attributes. To this rich data, we apply robust methods that have themselves been the focus of research (see, e.g., Gelman, Carlin et al., 2013). Specifically, we use Bayesian mixed effects models to address three technical problems that are common to meta-analyses. First, in order to model sources of unobserved heterogeneity but guard against over-fitting, we estimate models with group-

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<sup>1</sup> To improve the comparability of our data and keep our task manageable, we adopt several inclusion criteria. These criteria are discussed in more detail in Section 2.1.

<sup>2</sup> We apologise in advance to the authors of studies that we have unintentionally overlooked and welcome further correspondence on studies that may be suitable for inclusion.

level (“random”) effects for individual studies and countries. Second, as our dependent variable—that is, estimates of agglomeration economies—is measured with uncertainty, we estimate models that allow for “errors-in-outcomes”. Third, to manage the influence of extreme values in our data, we relax the conventional assumption that our dependent variable is normally distributed and instead allow it to follow a Student’s *t*-distribution. By addressing these technical problems within a coherent quantitative framework, Bayesian mixed effects models provide a robust platform for our meta-analysis.

Turning to the results, we identify a range of attributes that exert a systematic influence on estimates of agglomeration economies. In terms of contextual attributes, we find smaller estimates for manufacturing sectors (−0.6%) and published studies (−2.1%). As for methodological attributes, the list is long: We find effects for dependent variables that measure labour productivity (−1.1%); monetary indicators (1.7%); density (0.3%), isochrone (−0.8%), and potential (−0.7%) measures; secondary measures of agglomeration (−1.0%); and the use of instrumental variables (−0.3%). We also identify effects for various controls, such as sectoral composition (−0.2%), own skills (−0.9%), capital intensity (−2.4%), and individual worker effects (−1.1%). Controls associated with the urban environment, such as levels of human (−0.5%) and social (−0.8%) capital; housing (−3.8%) and wage (−1.2%) effects; and input links (−2.1%), innovation (−1.2%), and competition (−3.1%), also exert an effect. Somewhat uniquely, we quantify effects for the spatial scope of agglomeration: Compared to the local level, we find smaller estimates when agglomeration has a metropolitan (−1.9%) or regional (−0.8%) scope vis-à-vis a national (1.2%) or international scope (6.5%). These results withstand several sensitivity tests, including for publication bias. For our preferred combination of contextual and methodological attributes, we find elasticities lie in the range 2.7–6.4% with 90% probability. These results are broadly comparable to those of earlier reviews and confirm the controls enabled by detailed data give rise to smaller estimates.

At the same time, we extend the literature in four areas. First, in addition to confirming many of the results of earlier reviews, we unite them within a single statistical model. Second, although our results are similar to earlier reviews in aggregate, we note several points of difference. Unlike Ahlfeldt and Pietrostefani (2019), for example, we observe no clear link between the magnitude of estimates and the income-levels of countries. Third, this meta-analysis is—as far as we know—the first to estimate precise effects for several attributes listed above, such as spatial scope. Fourth, and perhaps most intriguingly, we detect trends in agglomeration economies, with estimates rising from 1980–2000 and then falling. At the sectoral level, estimates for manufacturing sectors fell for the entire

six decades covered by our data while those for non-manufacturing activities rose from 1980–2000 before starting to fall. We speculate on the possible causes of these trends, such as congestion costs arising from sustained urban growth, the localised effects of information and communications technologies (ICT)<sup>3</sup>, declining freight costs (Glaeser and Kohlhase, 2003), and stricter environmental regulations (Greenstone et al., 2012; Walker, 2011). Regardless of their cause, these trends imply agglomeration economies in production—or, more precisely, the underlying causal mechanisms they capture—are not static and instead are a function of the prevailing socioeconomic milieu. Whereas earlier studies have advanced similar arguments, this study is—as far we are aware—the first meta-analysis to present statistical evidence of these trends.

The findings of this study have several implications for further research. First, notwithstanding our efforts, large amounts of heterogeneity in estimates of agglomeration economies remains unexplained. Our meta-analysis models, for example, explain only around one-quarter of the variation that exists in the data. To arrive at a more cogent body of empirical literature, we recommend primary researchers consider methods to manage problems—such as extreme values and over-fitting—that may give rise to excessive heterogeneity. Second, we see value in primary research that traces the evolution of agglomeration economies over time, holding constant other contextual and methodological attributes. Perhaps the best example of primary research in this spirit is Martínez-Galarraga et al. (2008), which presents estimates for Spain extending back to the 1860s. And, finally, to develop a fuller understanding of the relative advantages of cities, we advocate for more primary empirical research into agglomeration economies in consumption. Indeed, if their productive advantages have fallen in recent decades, as our results seem to suggest, then future urban growth may depend more on the consumer advantages of cities, as argued by the likes of Glaeser, Kolko et al. (2001), among others. Our results add weight to such arguments.

The following sections of this paper are structured as follows: Section 2 summarises our methodology; Section 3 explores the data; Section 4 presents regression results; Section 5 discusses our findings; and Section 6 concludes.

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<sup>3</sup> Although a “general purpose technology”, Dijkstra et al. (2013) notes ICT was initially concentrated in larger cities before becoming more widely distributed. Section 5 returns to this question.

## 2. Methodology

### 2.1. Systematic Review

Our systematic review sought to identify suitable estimates in published articles and books as well as “grey literature”, such as working papers, theses, dissertations, and conference papers. The review proceeded in four steps, of which the first was to search Google Scholar for the following terms:<sup>4</sup>

- All combinations of “agglomeration” or “urbanisation” (and its American English counterpart, “urbanization”) paired with “economies” or “elasticities”;
- All combinations of “accessibility”, “urban density”, “market potential” or “market access” paired with “productivity” or “wages”; and
- “spatial wage” and “urban wage premium”.

For these search terms, we downloaded information on 9,240 records. We excluded records associated with citations (444) and duplicates (1,040).

In the second step we manually screened the remaining 7,756 records to identify suitable estimates. We excluded 5,383 records that are unrelated to our study, for example they consider other topics or are descriptive in nature. A further 131 records are excluded for being superseded by another record that we prefer. We have a preference, for example, for published articles over earlier working papers.<sup>5</sup> To ensure the comparability of estimates, we applied several inclusion criteria. Like other meta-analyses, we focus on so-called “constant elasticities”.<sup>6</sup> Specifically, we included constant elasticity estimates derived from models in which the dependent variable measures either multi-factor productivity, economic output, labour productivity, wages, or commercial property rents.<sup>7</sup> We excluded

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<sup>4</sup> The search was undertaken on 9 August 2020; detailed results are available from the authors on request.

<sup>5</sup> We prefer working papers only where they contain more estimates than the published version.

<sup>6</sup> As their magnitude is independent of levels of production and agglomeration, constant elasticities provide a convenient, standardised dependent variable for meta-analysis. This inclusion criterion is satisfied when both the dependent variable and the agglomeration measure are expressed in natural logarithms. Where possible, we converted non-constant elasticities to point elasticities at the mean of the sample.

<sup>7</sup> To improve the consistency of our data and align with Melo et al. (2009) and Ahlfeldt and Pietrostefani (2019), we exclude estimates where the dependent variable measures employment, innovation, location, foreign direct investment (FDI), or residential land values (NB: The latter is likely to capture agglomeration



1,390 records on this criterion. For agglomeration, we included only those records that contain estimates based on population measures, such as the number of residents or jobs, or monetary measures, such as wages or output. This leads to the exclusion of 272 records. We also limited ourselves to records containing estimates for the economy or manufacturing and service sectors contained therein, which excluded 95 records associated with primary sectors, such as agriculture, forestry, and mining. Third, we limited ourselves to estimates published from 1960 onwards, which excludes 52 records. Beyond these criteria, we also excluded 89 records that are not in English<sup>8</sup>, 29 records that are not available via databases we could access; 28 records with reporting issues, such as insufficient information; and 8 records due to various technical issues. After screening, we have 279 records containing estimates that meet the inclusion criteria.

In the third step of the systematic review, we added 8 records identified via informal sources, such as from our own records, bringing us to 287 records. Then, in the fourth and final step, we reviewed all sources cited in these 287 records to identify other suitable records—a process often referred to as “snowballing”. Where the process of snowballing led us to identify new records, then we snowballed again. That is, we snowballed indefinitely until we have screened all sources cited in all suitable records. In this way, we identified another 48 records, leaving us with a total of 335 suitable records. Figure 1 summarises the flow of records through the four steps in the systematic review.

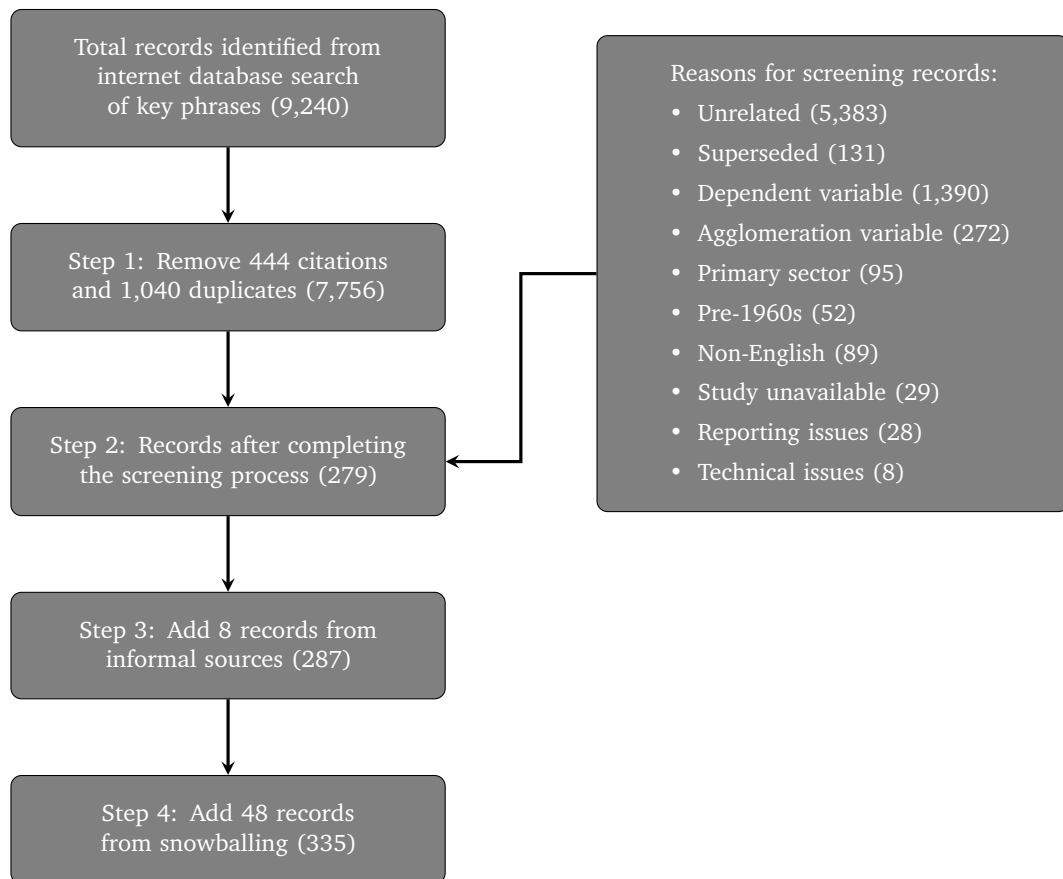
From these 335 studies, we extract 10,431 estimates of agglomeration elasticities and their associated attributes.<sup>9</sup> We use our judgement to identify attributes most likely to explain systematic variation in estimates, drawing on our reading of the literature—especially earlier reviews like Rosenthal and Strange (2004) and Melo et al. (2009). Table 1 summarises the main contextual and methodological attributes that form the basis for our subsequent meta-analysis. In most cases, attributes have only two levels, where “No” defines the base category, that is, the absence of the attribute. Appendix A provides further details on our approach to coding attributes, highlighting differences and commonalities in the literature as well as several interesting edge cases.

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economies in consumption). See Jones (2017) for a meta-analysis of agglomeration economies in FDI.

<sup>8</sup> Usually, these records are unpublished research, such as theses or dissertations.

<sup>9</sup> We extract all estimates from all studies, with two exceptions. Specifically, we exclude several estimates from Turgut (2014), which the author describes as “implausible” due to their “huge fluctuations”. We also exclude estimates contained in Table 6 of Lin and Truong (2012), which tests parameter values for the decay of agglomeration economies that are, in our view, often implausible.



**Figure 1:** Flow of records through the four steps in our systematic review (adapted from Moher et al., 2009)

**Table 1:** Main contextual and methodological attributes of our data

<b>Attribute</b>	<b>Description</b>
Estimate	The magnitude of the estimate
Standard error	The standard error of the estimate
Study	A unique identifier per study
Country	A unique identifier per country or group of countries
Sector	“Economy” (base), “Services”, and “Manufacturing”
Published	“Yes”, for journal or book versus “No” otherwise (base)
Micro-data	“Yes”, for micro-data versus “No” for aggregate data (base)
Panel data	“Yes” for panel data versus “No” for cross-sectional data (base)
Dependent variable	“Multi-factor productivity” (base), “Economic output”, “Labour productivity”, “Wages”, and “Commercial property rents”
Agglomeration indicator	“Pop.” (base), e.g. people or jobs, versus “Monetary”, e.g. wages or output
Agglomeration measure	“Size” (base), “Density”, “Isochrone”, and “Potential”
Secondary measure	“Yes”, where the model includes a secondary measure of agglomeration
Secondary magnitude	The magnitude of the secondary measure, if included (continuous)
Worker effects	“Yes”, where the model controls for individual workers
Firm effects	“Yes”, where the model controls for individual firms or plants
Sectoral controls	“Yes”, where the model controls for sector, e.g. fixed effects or shares
Occupational controls	“Yes”, where the model controls for occupation, e.g. fixed effects or shares
Time controls	“Yes”, where the model controls for time, e.g. fixed effects or trends
Geographic controls	“Yes”, where the model controls for geography, e.g. spatial units
Own skills	“Yes”, where the model controls for skills, e.g. of workers, firms, or sectors
Labour (L)	“Yes”, where the model controls for labour inputs into production
Capital (K)	“Yes”, where the model controls for capital inputs into production
K/L ratio	“Yes”, where the model controls for capital intensity
Human capital	“Yes”, where the model controls for levels of human capital in an area
Social capital	“Yes”, where the model controls for levels of social capital in an area
Housing	“Yes”, where the model controls for the supply or price of housing
Spatial scope	The spatial scope of agglomeration: Local (pop. < 0.2m), Metro (0.2m < pop. < 1.0m), Regional (1.0m < pop.), National, and International
Wage	“Yes”, where the model controls for wage levels, e.g. in firm, sector, or area
Localisation	“Yes”, where the model controls for intra-industry agglomeration (that is, “Marshallian” externalities)
Input links	“Yes”, where the model controls for input links, such as access to suppliers
Innovation	“Yes”, where the model controls for levels of innovation, such as patents
Diversity	“Yes”, where the model controls for economic diversity, e.g. industrial composition (that is, “Jacobs” externalities).
Competition	“Yes”, where the model controls for levels of competition, e.g. distribution of revenues across firms (that is, “Porter” externalities).
Instrumental variables (IV)	“Yes”, where the model controls for endogeneity of the agglomeration measure

## 2.2. Quantitative Methods

Our choice of quantitative methods addresses three technical problems common to meta-analyses. To help frame the discussion, consider the following simple model:

$$y_i = \mu + X_i\beta + \epsilon_i, \quad (1)$$

where  $y_i$  denotes estimate  $i$ ,  $\mu$  denotes the overall mean for the base category;  $X_i$  and  $\beta$  denotes vectors of attributes and parameters, respectively; and  $\epsilon_i$  denotes an error term with variance  $\sigma^2$ . The primary goal of our meta-analysis is to identify  $\mu$  and  $\beta$ . The first technical problem we consider is unobserved heterogeneity. Notwithstanding our best efforts, the vector of attributes  $X_i$  is unlikely to capture all sources of heterogeneity that induce systematic variation in  $y_i$ .<sup>10</sup> As a result, the estimates of  $\mu$  and  $\beta$  derived from Eq. (1) may be biased. For this reason, meta-analyses often control for groups in the data. Melo et al. (2009), for example, include random and fixed effects for individual studies and countries, respectively. In this spirit, we extend Eq. (1) to control for individual studies and countries—denoted by  $\zeta_s$  and  $\zeta_c$ , respectively—as per Eq. (2):

$$y_i = \mu + X_i\beta + \zeta_s + \zeta_c + \epsilon_i. \quad (2)$$

As our data contains relatively few—often singular—observations for individual studies and countries, treating  $\zeta_s$  and  $\zeta_c$  as fixed effects runs the risk of over-fitting. To mitigate this risk, we follow recent scholarship on mixed effects models, which combine fixed (or “population-level”) effects, like  $\mu$  and  $\beta$ , with random (or “group-level”) effects, like  $\zeta_s$  and  $\zeta_c$  (see, e.g., Gelman and Hill, 2007; Harrison et al., 2018). Let us re-write Eq. (2) as a mixed effects model in distributional notation:

$$\begin{aligned} y_i &\sim \mathcal{N}(\mu + X_i\beta + \zeta_s + \zeta_c, \sigma^2) \\ \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\ \zeta_c &\sim \mathcal{N}(0, \sigma_c^2), \end{aligned} \quad (3)$$

where we assume  $\zeta_s$  and  $\zeta_c$  follow Gaussian distributions with zero means and variances denoted by  $\sigma_s^2$  and  $\sigma_c^2$ , respectively.<sup>11</sup> By assuming group-level effects are drawn from

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<sup>10</sup> Heterogeneity may, for example, reflect unobserved differences in the experimental context.

<sup>11</sup> This assumption is common to the empirical literature on mixed effects models. Bell et al. (2019) conclude it introduces only “modest biases” for linear models with continuous dependent variables, like ours.

common distributions, Eq. (3) allows information to be shared, or pooled, between groups. Where an individual group contains little information, the individual group effect will “shrink” towards the mean of the sample, and vice versa.<sup>12</sup> In this way, the mixed effects model in Eq. (3) balances the information contained in individual groups with that contained in the wider sample, modelling sources of heterogeneity but guarding against over-fitting (Gelman and Hill, 2007).<sup>13</sup> To estimate Eq. (3), we can use restricted maximum likelihood or Bayesian methods.<sup>14</sup> One advantage of the latter is that it directly estimates the group-level variances, or “hyper-parameters”,  $\sigma_s^2$  and  $\sigma_c^2$ .

Bayesian methods also help to address a second technical problem that is common to meta-analyses: Estimates,  $y_i$ , are random variables measured with error. To address this problem, non-Bayesian meta-analyses will often use weighted least squares, where weights are inversely proportional to the observation’s variance,  $s_i^2$  (see, e.g., Borenstein et al., 2010). In contrast, when using Bayesian methods one can instead explicitly model the variation in  $y_i$  (“errors-in-outcomes”). To proceed, we assume estimates,  $y_i$ , follow a Gaussian distribution with true mean,  $y_i^t$ , and variance,  $s_i^2$ , as per Eq. (4):

$$\begin{aligned}
 y_i &\sim \mathcal{N}(y_i^t, s_i^2) \\
 y_i^t &\sim \mathcal{N}(\mu + X_i\beta + \zeta_s + \zeta_c, \sigma^2) \\
 \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\
 \zeta_c &\sim \mathcal{N}(0, \sigma_c^2).
 \end{aligned}
 \tag{4}$$

The structure of Eq. (4) highlights why such models are sometimes referred to as “Bayesian multi-level models”: We model errors-in-outcomes on the top level below which lies the more conventional (mixed effects) linear regression model.

Extreme values present a third technical problem common to meta-analyses. In their meta-analysis guidelines, Havránek et al. (2020) recommend that researchers specify the methods they use to “. . . identify outliers, leverage, or influence points . . .”. Traditionally,

<sup>12</sup> As hyper-parameters for the study and country group-effects tend towards infinity—that is,  $\sigma_s^2 \rightarrow \infty$  and  $\sigma_c^2 \rightarrow \infty$ , respectively—the individual group-effects approach conventional “fixed effects” parameters.

<sup>13</sup> One problem with mixed effects models is known as “artificial shrinkage”. George et al. (2017) note “Contrary to the commonly held belief that shrinkage estimation can do no harm . . . shrinkage estimation with a model that is at odds with the data can be very detrimental.” Partly for this reason, several researchers have recommended the use of Bayesian models, which penalise parameters that depart from the specified priors unless supported by data (Gelman, Carlin et al., 2013; Higgins et al., 2009).

<sup>14</sup> Estimating Eq. (3) as a Bayesian model with Gaussian priors is analogous to maximum likelihood estimation (MLE) with Tikhonov regularization—also known as “ridge regression”. The latter extends the MLE loss function with an extra term that measures the difference between parameters and their priors.

researchers have used statistical measures, such as Cook’s distance, to identify and exclude extreme values (for a review, see Viechtbauer and Cheung, 2010). Using statistical measures of influence as a basis for excluding extreme values, however, raise two issues: First, researchers must make subjective, albeit informed, judgments on what constitutes excessive influence. Second, removing observations may reduce the information available for statistical inferences. Fortunately, Bayesian methods offer a way to manage extreme values that avoids both issues. Rather than assuming our response variable  $y_i^t$  follows a Gaussian distribution, we instead assume it follows a Student’s  $t$ -distribution. Under this assumption, the second level in Eq. (4) becomes  $y_i^t \sim t(\mu + X_i\beta + \zeta_s + \zeta_c, \nu)$ , where  $\nu$  denotes the degrees-of-freedom (DOF) parameter for the Student’s  $t$ -distribution.<sup>15</sup> By allowing more mass in the tails of the probability distribution, the Student’s  $t$ -distribution reduces the influence of extreme values. And as  $\nu \rightarrow \infty$ , the Student’s  $t$ -distribution approaches the Gaussian distribution, such that the former is a general case of the latter.

To summarise, we adopt quantitative methods that address three technical problems common to meta-analyses. First, to model heterogeneity but guard against over-fitting, we estimate mixed effects models that include study and country group-level effects. Second, to capture uncertainty in our dependent variable, we model errors-in-outcomes. Third and finally, to manage extreme values, we allow our response variable to follow a Student’s  $t$ -distribution. By addressing these three technical problems within a unified quantitative framework, Bayesian models provide a robust platform for our meta-analysis.

### 3. Exploratory Data Analysis

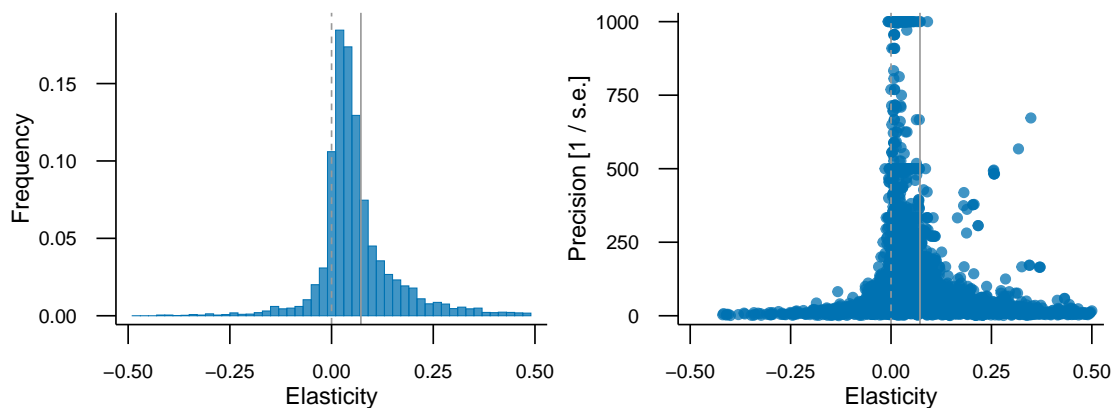
#### 3.1. Benchmark Sample

Our raw data comprises 10,431 observations drawn from 335 studies. To arrive at our benchmark sample, we apply three filters: First, to model errors-in-outcomes we include only those estimates for which standard errors,  $s_i$ , are reported or readily imputed. Applying this filter leaves us with 8,448 observations. Second, we include only those estimates where agglomeration includes the area to which the dependent variable pertains. Formally, this excludes observations where the dependent variable relates to area  $j$  but

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<sup>15</sup> When the DOF parameter  $\nu$  is unknown, Fernández and Steel (1999) show MLE is not guaranteed to find a global maximum and recommend Bayesian methods.

agglomeration relates to another area  $k$ , where  $j \notin k$ .<sup>16</sup> Applying this filter leaves us with 7,010 observations. Third, we include only those estimates that measure the total effect, excluding estimates from models that include spatially lagged values of the dependent variable. This leaves us with 6,684 observations from 295 studies and 54 countries.

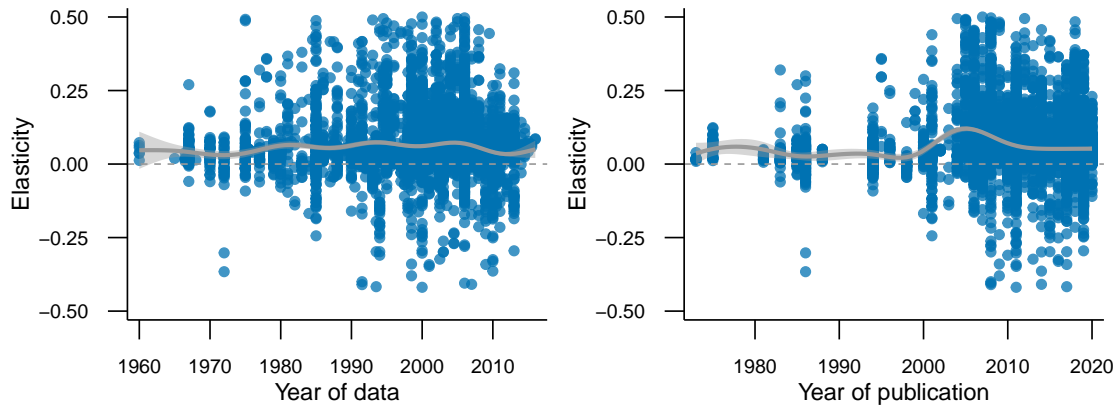


**Figure 2:** Histogram of estimates (left panel) and funnel graph (right panel), where the solid vertical line indicates the sample mean. In both panels the horizontal axes is restricted to  $[-0.50, 0.50]$ .

Figure 2 presents a histogram of estimates (left panel) and a “funnel graph” (right panel) for the benchmark sample. The left panel of Figure 2 reveals estimates are centered around small positive values with some apparent positive skew. This aligns with the summary statistics presented below in Table 2, which shows the mean (7.2%) of the benchmark sample is larger than the median (4.5%). Turning to the right panel of Figure 2, the funnel graph plots the magnitude of estimates on the horizontal axis versus their precision on the vertical axis—where the latter is defined as the inverse of the standard error,  $1/s_i$ . The funnel graph hints at the presence of asymmetry in the benchmark sample, specifically there are a larger number of relatively precise estimates on the right-hand side of the funnel. The asymmetry of the funnel graph provides informal evidence of publication bias, which Section 4.2.2 considers in more detail.

Figure 3 plots elasticities (vertical axis) versus time (horizontal axis), where we measure time in two ways: The year of data (left panel) and the year of publication (right panel). Where an estimate is based on panel data, we use the mid-point of the years spanned by the data. Both panels show the median and 95% credible intervals for a generalized additive model (“GAM”), which is a non-parametric trend line (for an introduction to GAMs, see Wood, 2017). In the left panel, we find slightly larger estimates circa 1980–

<sup>16</sup> Many researchers calculate market potential excluding the own area for which the dependent variable is measured (see, e.g., Combes et al., 2010). We exclude such observations from the benchmark sample.



**Figure 3:** Time trends by year of data (left panel) and year of publication (right panel).

2000. In the right panel, we find a spike in estimates circa 2005, which then dissipates. Inspection of the data suggests this spike is associated with estimates from so-called “New Economic Geography” (NEG) models. Later sections seek to provide insight into why these models are associated with larger estimates, for example, because they use aggregate data or have a larger spatial scope. The primary goal of our meta-analysis is to identify those attributes that induce systematic variation into estimates.

### 3.2. Summary Statistics

Table 2 presents summary statistics for the benchmark sample per attribute. The base level is listed first: “Economy” is the base level of the “Sector” attribute, for example. The sum of studies for an attribute can exceed the 295 studies in the sample, as studies often contain estimates that are coded to more than one level. Both the mean (7.2%) and median (4.5%) of the sample are within the 3–8% range in Rosenthal and Strange (2004). Differences within attributes also align with our reading of the literature. The mean estimate for service sectors (9.6%), for example, is larger than that for the aggregate economy (8.1%), which is, in turn, larger than that for manufacturing sectors (3.6%). Similarly, the mean estimate when worker effects are included is smaller than when they are not. Table 2 reveals estimates are heterogeneous, with a standard deviation (17.0%) that is several times the mean and a range of  $[-1.906, 2.080]$ . Inspection of the data reveals many of these extreme estimates are also imprecise (c.f. right panel, Figure 2). Together, this underscores the emphasis on extreme values and errors-in-outcomes in Section 2.2. Appendix B presents summary statistics per study.



**Table 2:** Summary statistics for the benchmark sample per attribute

Attribute	Level	Studies	Estimates	(%)	Mean	Median	SD	Min	Max
Sector	Economy	217	3,923	58.69	0.081	0.046	0.171	-1.197	1.652
	Manufacturing	92	1,702	25.46	0.036	0.028	0.169	-1.906	1.749
	Services	36	1,059	15.84	0.096	0.072	0.164	-1.630	2.080
Published	No	89	2,663	39.84	0.096	0.051	0.168	-1.906	1.749
	Yes	206	4,021	60.16	0.056	0.041	0.171	-1.630	2.080
Micro-data	No	154	2,830	42.34	0.089	0.053	0.199	-1.630	2.080
	Yes	152	3,854	57.66	0.060	0.040	0.146	-1.906	1.749
Panel data	No	163	3,697	55.31	0.083	0.050	0.142	-0.697	1.749
	Yes	160	2,987	44.69	0.058	0.038	0.201	-1.906	2.080
Dependent variable	Productivity	37	868	12.99	0.041	0.040	0.122	-1.906	0.750
	Lab. Prod.	90	1,681	25.15	0.069	0.043	0.201	-1.630	2.080
	Wages	171	3,650	54.61	0.079	0.045	0.168	-1.445	1.652
	Output	24	448	6.70	0.076	0.059	0.149	-0.697	0.935
	Rents	2	37	0.55	0.224	0.274	0.120	0.016	0.456
Agglomeration indicator	Population	236	5,695	85.20	0.050	0.040	0.125	-1.906	1.749
	Monetary	78	989	14.80	0.198	0.138	0.298	-1.630	2.080
Agglomeration measure	Size	114	1,849	27.66	0.030	0.033	0.133	-1.445	1.721
	Density	124	2,380	35.61	0.039	0.038	0.126	-1.906	2.080
	Isochrone	17	282	4.22	0.026	0.020	0.067	-0.588	0.268
	Potential	104	2,173	32.51	0.150	0.091	0.219	-1.197	1.749
Secondary measure	No	265	5,387	80.60	0.083	0.049	0.165	-1.906	1.749
	Yes	87	1,297	19.40	0.026	0.025	0.186	-1.630	2.080
Worker effects	No	287	6,170	92.31	0.076	0.048	0.170	-1.906	2.080
	Yes	32	514	7.69	0.023	0.019	0.180	-1.197	1.652
Firm effects	No	287	6,348	94.97	0.073	0.045	0.171	-1.630	2.080
	Yes	25	336	5.03	0.048	0.025	0.162	-1.906	0.772
Sectoral controls	No	207	3,302	49.40	0.080	0.046	0.208	-1.630	2.080
	Yes	143	3,382	50.60	0.064	0.043	0.124	-1.906	1.749
Occupational controls	No	265	4,976	74.45	0.074	0.046	0.182	-1.906	2.080
	Yes	55	1,708	25.55	0.065	0.040	0.132	-1.197	1.652
Temporal controls	No	199	4,115	61.56	0.087	0.050	0.161	-0.859	1.749
	Yes	130	2,569	38.44	0.048	0.036	0.183	-1.906	2.080
Geographic controls	No	185	3,581	53.58	0.087	0.051	0.160	-1.197	1.749
	Yes	196	3,103	46.42	0.055	0.038	0.182	-1.906	2.080

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Table 2 – continued from previous page

Attribute	Level	Studies	n	n(%)	Mean	Median	SD	Min	Max
Own skills	No	212	3,692	55.24	0.095	0.057	0.198	-1.630	2.080
	Yes	127	2,992	44.76	0.043	0.032	0.125	-1.906	1.652
Labour inputs	No	229	4,733	70.81	0.085	0.050	0.186	-1.630	2.080
	Yes	90	1,951	29.19	0.041	0.029	0.121	-1.906	1.351
Capital inputs	No	248	5,359	80.18	0.076	0.044	0.178	-1.630	2.080
	Yes	61	1,325	19.82	0.057	0.046	0.136	-1.906	0.935
K/L ratio	No	266	6,020	90.07	0.078	0.047	0.177	-1.906	2.080
	Yes	38	664	9.93	0.019	0.015	0.095	-0.796	0.495
Human capital	No	229	4,515	67.55	0.072	0.043	0.177	-1.906	2.080
	Yes	129	2,169	32.45	0.071	0.048	0.158	-1.445	1.721
Social capital	No	289	6,532	97.73	0.072	0.045	0.172	-1.906	2.080
	Yes	14	152	2.27	0.061	0.031	0.128	-0.102	0.911
Housing	No	286	6,526	97.64	0.069	0.044	0.168	-1.906	2.080
	Yes	18	158	2.36	0.188	0.058	0.234	-0.059	1.040
Spatial scope	Local	54	1,070	16.01	0.049	0.039	0.105	-0.647	1.721
	Metropolitan	138	2,788	41.71	0.032	0.030	0.086	-1.906	0.911
	Regional	66	1,499	22.43	0.062	0.068	0.179	-1.630	2.080
	National	60	1,064	15.92	0.182	0.094	0.279	-1.197	1.749
	International	27	263	3.93	0.202	0.154	0.197	-0.160	1.453
Wages	No	288	6,246	93.45	0.073	0.045	0.174	-1.906	2.080
	Yes	10	438	6.55	0.054	0.045	0.130	-0.366	1.721
Localisation	No	243	4,805	71.89	0.085	0.048	0.173	-1.445	1.749
	Yes	74	1,879	28.11	0.040	0.028	0.161	-1.906	2.080
Input links	No	286	6,527	97.65	0.074	0.045	0.172	-1.906	2.080
	Yes	12	157	2.35	0.003	0.011	0.096	-0.310	0.300
Diversity	No	271	6,133	91.76	0.077	0.046	0.175	-1.906	2.080
	Yes	43	551	8.24	0.022	0.024	0.099	-0.697	0.495
Innovation	No	290	6,609	98.88	0.072	0.044	0.172	-1.906	2.080
	Yes	12	75	1.12	0.071	0.069	0.086	-0.061	0.416
Competition	No	286	6,507	97.35	0.074	0.045	0.172	-1.906	2.080
	Yes	13	177	2.65	0.002	-0.003	0.108	-0.647	0.453
IV	No	268	4,940	73.91	0.077	0.047	0.150	-1.906	1.749
	Yes	151	1,744	26.09	0.059	0.040	0.220	-1.630	2.080
<i>Sample</i>	<i>Estimates</i>	295	6,684	100	0.072	0.045	0.171	-1.906	2.080

## 4. Regression Results

### 4.1. Benchmark Models

Drawing on the discussion of quantitative methods in Section 2.2, we now present five benchmark models. The purpose of each model is to build sequentially towards the most general Bayesian mixed effects model, that is, [Model \(5\)](#), to highlight individual methodological choices. To start, we estimate [Model \(1\)](#), which includes only the intercept,  $\mu$ , and the population-level effects,  $\beta$ :

$$y_i \sim \mathcal{N}(\mu + X_i\beta, \sigma^2). \quad (\text{Model (1)})$$

[Model \(2\)](#) includes the intercept,  $\mu$ , and group-level effects for individual studies,  $\zeta_s$ , and countries,  $\zeta_c$ :

$$\begin{aligned} y_i &\sim \mathcal{N}(\mu + \zeta_s + \zeta_c, \sigma^2) \\ \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\ \zeta_c &\sim \mathcal{N}(0, \sigma_c^2). \end{aligned} \quad (\text{Model (2)})$$

[Model \(3\)](#) includes the intercept,  $\mu$ , and both the population- and group-level effects:

$$\begin{aligned} y_i &\sim \mathcal{N}(\mu + X_i\beta + \zeta_s + \zeta_c, \sigma^2) \\ \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\ \zeta_c &\sim \mathcal{N}(0, \sigma_c^2). \end{aligned} \quad (\text{Model (3)})$$

[Model \(4\)](#) extends [Model \(3\)](#) to model errors-in-outcomes:

$$\begin{aligned} y_i &\sim \mathcal{N}(y_i^t, s_i^2) \\ y_i^t &\sim \mathcal{N}(\mu + X_i\beta + \zeta_s + \zeta_c, \sigma^2) \\ \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\ \zeta_c &\sim \mathcal{N}(0, \sigma_c^2). \end{aligned} \quad (\text{Model (4)})$$

And, finally, [Model \(5\)](#) assumes  $y_i^t$  follows a Student’s  $t$ -distribution,

$$\begin{aligned}
 y_i &\sim \mathcal{N}(y_i^t, s_i^2) \\
 y_i^t &\sim t(\mu + X_i\beta + \zeta_s + \zeta_c, \nu) \\
 \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\
 \zeta_c &\sim \mathcal{N}(0, \sigma_c^2).
 \end{aligned}
 \tag{Model (5)}$$

These five benchmark models are, in fact, simpler than they may appear at first glance. [Model \(1\)](#) is a linear regression of population-level effects and [Model \(2\)](#) is an intercept-only model with group-level (“random”) effects. [Model \(3\)](#) includes both population- and group-level effects. In principle, [Model \(1\)](#), [Model \(2\)](#), and [Model \(3\)](#) could be estimated using either MLE or Bayesian methods.<sup>17</sup> This is not the case, however, with [Model \(4\)](#) and [Model \(5\)](#), which extend [Model \(3\)](#) to explicitly model errors-in-outcomes and allow the response variable to follow a Student’s  $t$ -distribution, respectively. On this basis, the primary advantage of adopting Bayesian mixed effects models is their ability to estimate [Model \(4\)](#) and [Model \(5\)](#).

Table 3 presents results for all five models.<sup>18</sup> We prefer [Model \(5\)](#) for theoretical and empirical reasons. Theoretically, and as per Section 2.2, [Model \(5\)](#) is a general case of [Model \(4\)](#); the two models are equivalent when the DOF parameter in the former approaches infinity, that is,  $\nu \rightarrow \infty$ . Results in Table 3 indicate  $\nu = 1.760$ , which implies more mass exists in the tails of the probability distribution than is predicted by a Gaussian distribution. Empirically, [Model \(5\)](#) also performs well on two key metrics: First, [Model \(5\)](#) usually produces more precise parameters, both for the attributes listed in Table 3 as well as the individual study effects illustrated in Appendix C.1. Second, [Model \(5\)](#) has the best predictive performance, as measured by PSIS-LOO information criterion.<sup>19</sup> For these reasons, the subsequent discussion focuses on results for [Model \(5\)](#).

<sup>17</sup> In theory, Bayesian methods offer two advantages: First, the use of priors can help regularise results and, second, hyper-parameters,  $\sigma_s^2$  and  $\sigma_c^2$ , for group-level effects are estimated directly. In practice, we consider it unlikely these advantages give rise to meaningful differences vis-à-vis MLE.

<sup>18</sup> All models are estimated using the statistical package R in the RStudio environment with the `brms` package (R Core Team, 2020; RStudio Team, 2020; Bürkner, 2017; Bürkner, 2018). We assume weakly informative priors for population-level parameters, that is,  $\mu \sim \mathcal{N}(0, 1)$  and  $\beta \sim \mathcal{N}(0, 1)$ , and otherwise use defaults.

<sup>19</sup> PSIS-LOO measures the point-wise out-of-sample prediction accuracy of models by evaluating the log-likelihood at the posterior simulations of the parameter values. Vehtari et al. (2017) find PSIS-LOO is a robust measure of model performance in cases with weak priors and influential observations, both of which apply to our setting. [Model \(5\)](#) has the best predictive performance but a lower  $R^2$  value than both [Model \(3\)](#) and [Model \(4\)](#). When considered together, the PSIS-LOO and  $R^2$  values imply modelling errors-in-outcomes and a Student’s  $t$ -distribution leaves [Model \(5\)](#) less at risk of over-fitting.

**Table 3: Meta-analysis regression results—Benchmark models**

Attribute	Level	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept		0.105*** (0.014)	0.094*** (0.012)	0.146*** (0.025)	0.126*** (0.016)	0.112*** (0.012)
Sector	Manufacturing	-0.020*** (0.006)		-0.005 (0.011)	-0.005 (0.006)	-0.006** (0.002)
	Service	0.001 (0.007)		0.017* (0.010)	0.013*** (0.005)	-0.000 (0.002)
Published	Yes	-0.031*** (0.005)		-0.035** (0.016)	-0.015 (0.014)	-0.021* (0.013)
Micro-data	Yes	0.028*** (0.007)		-0.016 (0.014)	-0.010 (0.007)	-0.002 (0.002)
Panel data	Yes	0.006 (0.008)		0.056*** (0.013)	0.081*** (0.007)	0.000 (0.002)
Dep. variable	Lab. prod.	0.017 (0.010)		-0.018 (0.015)	-0.017** (0.007)	-0.011*** (0.003)
	Wages	-0.019* (0.011)		-0.014 (0.017)	-0.009 (0.008)	0.001 (0.003)
	Output	-0.005 (0.011)		-0.001 (0.023)	0.018 (0.015)	-0.000 (0.011)
	Rents	0.172*** (0.028)		0.123 (0.087)	0.125* (0.074)	0.107 (0.068)
Agg. indicator	Monetary	0.083*** (0.009)		0.060*** (0.016)	0.071*** (0.009)	0.017*** (0.004)
Agg. measure	Density	0.010* (0.005)		-0.006 (0.009)	-0.011*** (0.004)	0.003** (0.001)
	Isochrone	-0.011 (0.012)		-0.014 (0.020)	-0.022** (0.010)	-0.008*** (0.003)
	Potential	0.025** (0.010)		0.000 (0.016)	-0.017** (0.008)	-0.007*** (0.002)
Secondary measure	Yes	-0.035*** (0.005)		-0.019*** (0.007)	-0.009*** (0.003)	-0.007*** (0.001)
	Magnitude	-0.021* (0.011)		-0.046*** (0.010)	-0.062*** (0.007)	-0.040*** (0.003)
Worker effects	Yes	-0.023*** (0.008)		-0.012 (0.011)	-0.010** (0.005)	-0.011*** (0.001)
Firm effects	Yes	0.027*** (0.011)		-0.004 (0.015)	-0.010 (0.007)	-0.002 (0.003)
Sec. controls	Yes	-0.008 (0.005)		-0.017** (0.008)	-0.012*** (0.004)	-0.002* (0.001)
Occ. controls	Yes	0.014** (0.006)		0.008 (0.011)	0.014*** (0.005)	-0.000 (0.001)
Time controls	Yes	-0.039*** (0.008)		-0.064*** (0.014)	-0.070*** (0.007)	-0.001 (0.002)
Geo. controls	Yes	-0.008* (0.004)		0.003 (0.007)	-0.006** (0.003)	0.000 (0.001)
Own skills	Yes	-0.014** (0.007)		-0.004 (0.009)	-0.009** (0.004)	-0.009*** (0.001)

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Table 3 – continued from previous page

Attribute	Level	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Labour ( $L$ ) inputs	Yes	-0.009 (0.007)		0.015 (0.013)	0.020*** (0.006)	0.002 (0.002)
Capital ( $K$ ) inputs	Yes	-0.034*** (0.011)		-0.021 (0.015)	-0.026*** (0.007)	-0.001 (0.002)
$K/L$ ratio	Yes	-0.031*** (0.009)		-0.028* (0.015)	-0.026*** (0.008)	-0.024*** (0.005)
Human capital	Yes	-0.007 (0.005)		-0.022*** (0.008)	-0.015*** (0.004)	-0.005*** (0.001)
Social capital	Yes	0.009 (0.014)		-0.018 (0.018)	-0.017** (0.008)	-0.008*** (0.002)
Housing	Yes	0.027** (0.013)		-0.021 (0.020)	-0.044*** (0.011)	-0.038*** (0.004)
Spatial scope	Metro	-0.015** (0.006)		-0.031*** (0.011)	-0.022*** (0.005)	-0.019*** (0.002)
	Regional	-0.018** (0.008)		-0.037** (0.014)	-0.021*** (0.007)	-0.008** (0.003)
	National	0.061*** (0.011)		0.032 (0.020)	0.030*** (0.010)	0.012*** (0.004)
	International	0.057*** (0.014)		0.189*** (0.025)	0.064*** (0.013)	0.065*** (0.008)
Wages	Yes	-0.001 (0.009)		-0.024 (0.016)	-0.032*** (0.007)	-0.012*** (0.002)
Localisation	Yes	0.001 (0.005)		-0.024*** (0.008)	-0.024*** (0.004)	0.003 (0.002)
Input links	Yes	-0.036** (0.015)		-0.036 (0.035)	-0.007 (0.020)	-0.021** (0.008)
Innovation	Yes	0.019 (0.020)		-0.017 (0.030)	-0.015 (0.015)	-0.012** (0.006)
Diversity	Yes	0.009 (0.009)		0.012 (0.013)	0.003 (0.006)	0.002 (0.001)
Competition	Yes	-0.040** (0.015)		-0.013 (0.028)	-0.075*** (0.017)	-0.031** (0.012)
IV	Yes	-0.006 (0.005)		0.005 (0.005)	-0.002 (0.002)	-0.003*** (0.001)
Hyper-parameters	Overall ( $\sigma^2$ )	0.154*** (0.001)	0.134*** (0.001)	0.131*** (0.001)	0.051*** (0.001)	0.006*** (0.000)
	Studies ( $\sigma_s^2$ )		0.128*** (0.007)	0.111*** (0.006)	0.103*** (0.005)	0.092*** (0.005)
	Countries ( $\sigma_c^2$ )		0.044*** (0.016)	0.024*** (0.012)	0.033*** (0.008)	0.034*** (0.009)
	DOF ( $\nu$ )					1.760*** (0.049)
Errors-in-outcomes		No	No	No	Yes	Yes
Response variable		Normal	Normal	Normal	Normal	Student's $t$
Model performance	PSIS-LOO	-5, 943	-7, 596	-7, 885	-15, 451	-22, 652
	$R^2$	0.193	0.386	0.419	0.343	0.262

Notes: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ . All models use 6,684 observations, as per Section 3.1.

Turning now to our results in Table 3, the intercept (11.2%) relates to the base category, as per the definitions in Table 1. We also identify several attributes that affect estimates of agglomeration economies. In terms of contextual attributes, we find smaller estimates for manufacturing sectors (−0.6%) and published studies (−2.1%). For methodological attributes, the list is long: We find effects for dependent variables that measure labour productivity (−1.1%); monetary indicators (1.7%); density (0.3%), isochrone (−0.8%), and potential (−0.7%) measures; secondary measures of agglomeration (−1.0%)<sup>20</sup>; and the use of instrumental variables (−0.3%). We also identify effects for controls, such as sectoral composition (−0.2%), own skills (−0.9%), capital intensity (−2.4%), and individual worker effects (−1.1%). Several controls linked to the urban context, such as levels of human (−0.5%) and social (−0.8%) capital; housing (−3.8%) and wage (−1.2%) effects; and input links (−2.1%), innovation (−1.2%), and competition (−3.1%), also affect estimates. Finally, spatial scope also exerts systematic effects: Compared to the local level, we find smaller estimates when agglomeration has a metropolitan (−1.9%) or regional (−0.8%) scope vis-à-vis a national (1.2%) or international scope (6.5%).

## 4.2. Sensitivity Tests

### 4.2.1. Sample bias

Modelling errors-in-outcomes means that estimates where standard errors ( $s_i$ ) are not reported or readily imputed must be dropped from the benchmark sample. To understand the effects of excluding these observations, we consider a sensitivity test in which we predict values for  $s_i$ . We draw on Weir et al. (2018), which reviews methods for predicting standard errors, to formulate the following simple Bayesian mixed effects model:

$$\begin{aligned}
 s_i &\sim \text{Lognormal}(Z_i\delta + \zeta_s + \zeta_e, \sigma^2) \\
 \zeta_s &\sim \mathcal{N}(0, \sigma_s^2) \\
 \zeta_e &\sim \mathcal{N}(0, \sigma_e^2).
 \end{aligned}
 \tag{Model (6)}$$

<sup>20</sup> This is a composite effect. For example, for a secondary measure whose magnitude equals the mean (7.2%) of the benchmark sample, the effect is  $-0.007 - 0.04 \cdot 0.072 = -0.01$ .

Where we assume  $s_i$  is distributed log-normal;  $Z_i$  and  $\delta$  denote vectors of population-level attributes and parameters; and  $\zeta_s$  and  $\zeta_e$  denote group-level effects for studies and estimation methods. The vector  $Z_i$  includes an intercept; the absolute value of the estimate,  $|y_i|$ ; the square root of the number of observations (measured in thousands),  $\sqrt{n_i/1,000}$ ; attributes that may affect measurement error, such as the dependent variable; and the absolute value and standard error of the secondary elasticity,  $|y_{2(i)}|$  and  $s_{2(i)}$ . We estimate [Model \(6\)](#) using default priors; [Table 4](#) presents results. As expected, standard errors decline with the number of observations. We also find smaller standard errors for wages, monetary indicators, and density measures. In contrast, published estimates have larger standard errors, as do those where the dependent variable measures output.

**Table 4:** Regression results—Modelling standard errors

Attribute	Level	Model (6)
Intercept		−4.354 (0.168)***
Published	Yes	0.258 (0.126)**
	Lab. Prod.	−0.064 (0.057)
Dependent variable	Wages	−0.404 (0.072)***
	Output	0.592 (0.140)***
	Rent	0.231 (0.686)
Agglomeration indicator	Monetary	−0.145 (0.087)*
	Density	−0.192 (0.049)***
Agglomeration measure	Isochrone	0.141 (0.106)
	Potential	0.011 (0.078)
Observations ( $\sqrt{n_i}/1,000$ )		−0.007 (0.001)***
Estimate ( $ y_i $ )		2.319 (0.072)***
Secondary estimate ( $ y_{2(i)} $ )		0.342 (0.158)**
Secondary standard error ( $s_{2(i)}$ )		0.837 (0.241)***
Hyper-parameters	$\sigma^2$ (overall)	0.669 (0.006)***
	$\sigma_s^2$ (studies)	0.937 (0.045)***
	$\sigma_e^2$ (method)	0.454 (0.098)***
Model performance	$R^2$	0.562
Observations		6,462

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

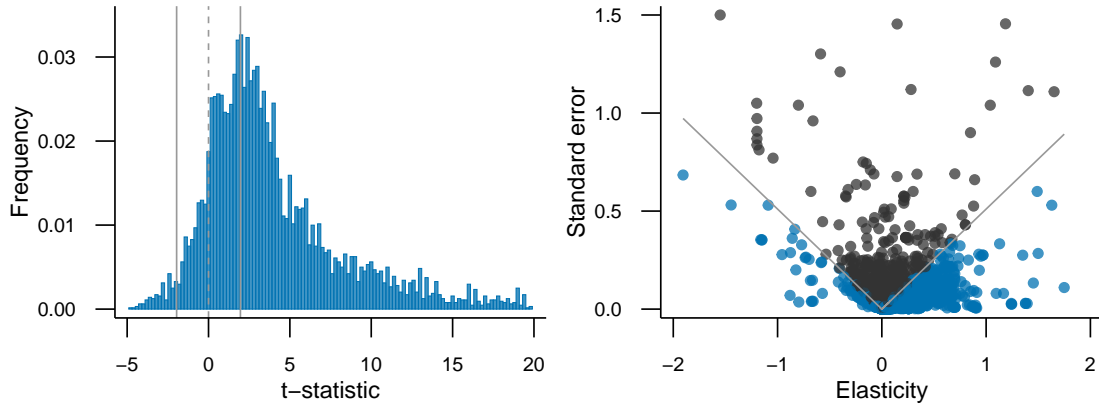
Using the results of [Model \(6\)](#), we predict missing values for  $s_i$ . Compared to the benchmark sample, this increases the number of observations by almost 14%. We then re-estimate [Model \(5\)](#) with the expanded sample, where we include a dummy for estimates with predicted  $s_i$ . Results are reported in [Table 5](#), c.f. Column 2. The dummy for estimates with predicted  $s_i$  is small (0.3%) and imprecise (standard error 0.2%). This suggests estimates that are dropped due to the absence of standard errors are of a similar magnitude to those in the benchmark sample, once other attributes are controlled for. The other parameters are largely unchanged except for localisation, which is now negative and precisely estimated. On this basis, we conclude dropping estimates without standard errors does not significantly affect our benchmark results.



#### 4.2.2. Publication bias

Publication bias arises when selection processes influence the empirical literature. These processes can influence researchers, who must decide which methods to use and which estimates to report; reviewers, who must advise on acceptance of and changes to papers; and editors, who must decide which studies to review and publish. A common example of how selection processes can bias the empirical literature is the difficulty involved in publishing so-called “null” results. Researchers have long grappled with questions of publication bias. Leamer (1983), for example, highlighted the vulnerability of empirical results to bias, which was later confirmed by De Long and Lang (1992). More recent research by Doucouliagos and Stanley (2013) finds the empirical economic literature suffers from widespread publication bias. The asymmetry of the funnel graph in the right panel of Figure 2—where we observe a larger number of relatively precise estimates on the right-hand side of the funnel—provides initial, albeit informal, evidence of publication bias. Our earlier regression results also hinted at the presence of publication bias, where we find evidence that estimates reported in published studies tend to be smaller (c.f. Table 3) and less precise (c.f. Table 4) than those in unpublished studies.

To assess whether publication bias affects our results, we begin by following the two-step method outlined in Stanley and Doucouliagos (2012). In the first step, we test for asymmetry in the funnel graph by including the standard error of the estimate,  $s_i$ , in Model (5). The result is clear: The parameter for  $s_i$  is positive and precise, confirming the direction of the bias suggested by the funnel graph. We then attempt to correct for this bias in the second step, where we re-estimate Model (5) but include the variance ( $s_i^2$ ) as an explanatory variable. Results for the latter are reported in Table 5, c.f. Column 3, where we find the parameter for  $s_i^2$  is positive (0.454) and precise (standard error 0.152) even if the other parameters are largely unchanged. Andrews and Kasy (2019) note the selection-corrected estimates produced by such methods, however, may nonetheless still be biased due to non-linearities in the relationship between estimates and their precision. Non-linearities in this relationship might arise, for example, where selection processes operate in response to thresholds of statistical significance. To gain insight into whether our data is likely to be affected by non-linearities arising from these types of selection processes, the left panel of Figure 4 illustrates the distribution of  $t$ -statistics ( $y_i/s_i$ ) for the benchmark sample. Inspection of Figure 4 reveals asymmetry in the distribution and some bunching in the vicinity of  $y_i/s_i = 1.96$ , which coincides with the 5% level of significance. On this basis, the data gives us cause for pause.



**Figure 4:** Left panel shows the frequency distribution of t-statistics ( $y_i/s_i$ ). Right panel shows a scatter plot with  $y_i$  and  $s_i$  on the horizontal and vertical axes, respectively. Both panels use the benchmark sample and solid lines indicate the critical values where  $y_i/s_i = \pm 1.96$ .

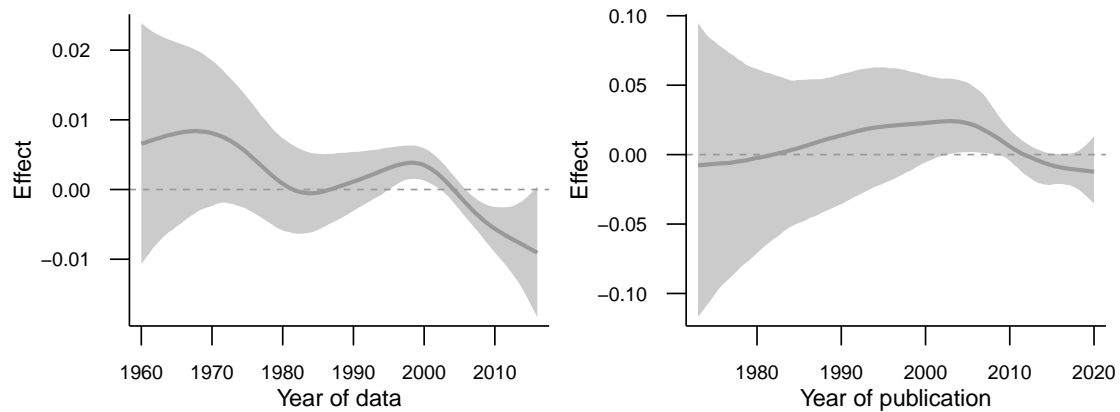
To explore these issues, we estimate the publication selection model developed by Andrews and Kasy (2019), assuming a symmetric publication probability with a significance threshold of 1.96.<sup>21</sup> Results confirm the presence of publication selection hinted at by the asymmetry of the distribution illustrated in the left panel of Figure 4. Indeed, results suggest non-significant estimates are only 19% as likely to be published as significant estimates. In light of evidence of potential non-linearities in publication bias, we adapt the second step of the process in Stanley and Doucouliagos (2012), such that  $s_i^2$  enters the model as the argument of a GAM.<sup>22</sup> This adaptation allows for a more flexible, non-linear relationship between estimates and their variance. Even when allowing for these non-linearities, however, the parameters in our model remain largely unchanged (c.f. Appendix D, Column 2). Ultimately, we find evidence the empirical literature on agglomeration economies is affected by publication bias, although correcting for this bias does not appear to affect our results. This may be because publication bias acts on multiple margins, giving rise to divergent and countervailing effects.

<sup>21</sup> We download code for the publication selection model developed in Andrews and Kasy (2019) from the latter’s personal website: <https://maxkasy.github.io/home/code-and-apps/>.

<sup>22</sup> Alternatively, one could incorporate the selection model developed by Andrews and Kasy (2019) into Model (5). We see two potential approaches. First, one could use a two-step process that estimates updated standard errors controlling for publication selection, which are then used to estimate Model (5). The validity of the statistical inferences resulting from this approach are unclear, however, due to potential dependencies between the relationships that are modelled in each step. The second approach is to incorporate the selection model as an additional level in Model (5), further exploiting its multi-level structure. This approach is theoretically preferred but likely to be computationally intensive—noting it took several days to estimate the selection model for our data, even when it was de-coupled from Model (5). Ultimately, we leave this as an area for further research. We are grateful to Isaiah Andrews and Maximilian Kasy for their comments on this question.

### 4.2.3. Time trends

Figure 3 presented trends in estimates with respect to the year of data and the year of publication. To test whether our benchmark results are sensitive to these trends, we extend Model (5) to include the same two GAMs. Compared to parametric approaches, like decade dummies, GAMs offer a more flexible way to model trends (see Wood, 2017, for further details). Results are reported in Table 5, c.f. Column 4. The hyper-parameters for both trends are positive and precise, which implies the trends do explain variation in our data. Other parameters are, however, largely unchanged.



**Figure 5:** Residual time trends by year of data (left panel) and year of publication (right panel). The shaded band indicates the 95% credible interval around the median effect.

Figure 5 plots the median effect and 95% credible intervals for both trends. Where the credible interval excludes zero, there is evidence of a non-zero trend. Considering the year of data trend in the left panel of Figure 5, there is a small positive effect around the end of the 1990s and the start of the 2000s, which subsequently turns negative from the mid-2000s onwards. By 2020, estimates are approximately 1.5% smaller than they were two decades prior. Turning to the year of publication trend in the right panel of Figure 5, there is no clear evidence of a non-zero trend. The wide credible interval for the year of publication trend in the right panel likely reflects the difficulty in identifying these effects separately from individual study effects,  $\zeta_s$ . Notwithstanding the fact that our findings are robust to residual time trends, we return to discuss the latter in more detail in Section 5.

#### 4.2.4. Sub-samples

Many estimates pertain to socioeconomic or demographic sub-samples, such as male vis-à-vis female workers and high vis-à-vis low skilled workers or firms. Distinguishing between sub-samples seems to have become more common in recent years, due to the increased availability of micro-data and the opportunities it offers for partitioning data based on individual characteristics (see, e.g., Håkansson and Isacsson, 2019; Groot and de Groot, 2020; Barufi et al., 2016). We record where estimates relate to common sub-samples, namely gender (male or female); income (high, medium, or low); education or skills (high, medium, or low); technology (high, medium, or low); migrant worker (yes or no); formal contract (yes or no); trading firm (yes or no); firm size (large, medium, or small) and age (old, medium, or young); and number of plants (multi or single). Each sub-sample is recorded as an attribute, where the base category is the entire sample and other levels are as described in parentheses. We then extend [Model \(5\)](#) to control for sub-samples, with the results presented in [Table 5](#), c.f. [Column 5](#). We find effects for several sub-samples, specifically high- and low-skilled workers or firms (0.8% and  $-1.1\%$ , respectively); non-migrant and migrant workers (5.9% and  $-0.6\%$ , respectively); formal contracts ( $-1.4\%$ ); old and young firms (1.8% and  $-3.8\%$ , respectively); and single plant firms (1.9%). As for model performance, including sub-samples leads to a small improvement in PSIS-LOO. Nevertheless, the parameters in [Column 5](#) are similar to those in [Model \(5\)](#), which suggests our results are robust to sub-samples.

#### 4.2.5. Priors

As a final check, we test the sensitivity of our results to assumptions for prior distributions. The previous results for [Model \(5\)](#) assume standard normal priors for the population-level effects—that is,  $\mu \sim \mathcal{N}(0, 1)$  and  $\beta \sim \mathcal{N}(0, 1)$ . In contrast, we test the effects of assuming uniform prior distributions with the range  $[-\infty, \infty]$ . Intuitively, using less informative priors like this will place greater weight on the data, with results closer to those for a conventional mixed effects regression estimated using (restricted) MLE. Results for [Model \(5\)](#) under these less informative priors are summarised in [Appendix D](#), [Column 4](#). This reveals little difference to those for [Model \(5\)](#) in [Table 3](#). Given the large number of observations in our data, we are not surprised to find the choice of prior distributions has negligible effects on the results.

**Table 5: Meta-analysis regression results—Sensitivity tests**

Attribute	Level	Model (5)	Column 2	Column 3	Column 4	Column 5
Intercept		0.112*** (0.012)	0.116*** (0.012)	0.112*** (0.012)	0.113*** (0.012)	0.112*** (0.012)
Sector	Manufacturing	-0.006** (0.002)	-0.006*** (0.002)	-0.006** (0.002)	-0.006*** (0.002)	-0.005*** (0.002)
	Service	-0.000 (0.002)	-0.002 (0.002)	-0.000 (0.002)	-0.000 (0.002)	0.000 (0.002)
Published	Yes	-0.021* (0.013)	-0.021* (0.011)	-0.022* (0.012)	-0.024** (0.013)	-0.022* (0.012)
Micro-data	Yes	-0.002 (0.002)	-0.004 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)
Panel data	Yes	0.000 (0.002)	0.002 (0.002)	0.000 (0.002)	-0.000 (0.002)	0.001 (0.002)
Dependent variable	Lab. Prod.	-0.011*** (0.003)	-0.014*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)
	Wages	0.001 (0.003)	-0.003 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.002)
	Output	-0.000 (0.011)	-0.010 (0.009)	-0.000 (0.011)	-0.001 (0.011)	-0.001 (0.011)
	Rents	0.107 (0.068)	0.104 (0.064)	0.106 (0.067)	0.113* (0.067)	0.109 (0.067)
Agg. indicator	Monetary	0.017*** (0.004)	0.015*** (0.004)	0.017*** (0.004)	0.017*** (0.004)	0.017*** (0.004)
Agg. measure	Density	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)
	Isochrone	-0.008*** (0.003)	-0.007** (0.003)	-0.008*** (0.003)	-0.008*** (0.003)	-0.008*** (0.003)
	Potential	-0.007*** (0.002)	-0.006** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.008*** (0.002)
Secondary measure	Yes	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
	Magnitude	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)
Worker effects	Yes	-0.011*** (0.001)	-0.010*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)
Firm effects	Yes	-0.002 (0.003)	-0.003 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.000 (0.003)
Sectoral controls	Yes	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.002 (0.001)
Occ. controls	Yes	-0.000 (0.001)	0.001 (0.002)	-0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)
Time controls	Yes	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Geo. controls	Yes	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
Own skills	Yes	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)

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Table 5 – continued from previous page

Attribute	Level	Model (5)	Column 2	Column 3	Column 4	Column 5
Labour ( $L$ ) inputs	Yes	0.002 (0.002)	-0.000 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Capital ( $K$ ) inputs	Yes	-0.001 (0.002)	-0.004 (0.003)	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)
$K/L$ ratio	Yes	-0.024*** (0.005)	-0.013*** (0.004)	-0.023*** (0.005)	-0.024*** (0.005)	-0.024*** (0.005)
Human capital	Yes	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Social capital	Yes	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)	-0.007*** (0.002)
Housing	Yes	-0.038*** (0.004)	-0.035*** (0.004)	-0.038*** (0.004)	-0.038*** (0.004)	-0.038*** (0.004)
Spatial scope	Metro	-0.019*** (0.002)	-0.018*** (0.002)	-0.019*** (0.002)	-0.019*** (0.002)	-0.019*** (0.002)
	Regional	-0.008** (0.003)	-0.010*** (0.003)	-0.008** (0.003)	-0.008*** (0.003)	-0.007** (0.003)
	National	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)
	International	0.065*** (0.008)	0.058*** (0.007)	0.065*** (0.008)	0.063*** (0.008)	0.069*** (0.011)
Wages	Yes	-0.012*** (0.002)	-0.011*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)
Localisation	Yes	0.003 (0.002)	-0.005** (0.002)	0.003* (0.002)	0.003* (0.002)	0.002 (0.002)
Input links	Yes	-0.021** (0.008)	-0.019** (0.009)	-0.021** (0.008)	-0.021** (0.008)	-0.021** (0.008)
Innovation	Yes	-0.012** (0.006)	-0.013** (0.006)	-0.012** (0.006)	-0.012** (0.006)	-0.012** (0.006)
Diversity	Yes	0.002 (0.001)	0.002 (0.002)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Competition	Yes	-0.031** (0.012)	-0.027** (0.012)	-0.031** (0.012)	-0.032** (0.012)	-0.031** (0.012)
IV	Yes	-0.003*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)
Hyper-parameters	Studies ( $\sigma_s^2$ )	0.092*** (0.005)	0.088*** (0.005)	0.092*** (0.005)	0.092*** (0.005)	0.092*** (0.005)
	Countries ( $\sigma_c^2$ )	0.034*** (0.009)	0.035*** (0.009)	0.034*** (0.008)	0.035*** (0.009)	0.035*** (0.009)
	DOF ( $\nu$ )	1.760*** (0.049)	1.685*** (0.043)	1.759*** (0.050)	1.762*** (0.049)	1.767*** (0.049)
Sensitivity test	Predicted $s_i$	No	Yes	No	No	No
	Publication bias	No	No	Yes	No	No
	Time trends	No	No	No	Yes	No
	Sub-samples	No	No	No	No	Yes
Model performance	PSIS-LOO	-22, 652	-24, 260	-22, 627	-22, 664	-22, 836
	$R^2$	0.262	0.140	0.379	0.263	0.264

Notes: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ . All models use the benchmark sample, except Column 2 as per Section 4.2.1.

## 5. Discussion

We begin by comparing our results to three earlier influential reviews, namely Rosenthal and Strange (2004), Melo et al. (2009), and Ahlfeldt and Pietrostefani (2019). Differences in approaches mean these comparisons are neither trivial nor precise. Instead, the goal is simply to place the various results on a broadly comparable footing. To do so, we estimate a simplified version of our benchmark model, which limits the spatial scope attribute to just two levels: domestic and international, where the focus is on the former.<sup>23</sup> Using this simplified model, we generate distributions of meta-estimates for combinations of attributes that—in our view—are most comparable to earlier reviews.

Figure 6 presents the results of these comparisons. First, the top-left panels shows the distribution of meta-estimates we compare to Rosenthal and Strange (2004).<sup>24</sup> In contrast to the 3–8% identified in the latter, we find a median elasticity of 5.7% and a 90% credible interval of 3.9–7.5%. Second, the top-right panel of Figure 6 presents the distribution of meta-estimates we compare to Melo et al. (2009).<sup>25</sup> Where the latter implies a point estimate of 3.0% for the U.S., we find a median elasticity of 5.0% and a 90% credible interval of 2.9–6.9%.<sup>26</sup> Third, the bottom-left panel in Figure 6 presents the distribution of estimates we compare to Ahlfeldt and Pietrostefani (2019).<sup>27</sup> Where the latter suggests 4.0% and 8.0% for high- and non-high-income countries, respectively, we find a median elasticity of 6.2% and a 90% credible interval of 4.2–8.0%. On this basis, our results appear broadly similar to those of earlier reviews, with the possible exception of Melo et al. (2009)—for which we arrive at somewhat larger estimates.

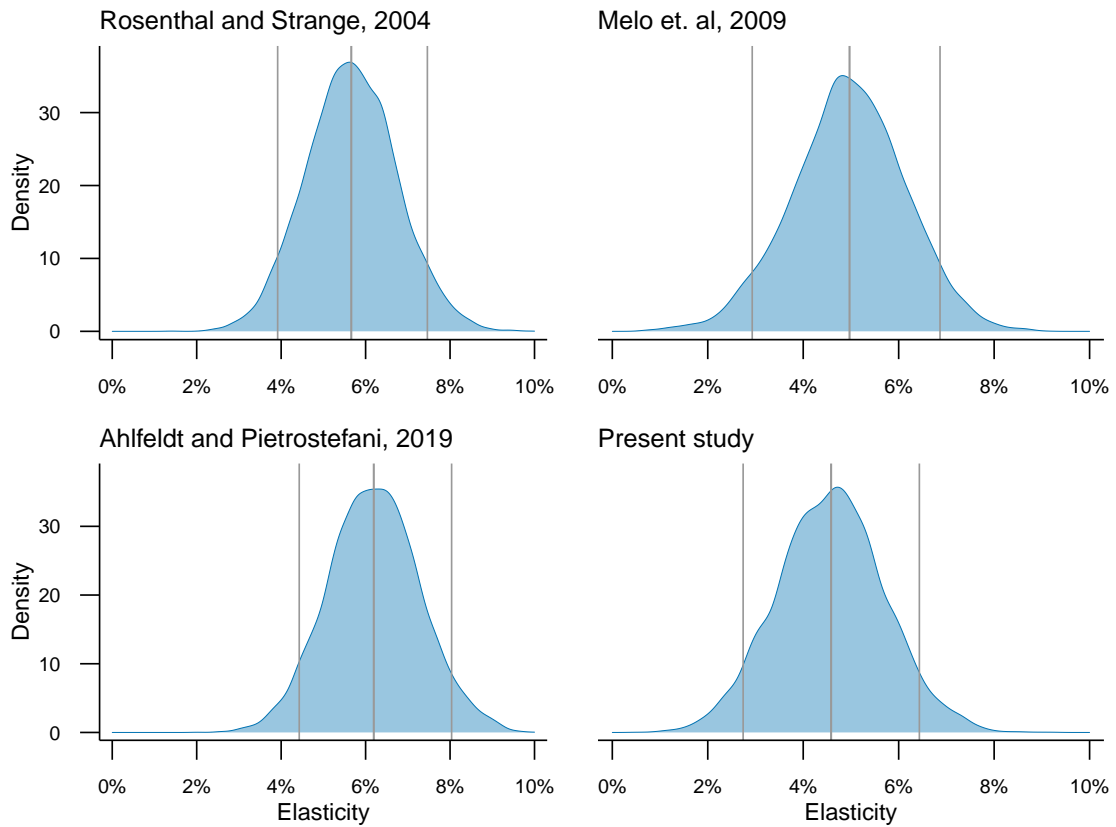
<sup>23</sup> Results for the simplified model are similar to Model (5), as per Appendix D, Column (4).

<sup>24</sup> That is, we consider a published elasticity of productivity with respect to population that is derived from a panel of micro-data and controls for own skills; labour and capital inputs; sectoral and occupational composition; time trends and geographic factors; and human and social capital.

<sup>25</sup> That is, we consider a published elasticity of productivity with respect to population for the U.S. that is derived from a panel of micro-data and controls for worker and firm effects as well as human capital.

<sup>26</sup> See column (2), Table 4 in Melo et al. (2009). To the intercept (0.1218), we add panel data (−0.0255), micro-data (0.0035), cross-sectional heterogeneity (−0.0158), and human capital (−0.0596).

<sup>27</sup> That is, a published elasticity of wages with respect to population density that is derived from a panel of micro-data and controls for own skills; sectoral and occupational composition; and human and social capital. We assume instrumental variables is used to address endogeneity, as per Ahlfeldt and Pietrostefani (2019)'s discussion of “plausible exogenous variation”. We exclude individual worker and firm effects as the main estimates in Ahlfeldt and Pietrostefani (2019) do not control for “selection effects”.



**Figure 6:** Comparing our findings to the results of earlier reviews for combinations of study attributes as described in the text. Dashed vertical lines indicate medians and 90% credible intervals.

Similarities between our results vis-à-vis those of earlier reviews also extends to the bottom-right panel in Figure 6, which presents the distribution of meta-estimates for our preferred combination of study attributes. Like Ahlfeldt and Pietrostefani (2019), we prefer estimates of the elasticity of wages with respect to population density. We do so for two reasons: First, wages are—unlike productivity—readily observed and, second, we find evidence using wages and population density yields more precise estimates (c.f. Section 4.2.1). We differ from Ahlfeldt and Pietrostefani (2019), however, by including individual worker and firm effects to control for unobserved sources of heterogeneity, such as the sorting of more productive workers and firms into more agglomerated areas. In contrast to Ahlfeldt and Pietrostefani (2019), who suggest “net of selection effects, elasticity estimates about halve” (p. 103), we find the inclusion of individual worker and firm effects reduces our meta-estimates by approximately one-third, or 1.5%. For our preferred combination of study attributes, we find a median elasticity of 4.6% and a 90% credible interval of 2.7—6.4%, which is similar to the results of earlier reviews.



Although comforting, the preceding discussion begs the question: How do our results extend earlier reviews? We make four points in response to this question. First, in addition to confirming the results of earlier reviews, we unite them within a single statistical model. To do so, we leverage both rich data, which includes—but is not limited to—the attributes considered in earlier reviews, and robust methods, which generate distributions of parameter estimates that are straightforward to combine and interpret. Second, though our results are similar to earlier reviews in aggregate, we observe several notable points of departure. Melo et al. (2009), for example, report parameters for human capital that are approximately ten-times larger than ours.<sup>28</sup> And, in contrast to Ahlfeldt and Pietrostefani (2019), we do not observe clear differences in agglomeration economies between countries based on their income levels.<sup>29</sup> Due to differences in data and methods, we cannot trace the root causes of these discrepancies.

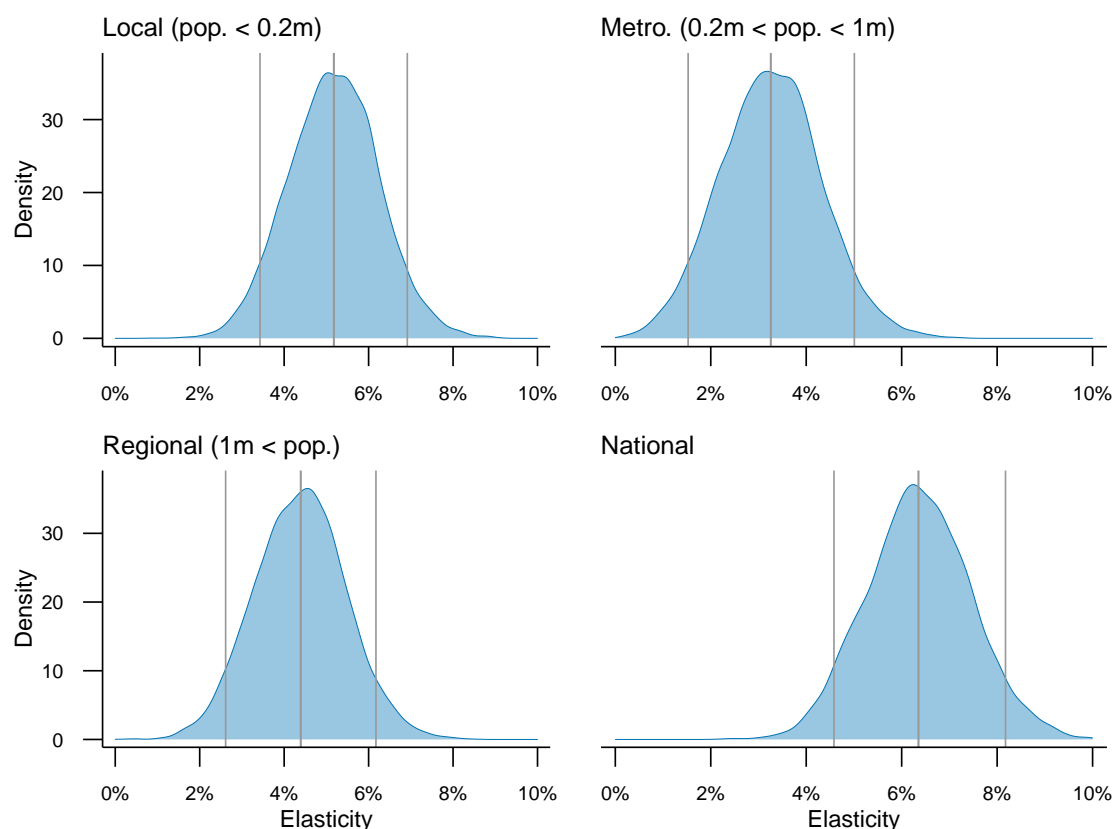
Third, and as far as we understand, we are the first meta-analysis to find precise effects for several attributes that exert a systematic influence on estimates of agglomeration economies. This includes contextual attributes, such as effects for published studies, and a long list of methodological attributes, including the choice of dependent variable, the measurement of agglomeration, and the use of instrumental variables. Similarly, we find precise effects for a range of controls, like sectoral composition, own skills, capital intensity, and characteristics of the urban environment—such as social capital, housing supply, input links, innovation, and competition. Perhaps the most notable attribute for which we find precise effects is the spatial scope of agglomeration. Figure 7 presents, for example, the four domestic levels of spatial scope from Model (5) for our preferred combination of study attributes, as described above.<sup>30</sup> For the metro and national levels of spatial scope, for example, we find median elasticities of 3.3% and 6.4% with 90% probability intervals of 1.5–5.0% and 4.6–8.2%, respectively. These differences are meaningful, given the small magnitude of elasticities. For these attributes, the results of this study provide researchers and policy-makers with additional insight into potential sources of heterogeneity that affects estimates of agglomeration economies.

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<sup>28</sup> Where Melo et al. (2009) report estimates for human capital that range from 4–6%, we find estimates for the effect of human capital in Table 3 of –2.2% in Model (3), –1.5% in Model (4), and –0.5% in Model (5). Finding a smaller effect for human capital may reflect both the choice to model errors-in-outcomes and use a Student *t*-distribution in Model (4) and Model (5), respectively, as well as the inclusion of controls for own skills; sectoral and occupational composition; and social capital.

<sup>29</sup> Appendix C.2 reports country effects,  $\xi_i$ , from Model (5). Informal inspection of these effects does not reveal an association with income levels. This may be because, in contrast Ahlfeldt and Pietrostefani (2019)'s focus on elasticities of labour productivity and wages with respect to density, we impose common country effects across dependent variables, agglomeration measures, and agglomeration indicators.

<sup>30</sup> The distribution of meta-estimates for the international spatial scope has a median elasticity of 11.6% and a 90% credible interval of 9.6–13.7%.



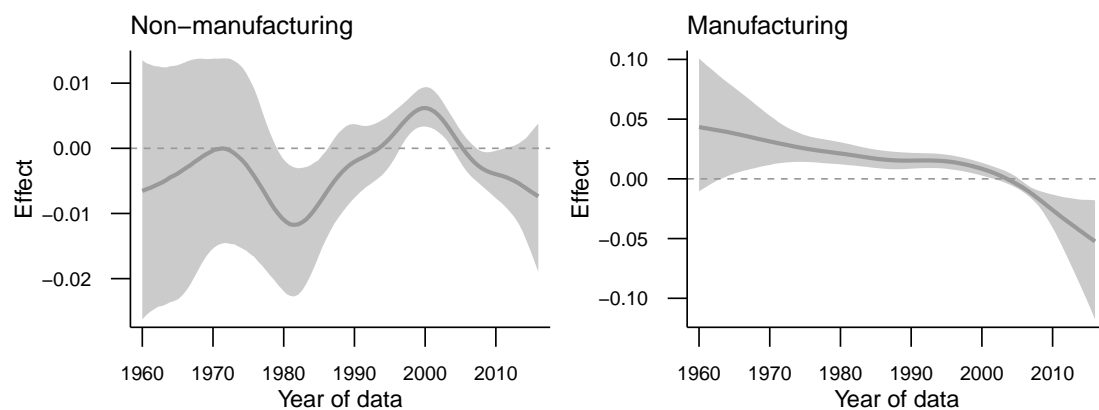
**Figure 7:** Distributions of meta-estimates by spatial scope (Note: Level of spatial scope indicated for each panel). Dashed vertical lines indicate median and 90% credible intervals.

The fourth and final area we extend earlier reviews is by providing greater insight into underlying trends in estimates of agglomeration economies.<sup>31</sup> Consider the left panel of Figure 5 in Section 4.2.3, which shows a downwards trend starting circa 1999. If we take this trend at face value, then it suggests agglomeration economies in production have declined approximately 1.5% in the two decades since Rosenthal and Strange (2004) completed their review. This begs two questions. First, what drove the decline in estimates? Perhaps the most obvious potential explanation is that increased congestion costs arising from sustained urban growth is undermining the productive advantages of cities. Second, if the productive advantages of cities have indeed declined over the last two decades, then what has underpinned the widespread urban growth that occurred in the same period? One possible answer to this question is provided by the “consumer city” literature, which emphasises the growing appeal of cities to consumers (Glaeser, Kolko

<sup>31</sup> We emphasise the results of meta-analysis merely serve to highlight statistical associations in the data; they do not provide evidence of causal mechanisms. As such, this discussion of trends is purely speculative, even if our explanations draw on findings from the wider economic literature.

et al., 2001). In short, weaker agglomeration economies in production may have been offset by stronger agglomeration economies in consumption.

Going one step further, we estimate a variant of Model (5) that includes separate trends in the year of data for manufacturing sectors vis-à-vis the economy and service sectors (“non-manufacturing”), again modelled using GAMs. These trends are illustrated in Figure 8. For non-manufacturing activities, we find a positive trend from 1980–2000 that subsequently reverses. One possible explanation for these dynamics is that, starting in the 1980s, non-manufacturing firms in urban areas started to benefit from access to nascent information and communications technologies (ICT) (Dijkstra et al., 2013).<sup>32</sup> The ICT explanation is seductive as it potentially explains both the positive trend from 1980–2000 and the subsequent negative trend thereafter, in which time ICT started to become more widely available outside of urban areas.



**Figure 8:** Residual time trends for non-manufacturing (left panel) and manufacturing (right panel). The shaded band indicates the 95% credible interval around the median effect.

The right panel of Figure 8 reveals that estimates for manufacturing fell for the entire six decades covered by our data, especially from around 2000 onwards. By 2020, estimates for manufacturing were approximately 10% smaller than they were in 1960. This is an economically meaningful effect, which—if accurate—may explain urban industrial flight. The economic literature highlights at least two possible causes of declining agglomeration economies in manufacturing. First, evidence finds long-distance freight costs have

<sup>32</sup> We see three reasons why ICT, even as a general-purpose technology, may have initially enhanced the productivity of cities more so than less urbanised areas. First, the adoption of ICT initially incurred high fixed costs, creating internal economies of scale that were more easily realised by larger firms that are more common in urban areas. Second, ICT often relies on social and physical networks that may initially have been more readily available in cities. And third, deployment of ICT initially relied relatively heavily on access to high-skilled people who tend to be over-represented in cities.

fallen significantly over the course of several decades, potentially reducing the benefits cities offer to manufacturing sectors (Glaeser and Kohlhase, 2003). Second, changes to environmental regulations, such as stricter air quality controls, have been linked to lower productivity for manufacturing firms located in urban areas (Greenstone et al., 2012; Walker, 2011). Regardless of their cause, these trends imply agglomeration economies in production—or, more precisely, the causal mechanisms they capture—are not static but instead are a function of the prevailing socioeconomic milieu. Whereas earlier studies have advanced similar arguments, the present study is—as far we understand—the first meta-analysis to find statistical evidence of such effects.

These findings have several implications for further research. First, we remain concerned by large variation in estimates of agglomeration economies. Notwithstanding the merits of our models, they explain only around one-quarter to one-third of the variation that exists in the data. To arrive at a more cogent body of empirical literature, we recommend primary researchers consider methods to manage problems—such as extreme values and over-fitting—that may give rise to excessive heterogeneity. Second, we see value in primary research that traces the evolution of agglomeration economies over time, holding constant other contextual and methodological attributes. Perhaps the best example of primary research in this spirit is Martínez-Galarraga et al. (2008), which presents estimates for Spain extending back to 1860. And, finally, to develop a fuller understanding of urban advantages, we advocate for more primary research into agglomeration economies in consumption. Indeed, if the productive advantages of cities have fallen in recent decades, as our results suggest, then future urban growth may depend more on the consumer advantages of cities, as argued by Glaeser, Kolko et al. (2001), among others.

To finish, we discuss two limitations of our study. First, we test and correct for publication bias but do not model the underlying selection processes in detail, which is instead leave as an area for further research. Second, our results may be criticised on the grounds we do not account for quality differences between estimates. We present three responses to this criticism. First, several aspects of our methodology seek to explicitly address questions of quality, such as the inclusion of individual study effects, the choice to model errors-in-outcome, and allowing our response variable to follow a Student's *t*-distribution. Second, we note that our results are similar to those for Rosenthal and Strange (2004) and Ahlfeldt and Pietrostefani (2019), which consider quality factors more explicitly. Third and finally, we suggest quantitative approaches like that used in this study are viewed as a complement to, rather than a substitute for, approaches that give a more prominent role to the perceived quality of estimates.

## 6. Conclusions

A large and rapidly growing body of literature considers the productive advantages of cities, or agglomeration economies. Whereas most empirical studies tend to report positive agglomeration economies, large variation exists in the magnitude of estimates. We use a meta-analysis to explore this variation, drawing on 6,684 estimates from 295 studies that cover 54 countries and span six decades. For our preferred set of attributes, we find agglomeration elasticities lie in the range 2.7–6.4% with 90% probability. These results are broadly comparable to those of earlier reviews and confirm the conventional wisdom that controls enabled by detailed data give rise to smaller estimates.

By combining rich data with robust methods, we extend the literature in four ways. First, in addition to confirming the results of earlier reviews, we unite them within a single statistical model. Second, similar aggregate results co-exist with several notable points of departure. Third, and as far as we understand, we are the first meta-analysis to identify precise effects for several study attributes—providing researchers and policy-makers with additional insight into sources of heterogeneity. Fourth, we identify some intriguing underlying trends in estimates and speculate on potential explanations, such as urban congestion, technological shocks, freight costs, and regulatory settings. Notwithstanding uncertainty over their causes, the implication of these trends seems clear: The productive advantages of cities are not constant but rather ebb and flow with time. Earlier studies have advanced similar arguments, although this study is—as far we understand—the first meta-analysis to present statistical evidence of such trends.

Our findings have several implications for further research. First, the empirical literature on agglomeration economies is characterised by considerable heterogeneity. To arrive at a more cogent body of empirical literature, we recommend primary researchers take steps to manage problems—such as extreme values and over-fitting—that may give rise to excessive heterogeneity. Second, we see value in more primary studies that trace the evolution of agglomeration economies over time, holding constant other contextual and methodological attributes to the extent practicable. And, finally, to develop a fuller understanding of urban advantages, we advocate for primary research that seeks to estimate agglomeration economies in consumption. Indeed, if their productive advantages have fallen in recent decades, as our results seem to suggest, then one might expect to find a growing role for the consumer advantages of cities.

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## A. Approach to Coding

Table A: Approach to coding meta-data

Attribute	Notes
Estimate	The magnitude of the estimate. We convert non-linear estimates into point estimates at the mean of the sample, where the necessary summary statistics are reported.
Standard error	The standard error (s.e.) of the estimate. For some estimates, the s.e. is rounded to zero, e.g. 0.00. In these cases, we assume the s.e. equals the nearest positive value that—with two significant figures—would be rounded to zero, e.g. 0.0049. Where the s.e. is not reported, we often impute. Most often, we impute the s.e. as the ratio of the estimate and the <i>t</i> -statistic. In some cases, however, we must also impute the <i>t</i> -statistic using the reported <i>p</i> -value of the estimate and the DOF of the model. In turn, in some cases we also need to impute the DOF as the number of observations minus the number of model parameters. Observations for which the s.e. is not reported and cannot be imputed may still be used in our sensitivity test for sample bias (c.f. Section 4.2.1).
Country	A unique identifier for the country. If an estimate pertains to a group of countries, such as subsets of the EU and the OECD, then we use a unique identifier for each group.
Sector	“Economy” (base); “Services”; and “Manufacturing”. We exclude estimates associated with the primary sector, specifically agriculture, forestry, and mining.
Publication	“Yes”, if estimates are reported in an academic journal or book. “No”, if estimates are reported in a working paper, thesis, dissertation, or conference paper.
Micro-data	“Yes”, if using micro-data versus “No” for aggregate data (base). Many estimates use micro-data directly (see, e.g., Börjesson et al., 2019; Håkansson and Isacson, 2019). Others first estimate aggregate productivity differences that are subsequently used to estimate agglomeration economies (see, e.g., Matano, Obaco et al., 2020; Spanos, 2019). We code the latter “Yes”, even though the final step uses aggregate data.
Panel data	“Yes” if using panel data versus “No” for cross-sectional data (base). Most estimates use panel data directly (see, e.g., Ahlfeldt and Feddersen, 2018; Monkkonen et al., 2020). Others first estimate cross-sectional productivity differences that are subsequently used to estimate agglomeration economies. That is, the temporal dimension is removed prior to estimating agglomeration economies (see, e.g., Hamann et al., 2019; Verstraten et al., 2019). We code the latter as “Yes”, even if the final step uses cross-sectional data.
Dependent variable	“Productivity” (base), “Economic output”, “Labour productivity”, “Wages”, and “Commercial property rents”. “Productivity” is coded for measures of multi-factor productivity (see, e.g., Martin et al., 2011). “Economic output” is coded for measures of economic activity, such as regional product or value added (see, e.g., Wetwitoo and Kato, 2017). “Labour productivity” is coded for measures of output per labour input, for example, per capita or per worker (see, e.g., Brunow and Blien, 2015). A few studies measure labour inputs on a per hour basis (see, e.g., Moomaw, 1985). “Wages” is coded for labour income for any time period, such as annual or hourly (see, e.g., Lamorgese et al., 2019). Finally, a few studies use commercial property rents (see, e.g., Koster et al., 2014).

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Attribute	Notes
Agglomeration indicator	“Population” (base) measures total residents or workers. We exclude estimates for subsets of the population, such as manufacturing employment, and those derived from the number of firms. “Monetary” indicators of agglomeration are usually derived from measures of economic output (see, e.g., Kamal et al., 2012), although some are based on total wages or income (see, e.g., Wixe, 2015).
Agglomeration measure	“Size” (base) is coded for estimates that measure the level of agglomeration in a spatial unit (see, e.g., Ehrlich and Overman, 2020). “Density” is coded for measures that divide the agglomeration measure by the area of the spatial unit (see, e.g., Drut and Mahieux, 2017). “Isochrone” is coded for measures whose extent is defined by distance or time, inside of which agglomeration receives the same (unitary) weight (see, e.g., Artis et al., 2012). Finally, “potential” is coded for agglomeration measures whose boundaries are defined in terms of the distance or time from a point, within which agglomeration is weighted with a decay function (see, e.g., Öner, 2018).
Secondary measure	“Yes”, where the model includes a secondary measure of agglomeration that meets the inclusion criteria set out in Section 2.1 (see, e.g., Artis et al., 2012; J. P. Larsson, 2014).
Secondary magnitude	We code the magnitude of the estimate associated with the secondary measure, that is, the elasticity. We exclude a small number of estimates that include a secondary agglomeration measure yet do not report the resulting elasticity (see, e.g., Ahlfeldt and Feddersen, 2018; Brülhart and Mathys, 2008; Duranton, 2016; Fally et al., 2010).
Worker effects	“Yes”, where the model controls for individual worker effects. These can be “fixed”, as in Barufi et al. (2016), or “random”, as in Coll-Martínez et al. (2019). Krashinsky (2011) is an edge case that includes random effects per set of twins, which we code as “yes”.
Firm effects	“Yes”, where the model controls for individual firms or plants. These can be “fixed”, as in Martin et al. (2011), or “random”, as in Wixe (2015).
Sectoral controls	“Yes”, where the model controls for sectoral composition. Many models use sector fixed effects (see, e.g., Cunningham et al., 2016; Faberman and Freedman, 2016). Others control for sectoral shares (see, e.g., Ženka et al., 2015; Paredes, 2015). We adopt a broad definition, coding “yes” where models control for broad sectoral categories, such as the proportion of workers in service or manufacturing industries.
Occupational controls	“Yes”, where the model controls for occupational composition. Many models use occupational fixed effects (see, e.g., Combes, Démurger and S. Li, 2017; Matas et al., 2015). Others control for occupational shares (see, e.g., Ahrend, Farchy et al., 2017; Abel and Deitz, 2015). We adopt a broad definition, coding “yes” where models control for broad occupational categories, such as the proportion of white- and blue-collar workers.
Temporal controls	Yes”, where the model includes time controls. These come in two forms: First, are models that include time fixed effects (see, e.g., Briant et al., 2010; Dalmazzo and Blasio, 2011; Maré and Graham, 2013; Groot, de Groot and Smit, 2014). Second, are models that include time trends (see, e.g., Fingleton and Fischer, 2010; Otsuka, Goto et al., 2010).

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Attribute	Notes
Geographic controls	“Yes”, where the model includes one of four types of controls. First are models that use panel data and include individual spatial effects (fixed or random) for the cross-sectional dimension of their data. Second are models that include locational controls, such as dummies for capital cities (see, e.g., S. Liu, 2017). Third are models that control for geographic characteristics, such as topography, climate, coordinates, and urban structure (see, e.g., Duranton, 2016). Fourth, are models that control for the area of the spatial unit (see, e.g., Matano, Obaco et al., 2020).
Own skills	“Yes”, where the model controls for the skills of individual workers, firms, or sector. For workers, indicators include age, education, and experience (see, e.g., Rosenthal and Strange, 2008; Bacolod et al., 2009). At the firm or sector level, indicators of own skills often include age, education, and managerial inputs (see, e.g., Rigby and Brown, 2015; Holl, 2016), which are averaged across the relevant workforce. Spanos (2019) represents an edge case that controls for the number of hierarchical levels within firms, which we code as “yes”.
Labour (L)	“Yes”, where the model controls for labour inputs. Most studies measure labour in terms of the number of employees (see, e.g., Le Néchet et al., 2012; Baldwin et al., 2010), although some use the number of hours (see, e.g., Holl, 2012; Maré and Graham, 2013). A small number of studies use categorical indicators of firm size (see, e.g., Barufi et al., 2016; Holl, 2014).
Capital (K)	Yes, where the model controls for capital inputs into production (see, e.g., Saito and Gopinath, 2009; Konings and Torfs, 2011). Koster et al. (2014) is an edge case that we code “yes”, in which the dependent variable measures commercial property rents and the model controls for the size and quality of the building.
K/L ratio	“Yes”, where the model controls for capital intensity, that is, the ratio of capital to labour inputs (see, e.g., Noonan et al., 2020; Rigby and Brown, 2015), including those that use proxies for capital intensity per worker (see, e.g., Soroka, 1994).
Human capital	“Yes” where the model controls for levels of human capital external to individual workers, firms, or sectors. Various measures are used in the literature, the most common being the share of educated or skilled workers (see, e.g., Andersson, Klaesson et al., 2016; Chatman and Noland, 2014; Hamann et al., 2019). Other studies use the average level of education or skills (see, e.g., Békés and Harasztosi, 2018; Groot, de Groot and Smit, 2014; Martínez-Galarraga et al., 2008). Less common measures include the number of college graduates (see, e.g., Farrokhi and Jinkins, 2019); the location quotient of human capital (see, e.g., Artis et al., 2012), and the adult literacy ratio (see, e.g., Amaral et al., 2010). Finally, Saito and Gopinath (2009) use an unspecified measure of human capital.
Social capital	“Yes”, where the model controls for levels of social capital. Some studies, like Kanemoto et al. (1996) and Gómez-Antonio and Fingleton (2012), include direct measures of social capital. Others use proxies for social capital. Duranton (2016), for example, control for public facilities, such as libraries, as well as crime rates (c.f. Table 9). Similarly, Hasan et al. (2017) control for the number of educational institutions. In contrast, Beugelsdijk et al. (2018) control for intangible measures, such as levels of trust and institutional quality.

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Attribute	Notes
Housing	“Yes”, where the model controls for housing supply or prices. Neffke et al. (2011) and Faberman and Freedman (2016) control for house prices; Donovan et al. (2020) and Kosfeld and Eckey (2010) control for housing rents; and Tabuchi and Yoshida (2000) control for land prices. In terms of edge cases, Hering and Poncet (2010b) control for living costs in which housing is identified as a core component.
Spatial scope	Categorical variables for the spatial scope of agglomeration: Local (pop. < 0.2m), Metro (0.2m < pop. < 1.0m), Regional (1.0m < pop.), National, and International. For measures based on size and density, spatial scope is defined by the average population of the spatial units, for example postcodes, statistical areas, administrative units, cities, and regions. Where possible, we use reported summary statistics to estimate the average population. In cases where the necessary information is not reported, we draw on external sources, such as administrative data on population and urbanisation at the time of the study. Details of these external sources are available from the authors on request. For isochrones, we code scope based on the associated travel-time. Specifically, we code the spatial unit as “local” when the travel-time is less than 30 minutes, “metro” when the travel-time is less than 60 minutes, and “regional” when the travel-time exceeds 60 minutes. Where isochrones are specified in terms of distance, then we convert it to time assuming an average speed of 50 kilometres per hour. For potential-based agglomeration measures, spatial scope is defined by the maximum extent of the measure, which is commonly either national or, in some cases, international.
Localisation	“Yes”, where the model controls for intra-sectoral spillovers. We observe two main types of localisation measures in the literature. The first type measures the absolute size of an industry sector, for example the total number of workers or firms in the surrounding area (see, e.g., Rigby and Brown, 2015). The second type is often described as “specialisation” and measures the relative size of a sector, for example using a location quotient of sectoral employment (see, e.g., Matano, Obaco et al., 2020).
Input links	“Yes”, where the model controls for access to inputs. We observe a variety of related indicators in the literature. The most common measures relate to labour pooling, that is the presence of workers with relevant skills (see, e.g., Wixe, 2015). In contrast, Drucker and Feser (2012) measure relative access to manufactured inputs and producer services; B. S. Lee et al. (2010) measure outsourcing potential, such as the share of employment in business services; Baldwin et al. (2010) and Rigby and Brown (2015) measure the density of up-stream suppliers based on shipments; Ehrl (2013) and Konings and Torfs (2011) measure the strength of inter-sectoral links based on input-output matrices; Feser (2002) measure access to material and service inputs; and Amiti and Cameron (2007) measure the market potential of inputs.
Innovation	“Yes”, where the model controls for levels of innovation. Most studies use simple measures, such as the total number of inventors, patents, or simple derivatives thereof—such as patents per capita or per worker (see, e.g., Artis et al., 2012; Beugelsdijk et al., 2018; Feser, 2002; Lobo et al., 2014; López-Rodríguez and Faiña, 2007; van Oort and Bosma, 2013). In contrast, Broersma and van Dijk (2007), López-Rodríguez, Faiña et al. (2011) and Drucker and Feser (2012) consider expenditure on research and development, whereas Noonan et al. (2020) consider research investment per sector.

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Attribute	Notes
Diversity	“Yes”, where the model controls for inter-sectoral diversity, sometimes referred to as “Jacobs” externalities. Various indices are used in the literature, such as the Hirschman-Herfindahl Index, the Krugman Specialisation Index, the Theil Index, the Ellison-Glaeser Index, and entropy or information criteria (see, e.g., Tao et al., 2019; Antonietti and Cainelli, 2011; Barufi et al., 2016; Groot, de Groot and Smit, 2014).
Competition	“Yes”, where the model controls for intra-sectoral competition, sometimes referred to as “Porter” externalities. We observe various indicators in the literature. The most common measure the concentration of employment, revenue, output, and value-added, often by way of indices (see, e.g., Amiti and Cameron, 2007; Cainelli et al., 2015; Fafchamps and Hamine, 2017; Feser, 2002; Groot, de Groot and Smit, 2014; B. S. Lee et al., 2010; Martin et al., 2011; Tao et al., 2019; Wixe, 2015). We also note two edge cases: First, studies that control for the mark-ups arising from monopolistic competition (Ehrl, 2013) and, second, the presence of large firms in specific industries (Neffke et al., 2011).
Instrumental variables	“Yes”, where the model uses instrumental variables to control for endogeneity in the agglomeration measure to which the estimate pertains.

## B. Summary Statistics per Study

Table B: Summary statistics for the benchmark sample per study

Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Abel and Deitz (2015)	4	0.04	0.00	0.04	0.04	-0.02	-0.04	0.01
Abel, Dey et al. (2012)	3	0.05	0.04	0.02	0.10	-0.01	-0.05	0.05
Åberg (1973)	9	0.02	0.01	0.01	0.04	-0.01	-0.05	0.03
Adamchik and Hyclak (2017)	6	0.03	0.02	0.01	0.05	-0.05	-0.12	0.02
Ahlfeldt and Feddersen (2008)	4	0.27	0.05	0.19	0.32	0.08	-0.01	0.16
Ahlfeldt and Feddersen (2018)	31	0.18	0.10	0.01	0.38	0.08	0.04	0.13
Ahlfeldt, Redding et al. (2015)	1	0.05		0.05	0.05	0.03	-0.02	0.07
Ahrend, Farchy et al. (2017)	87	0.03	0.02	0.01	0.07	-0.01	-0.03	0.01
Ahrend and Lembecke (2016)	36	0.02	0.01	0.01	0.06	-0.05	-0.08	-0.02
Albouy (2016)	2	0.05	0.00	0.05	0.05	-0.01	-0.03	0.01
Albouy et al. (2019)	4	0.06	0.01	0.06	0.07	-0.00	-0.02	0.02
Alvarado and Atienza (2014)	8	-0.03	0.14	-0.36	0.08	-0.10	-0.16	-0.03
Álvarez and Lenyn (2018)	15	0.05	0.02	0.03	0.09	-0.03	-0.09	0.04
Amaral et al. (2010)	1	0.29		0.29	0.29	0.18	0.02	0.25
Amiti and Cameron (2007)	16	0.16	0.05	0.00	0.22	0.12	0.06	0.19
Anastassova (2006)	28	0.05	0.02	0.02	0.09	-0.01	-0.04	0.02
Andersson, Klaesson et al. (2014)	17	0.02	0.02	-0.01	0.05	-0.03	-0.08	0.01
Andersson, Klaesson et al. (2016)	6	0.04	0.02	0.01	0.07	-0.02	-0.06	0.03
Andersson, J. P. Larsson et al. (2015)	5	0.00	0.00	-0.00	0.01	-0.06	-0.10	-0.01
Andersson and Lööf (2011)	10	0.03	0.01	0.00	0.04	-0.00	-0.04	0.04
Antonietti and Cainelli (2011)	3	-0.05	0.01	-0.06	-0.05	-0.07	-0.12	-0.01
Artis et al. (2012)	11	0.05	0.01	0.04	0.06	0.05	0.02	0.07
Au and Henderson (2006a)	2	0.59	0.08	0.54	0.65	0.14	-0.07	0.34
Au and Henderson (2006b)	4	0.05	0.11	-0.08	0.15	-0.04	-0.13	0.08
Bacolod et al. (2009)	45	0.06	0.02	0.04	0.11	0.01	-0.01	0.03
Baldwin et al. (2010)	9	-0.11	0.17	-0.31	0.30	-0.11	-0.19	-0.03
Bartelme (2015)	18	0.66	0.11	0.42	0.85	0.48	0.39	0.56
Barufi et al. (2016)	4	0.03	0.04	0.01	0.09	-0.04	-0.07	-0.01
Beckstead et al. (2010)	16	0.02	0.01	0.02	0.05	-0.06	-0.13	0.01
Behrens, Duranton et al. (2014)	3	0.05	0.01	0.04	0.06	-0.01	-0.04	0.02
Behrens and Robert-Nicoud (2009)	18	0.05	0.02	0.02	0.10	-0.04	-0.06	-0.01
Békés and Harasztosi (2018)	5	0.10	0.03	0.06	0.14	0.01	-0.07	0.09
Belloc et al. (2019)	35	0.02	0.02	-0.00	0.08	-0.05	-0.10	0.00
Beugelsdijk et al. (2018)	29	0.07	0.04	-0.01	0.14	0.02	-0.06	0.10
Blouri and Ehrlich (2020)	3	0.12	0.03	0.10	0.15	0.01	-0.07	0.10
Börjesson et al. (2019)	26	0.02	0.03	-0.01	0.09	-0.01	-0.05	0.03
Bosker, Brakman et al. (2010)	1	0.14		0.14	0.14	0.02	-0.08	0.11
Bosker, Brakman et al. (2012)	4	0.16	0.04	0.10	0.19	0.03	-0.01	0.08
Bosker, Park et al. (2018)	4	0.05	0.08	-0.03	0.14	-0.03	-0.10	0.06
Bosquet and Overman (2019)	6	0.03	0.02	0.01	0.07	0.00	-0.03	0.03
Boualam (2014)	3	0.61	0.49	0.04	0.91	-0.01	-0.04	0.03
Brakman, Garretsen, Gorter et al. (2005)	2	0.51	0.55	0.12	0.90	-0.03	-0.11	0.06
Brakman, Garretsen and van Marrewijk (2009)	14	0.08	0.02	0.04	0.13	0.04	-0.03	0.11
Brakman, Garretsen and Schramm (2004)	7	0.21	0.10	0.05	0.32	0.18	0.13	0.22
Brakman, Garretsen and Schramm (2006)	1	0.34		0.34	0.34	0.09	-0.08	0.22

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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Breinlich (2006)	21	0.23	0.11	0.02	0.46	0.11	0.06	0.16
Briant et al. (2010)	36	0.05	0.02	0.02	0.10	-0.01	-0.06	0.04
Broersma and van Dijk (2007)	2	0.35	0.01	0.34	0.36	0.11	-0.08	0.27
Broersma and Oosterhaven (2009)	1	0.03		0.03	0.03	-0.00	-0.07	0.07
Brühlhart and Mathys (2008)	57	-0.05	0.54	-1.63	2.08	-0.02	-0.11	0.06
Bruna (2015)	5	0.36	0.05	0.28	0.42	0.15	0.05	0.24
Bruna, Faíña et al. (2014)	16	0.19	0.08	0.08	0.42	0.03	-0.02	0.09
Bruna, López-Rodríguez et al. (2016)	4	0.41	0.14	0.28	0.61	0.18	0.11	0.26
Brunow and Blien (2015)	8	-0.04	0.06	-0.14	0.01	-0.01	-0.04	0.02
Cainelli et al. (2015)	7	0.01	0.01	-0.00	0.02	-0.00	-0.07	0.06
Carli (2017)	12	0.06	0.01	0.04	0.09	0.02	-0.03	0.07
Carlsen et al. (2012)	37	0.04	0.02	0.01	0.07	-0.02	-0.09	0.04
Carlsen et al. (2013)	84	0.04	0.01	0.01	0.07	-0.02	-0.08	0.04
Catela et al. (2010)	3	0.02	0.00	0.01	0.02	-0.03	-0.06	-0.00
Cervero (2001)	5	0.05	0.01	0.04	0.06	-0.01	-0.04	0.02
Chatman and Noland (2014)	15	0.00	0.12	-0.41	0.13	-0.03	-0.05	-0.01
Chauvin et al. (2017)	34	0.07	0.09	-0.05	0.32	-0.01	-0.03	0.01
Cicccone (2002)	7	0.05	0.00	0.04	0.05	-0.01	-0.09	0.07
Cicccone and Hall (1993)	16	0.05	0.02	0.01	0.08	-0.01	-0.04	0.01
Cieřlik and Rokicki (2013)	5	0.77	0.14	0.59	0.88	0.45	0.37	0.52
Cieřlik and Rokicki (2016)	12	0.01	0.00	0.01	0.01	-0.11	-0.17	-0.04
Cieřlik and Rokicki (2017)	10	0.33	0.58	0.01	1.50	-0.13	-0.20	-0.06
de Clairfontaine and Hammer (2018)	8	0.04	0.06	-0.03	0.14	-0.05	-0.12	0.01
Coll-Martínez et al. (2019)	37	-0.02	0.07	-0.14	0.27	-0.08	-0.11	-0.06
Collier et al. (2018)	51	0.05	0.08	-0.21	0.22	-0.01	-0.06	0.05
Combes, Démurger et al. (2013)	23	0.11	0.02	0.05	0.15	-0.01	-0.05	0.03
Combes, Démurger and S. Li (2015)	15	0.09	0.03	0.05	0.14	-0.01	-0.04	0.03
Combes, Démurger and S. Li (2017)	22	0.10	0.03	0.06	0.17	-0.00	-0.03	0.03
Combes, Démurger, S. Li and J. Wang (2020)	15	0.10	0.06	-0.02	0.18	-0.01	-0.05	0.03
Combes, Duranton and Gobillon (2008)	12	0.04	0.02	-0.03	0.06	-0.01	-0.06	0.04
Combes, Duranton, Gobillon and Roux (2010)	112	0.03	0.01	0.01	0.05	-0.01	-0.07	0.04
Cunningham et al. (2016)	12	0.07	0.01	0.05	0.08	0.02	-0.00	0.04
Dalmazzo and Blasio (2011)	7	0.01	0.01	-0.00	0.02	-0.05	-0.10	-0.00
Dauth et al. (2016)	6	0.02	0.00	0.02	0.02	-0.04	-0.08	-0.01
Davis and Weinstein (2001)	11	0.03	0.02	0.01	0.06	-0.07	-0.11	-0.03
De Bruyne (2009)	2	0.57	0.73	0.05	1.09	-0.03	-0.13	0.08
Dericks and Koster (2018)	26	0.29	0.07	0.19	0.46	0.12	-0.00	0.25
Di Addario and Patacchini (2008)	17	0.01	0.00	0.00	0.01	-0.03	-0.08	0.02
Díaz-Serrano (2015)	14	0.03	0.01	0.00	0.05	-0.03	-0.06	-0.00
Dogan (2001)	58	0.14	0.32	-0.24	1.72	-0.00	-0.09	0.08
Donovan et al. (2020)	6	0.20	0.02	0.18	0.23	0.10	0.03	0.17
Drennan (2005)	2	0.07	0.03	0.05	0.09	0.01	-0.03	0.05
Drucker and Feser (2012)	9	0.02	0.03	-0.01	0.08	-0.00	-0.04	0.03
Drut and Mahieux (2017)	13	0.04	0.02	0.03	0.06	-0.02	-0.07	0.04
Duffy (1988)	1	0.04		0.04	0.04	0.01	-0.05	0.07
Duranton (2016)	123	0.05	0.02	0.01	0.12	-0.12	-0.21	-0.05
Ehrl (2013)	5	0.01	0.03	-0.01	0.06	-0.01	-0.05	0.04
Ehrl (2014)	2	0.00	0.01	-0.00	0.01	-0.06	-0.09	-0.03

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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Ehrl and Monasterio (2016)	5	0.04	0.03	0.01	0.07	0.01	-0.02	0.04
Ehrl and Monasterio (2020)	9	0.02	0.03	0.01	0.10	-0.03	-0.05	-0.00
Ehrlich and Overman (2020)	8	0.07	0.01	0.04	0.08	0.02	-0.03	0.06
Elvery and Sveikauskas (2010)	20	0.01	0.01	-0.00	0.02	-0.08	-0.10	-0.05
Faberman and Freedman (2016)	32	0.03	0.01	0.02	0.08	0.02	-0.00	0.04
Fafchamps and Hamine (2017)	15	-0.03	0.02	-0.06	0.02	-0.05	-0.14	0.03
Fally et al. (2010)	25	0.11	0.04	-0.01	0.17	0.00	-0.03	0.03
Farmanesh (2009)	23	0.32	0.20	0.09	0.62	0.00	-0.08	0.09
Farrokhi and Jinkins (2019)	8	0.04	0.02	0.01	0.07	-0.00	-0.02	0.02
Ferranna et al. (2016)	10	0.08	0.00	0.07	0.08	0.02	-0.01	0.04
Feser (2001)	8	0.00	0.02	-0.02	0.02	-0.06	-0.09	-0.03
Feser (2002)	1	-0.04		-0.04	-0.04	-0.03	-0.11	0.05
Figueroa (2015)	8	0.02	0.02	-0.01	0.04	-0.08	-0.16	0.01
Fingleton (2005)	1	0.55		0.55	0.55	0.06	-0.13	0.27
Fingleton (2006)	8	0.20	0.20	0.03	0.58	-0.01	-0.04	0.02
Fingleton and Fischer (2010)	8	0.24	0.14	0.14	0.57	0.05	-0.04	0.13
Fingleton and Longhi (2013)	64	0.07	0.50	-1.20	1.65	0.02	-0.01	0.04
Florida et al. (2012)	48	0.03	0.02	-0.00	0.07	-0.02	-0.04	-0.00
Fontes et al. (2010)	2	0.07	0.01	0.06	0.08	0.03	-0.00	0.06
Foster and Stehrer (2009)	28	0.07	0.07	-0.02	0.21	-0.06	-0.11	-0.01
Fu and Hong (2011)	43	-0.02	0.22	-0.70	0.21	-0.04	-0.08	-0.01
Fu and Ross (2013)	20	0.02	0.02	0.01	0.07	-0.05	-0.07	-0.03
Fuchs (2011)	5	0.03	0.10	-0.14	0.10	-0.04	-0.08	-0.00
Gabe and Abel (2011)	21	0.05	0.02	0.02	0.09	-0.04	-0.06	-0.02
García (2018)	48	0.01	0.02	-0.04	0.04	-0.16	-0.25	-0.09
Gaubert (2018)	23	0.05	0.07	-0.06	0.20	-0.05	-0.10	0.01
Georgiadis and Kaplanis (2020)	58	0.02	0.05	-0.01	0.21	-0.03	-0.06	-0.00
Gerritse and Arribas-Bel (2018)	6	0.04	0.01	0.03	0.05	-0.01	-0.03	0.01
Glaeser and Gottlieb (2009)	4	0.07	0.04	0.04	0.13	0.00	-0.03	0.06
Glaeser and Resseger (2010)	9	0.05	0.04	0.02	0.13	-0.02	-0.04	0.01
Gómez-Antonio and Fingleton (2012)	6	0.18	0.07	0.14	0.32	0.09	0.06	0.12
Gorter and Kok (2009)	3	0.26	0.05	0.23	0.31	0.13	0.07	0.20
Graham (2000)	12	0.04	0.12	-0.17	0.29	0.00	-0.03	0.03
Graham (2006)	36	0.19	0.14	-0.04	0.50	0.08	0.04	0.11
Graham (2007)	28	0.11	0.13	-0.19	0.38	0.02	-0.03	0.06
Graham (2009)	27	0.10	0.14	-0.22	0.36	0.02	-0.02	0.06
Graham and van Dender (2011)	14	0.07	0.12	-0.16	0.34	0.04	-0.00	0.08
Graham, Melo et al. (2010)	88	0.04	0.04	-0.01	0.20	-0.03	-0.06	-0.00
Groot and de Groot (2020)	16	0.05	0.03	0.02	0.11	-0.01	-0.07	0.05
Groot, de Groot and Smit (2014)	6	0.03	0.01	0.02	0.05	-0.01	-0.07	0.05
Grujovic (2018)	6	0.04	0.02	0.01	0.07	-0.04	-0.07	-0.01
Guevara et al. (2015)	3	0.07	0.05	0.03	0.12	0.03	-0.05	0.11
Håkansson and Isacsson (2019)	30	0.01	0.01	-0.00	0.04	-0.02	-0.06	0.02
Hamann et al. (2019)	42	0.02	0.02	-0.05	0.07	-0.02	-0.05	0.01
Hanson (2005)	21	0.32	0.14	0.13	0.57	0.16	0.13	0.19
Harasztosi and Békés (2010)	27	0.07	0.03	0.04	0.17	-0.03	-0.11	0.05
Harris and Ioannides (2000)	36	0.05	0.03	0.01	0.11	-0.02	-0.05	0.00
Hasan et al. (2017)	72	0.03	0.06	-0.10	0.20	-0.04	-0.07	-0.01

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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Hashiguchi and Tanaka (2015)	3	0.01	0.01	-0.00	0.03	-0.07	-0.11	-0.02
He (2013)	10	0.03	0.01	0.02	0.04	-0.09	-0.12	-0.06
Head and Mayer (2006)	14	0.12	0.06	0.03	0.20	-0.04	-0.12	0.05
Henderson (1986)	52	0.00	0.09	-0.37	0.18	-0.02	-0.05	0.00
Henderson (2003)	8	0.02	0.12	-0.14	0.19	0.00	-0.08	0.07
Hering and Poncet (2009)	18	-0.06	0.31	-1.09	0.27	-0.13	-0.16	-0.09
Hering and Poncet (2010a)	3	0.04	0.08	-0.05	0.09	-0.10	-0.15	-0.05
Hering and Poncet (2010b)	21	0.13	0.16	-0.01	0.79	-0.06	-0.09	-0.02
Hirsch et al. (2020)	36	0.02	0.01	0.01	0.04	-0.05	-0.08	-0.02
Holl (2012)	27	0.05	0.03	-0.08	0.10	-0.02	-0.04	0.01
Holl (2014)	16	0.02	0.03	0.00	0.08	-0.03	-0.06	-0.00
Holl (2016)	18	0.03	0.07	-0.00	0.26	-0.06	-0.08	-0.03
Huang and Xiong (2018)	12	0.09	0.15	-0.03	0.39	-0.16	-0.20	-0.13
Isacsson et al. (2015)	12	0.01	0.02	-0.02	0.04	-0.05	-0.09	-0.00
Iturra (2018)	2	0.04	0.03	0.02	0.05	-0.03	-0.10	0.05
Jamaldeen (2015)	11	0.07	0.04	0.03	0.14	-0.01	-0.08	0.07
Jianyong (2007)	4	0.07	0.02	0.05	0.09	-0.04	-0.08	0.00
Kamal et al. (2012)	26	0.39	0.23	-0.03	0.68	0.12	0.08	0.17
Kanemoto et al. (1996)	10	0.08	0.09	0.00	0.25	-0.02	-0.06	0.01
Keisuke (2017)	28	0.03	0.02	0.00	0.09	-0.07	-0.11	-0.03
Khoirunurrofik (2014)	156	0.05	0.20	-1.91	0.66	-0.04	-0.10	0.03
Kiso (2005)	15	0.51	0.25	0.16	1.04	0.16	0.05	0.27
Klaesson and H. Larsson (2013)	10	0.02	0.01	0.01	0.05	-0.06	-0.10	-0.01
Knaap (2006)	6	0.18	0.07	0.11	0.26	0.05	0.02	0.11
Konings and Torfs (2011)	3	0.07	0.01	0.06	0.08	0.00	-0.08	0.09
Koritsky et al. (2018)	12	0.02	0.03	-0.03	0.05	-0.03	-0.11	0.04
Kosfeld and Eckey (2010)	21	0.08	0.07	0.01	0.23	-0.04	-0.07	-0.01
Koster et al. (2014)	11	0.06	0.03	0.02	0.13	-0.12	-0.25	0.01
Krashinsky (2011)	22	0.02	0.02	-0.01	0.06	-0.02	-0.05	-0.00
Lall et al. (1999)	18	0.02	0.05	-0.03	0.15	-0.07	-0.11	-0.03
Lamorgese et al. (2018)	16	0.06	0.12	0.00	0.44	-0.04	-0.09	0.01
Lamorgese et al. (2019)	11	0.01	0.01	0.00	0.04	-0.03	-0.07	0.02
J. P. Larsson (2014)	12	0.01	0.01	-0.00	0.01	-0.04	-0.09	-0.00
Le Néchet et al. (2012)	8	0.02	0.01	-0.00	0.05	-0.04	-0.09	0.02
B. S. Lee et al. (2010)	45	-0.01	0.03	-0.08	0.07	0.02	-0.05	0.09
Y. J. Lee, Yuhn et al. (2007)	49	-0.00	0.06	-0.11	0.20	-0.05	-0.12	0.03
Y. J. Lee and Zang (1998)	57	-0.00	0.03	-0.04	0.14	-0.03	-0.10	0.04
C. Li and Gibson (2014)	14	0.08	0.09	-0.07	0.23	-0.03	-0.08	0.01
C. Li (2010)	18	0.04	0.02	0.01	0.08	-0.09	-0.12	-0.06
H. Li et al. (2019)	32	0.21	0.11	-0.00	0.37	0.17	0.14	0.20
X. Li (2015)	40	0.11	0.04	0.01	0.20	-0.01	-0.04	0.03
Y. Li (2008)	38	0.46	0.25	0.12	0.97	0.14	0.07	0.21
Y. Li and X. Liu (2018)	4	0.03	0.00	0.03	0.04	-0.04	-0.07	-0.00
Lin and Truong (2012)	11	0.15	0.05	0.05	0.22	0.03	-0.01	0.07
S. Liu (2017)	30	-0.07	0.10	-0.34	0.09	-0.13	-0.18	-0.01
Lobko (2012)	6	0.04	0.00	0.04	0.05	-0.04	-0.11	0.04
Lobo et al. (2014)	4	0.07	0.01	0.06	0.07	0.02	-0.00	0.05
López-Rodríguez and Acevedo (2008)	16	0.82	0.32	0.54	1.63	0.68	0.59	0.75

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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
López-Rodríguez, Faiña et al. (2011)	9	0.10	0.02	0.07	0.12	-0.03	-0.12	0.05
López-Rodríguez and Faiña (2006)	5	0.50	0.14	0.33	0.71	0.28	0.18	0.36
López-Rodríguez and Faiña (2007)	8	0.38	0.12	0.23	0.57	0.18	0.10	0.26
López-Rodríguez, Márquez et al. (2008)	3	0.50	0.66	0.08	1.26	0.01	-0.05	0.08
Louri (1988)	5	0.05	0.00	0.04	0.05	0.01	-0.08	0.09
Lovely et al. (2019)	21	0.14	0.11	-0.17	0.28	0.02	-0.03	0.06
Maré and Graham (2013)	120	0.06	0.05	-0.10	0.22	-0.05	-0.11	0.02
Maré (2008)	90	0.32	0.33	-0.41	1.75	0.14	0.07	0.20
Maré and Fabling (2013)	16	0.06	0.18	0.01	0.75	-0.08	-0.14	-0.02
Maré and Timmins (2006)	47	0.04	0.15	-0.65	0.45	-0.02	-0.09	0.04
Martin et al. (2011)	29	-0.13	0.23	-0.86	0.14	-0.03	-0.08	0.03
Martín-Barroso et al. (2010)	49	0.05	0.01	0.03	0.10	-0.03	-0.06	0.00
Martínez-Galarraga et al. (2008)	4	0.02	0.02	-0.00	0.04	-0.03	-0.06	0.00
Matano and Naticchioni (2012)	44	0.01	0.01	0.00	0.02	-0.02	-0.07	0.03
Matano, Obaco et al. (2020)	82	0.06	0.05	-0.11	0.16	0.01	-0.05	0.07
Matas et al. (2015)	16	0.07	0.01	0.05	0.08	-0.00	-0.03	0.03
Mathä and Shwachman Kaminaga (2017)	11	0.34	0.40	0.09	1.45	-0.06	-0.11	-0.01
McCoy and Moomaw (1995)	8	0.27	0.17	0.06	0.58	0.20	0.05	0.33
Meijers (2013)	12	0.06	0.04	0.03	0.13	-0.01	-0.04	0.01
Meijers and Burger (2010)	4	0.09	0.02	0.07	0.11	0.06	0.03	0.10
Merkel and Holmgren (2020)	18	0.08	0.05	0.04	0.17	-0.00	-0.05	0.04
Midelfart (2004)	12	0.03	0.01	0.02	0.05	-0.04	-0.10	0.02
Mion (2004)	6	0.32	0.16	0.15	0.52	0.18	0.08	0.28
Mion and Naticchioni (2009)	7	0.01	0.01	0.00	0.02	-0.01	-0.06	0.03
Monkkonen et al. (2020)	13	-0.05	0.13	-0.25	0.09	-0.00	-0.05	0.05
Moomaw (1981)	14	0.03	0.01	0.01	0.05	-0.01	-0.03	0.02
Moomaw (1983)	46	0.04	0.06	-0.06	0.32	0.00	-0.02	0.03
Moomaw (1985)	21	0.06	0.06	-0.00	0.27	0.00	-0.02	0.03
Moomaw (1986)	11	0.00	0.02	-0.06	0.03	-0.01	-0.04	0.01
Moreno-Monroy (2008)	6	0.12	0.03	0.07	0.16	-0.02	-0.07	0.04
Moreno-Monroy (2011)	3	0.32	0.06	0.26	0.38	0.13	0.04	0.21
Morikawa (2011a)	20	0.15	0.09	0.07	0.43	0.02	-0.02	0.06
Morikawa (2011b)	7	0.05	0.01	0.04	0.06	-0.06	-0.10	-0.03
Morikawa (2016)	60	0.07	0.06	-0.00	0.27	-0.04	-0.07	0.00
Mudiriza and Edwards (2021)	29	0.19	0.09	0.01	0.34	0.05	-0.04	0.14
Mukkala (2004)	3	0.10	0.05	0.06	0.15	0.03	-0.06	0.12
Nabavi (2015)	54	0.01	0.01	-0.01	0.04	-0.05	-0.09	-0.00
Nakamura (1985)	38	0.03	0.03	-0.04	0.08	-0.03	-0.07	0.00
Nakamura (2008a)	10	0.11	0.07	0.03	0.23	0.03	-0.00	0.07
Nakamura (2008b)	42	0.02	0.02	-0.04	0.07	-0.02	-0.06	0.02
Nakamura (2012)	30	0.08	0.11	-0.06	0.49	-0.00	-0.04	0.04
Neffke et al. (2011)	19	0.03	0.05	-0.06	0.14	0.02	-0.04	0.06
Neves Jr et al. (2017)	8	0.03	0.01	0.01	0.04	-0.02	-0.05	0.00
Niebuhr (2004)	4	0.18	0.01	0.17	0.19	0.02	-0.03	0.07
Niebuhr (2006)	25	0.03	0.10	-0.16	0.20	-0.08	-0.17	0.01
Nilsen et al. (2017)	6	0.09	0.07	0.02	0.16	-0.01	-0.07	0.06
Noonan et al. (2020)	6	0.06	0.01	0.06	0.08	0.02	-0.06	0.11
Norman and Öner (2010)	6	0.03	0.02	0.01	0.06	-0.04	-0.08	0.01

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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Öner (2018)	13	0.30	0.25	-0.04	0.77	0.17	0.09	0.25
van Oort and Bosma (2013)	16	0.03	0.03	-0.06	0.10	-0.01	-0.09	0.07
Otsuka (2017)	2	0.28	0.01	0.27	0.29	0.17	0.09	0.24
Otsuka (2018)	4	0.31	0.03	0.27	0.34	0.23	0.17	0.28
Otsuka, Goto et al. (2010)	2	0.03	0.02	0.01	0.04	-0.06	-0.10	-0.01
Otsuka and Yamano (2008)	6	0.03	0.01	0.02	0.04	-0.04	-0.08	-0.00
Özgüzel (2020a)	14	0.01	0.00	0.00	0.01	-0.02	-0.05	0.00
Özgüzel (2020b)	47	0.06	0.01	0.04	0.07	-0.00	-0.07	0.07
Paluzie et al. (2009)	4	0.11	0.03	0.08	0.14	0.01	-0.03	0.05
Pan et al. (2016)	36	0.10	0.06	0.01	0.23	-0.04	-0.07	-0.00
Papageorgiou (2013)	5	0.04	0.02	0.02	0.06	-0.03	-0.06	-0.00
Paredes (2015)	10	0.02	0.00	0.02	0.03	-0.06	-0.13	0.01
Peng (2019)	10	0.10	0.05	0.04	0.19	0.01	-0.02	0.05
Pires (2006)	60	0.41	0.35	0.08	1.39	0.07	0.03	0.11
Prud'homme and C.-W. Lee (1999)	6	0.17	0.04	0.13	0.24	0.10	0.04	0.16
Quintero and Roberts (2018)	4	0.02	0.02	0.01	0.06	-0.05	-0.13	0.04
Rasekhi and Rostami (2013)	2	0.09	0.27	-0.10	0.28	0.02	-0.16	0.19
Rawnsley and Szafraneic (2010)	13	0.10	0.13	-0.14	0.37	0.01	-0.07	0.09
Rice et al. (2006)	46	0.03	0.02	-0.04	0.07	0.00	-0.02	0.03
Rigby and Brown (2015)	16	-0.14	0.12	-0.30	0.08	-0.13	-0.21	-0.04
Robbins (2006)	4	0.15	0.24	-0.06	0.42	-0.07	-0.15	0.07
Roberts et al. (2012)	6	0.20	0.08	0.14	0.36	0.05	-0.00	0.12
Rosenthal and Strange (2008)	9	0.04	0.01	0.03	0.06	-0.03	-0.05	-0.00
Rosero and Del Pozo (2020)	8	0.06	0.03	0.02	0.12	0.01	-0.05	0.07
Saito and Gopinath (2009)	1	0.07		0.07	0.07	0.02	-0.08	0.12
Saleh (2014)	102	0.03	0.03	-0.04	0.14	-0.04	-0.10	0.02
Shioji et al. (2005)	16	0.06	0.10	-0.04	0.42	-0.01	-0.04	0.03
Simões and Freitas (2014)	4	0.08	0.02	0.05	0.09	0.02	-0.01	0.05
Soroka (1994)	124	0.02	0.05	-0.09	0.19	-0.00	-0.07	0.06
de Sousa and Poncet (2011)	26	-0.38	0.52	-1.45	0.11	-0.12	-0.16	-0.09
Spanos (2019)	294	0.06	0.04	-0.03	0.29	0.00	-0.05	0.06
Sun et al. (2018)	1	0.04		0.04	0.04	-0.02	-0.05	0.01
Sveikauskas (1975)	42	0.06	0.03	0.01	0.12	0.00	-0.02	0.03
Sveikauskas et al. (1988)	8	0.01	0.00	0.01	0.02	-0.02	-0.05	0.01
Tabuchi (1986)	38	0.05	0.08	-0.08	0.30	-0.02	-0.05	0.02
Tabuchi and Yoshida (2000)	1	0.10		0.10	0.10	0.04	-0.07	0.13
Tao et al. (2019)	30	-0.06	0.14	-0.29	0.31	-0.17	-0.21	-0.12
Teulings et al. (2014)	18	0.02	0.02	-0.01	0.06	-0.07	-0.13	-0.01
Tian (2019)	20	0.05	0.05	0.00	0.17	-0.03	-0.06	0.00
Trubka (2011)	602	0.09	0.09	-0.17	0.57	-0.01	-0.08	0.06
Turgut (2014)	71	0.04	0.05	0.01	0.20	-0.09	-0.16	-0.02
Tveter (2018)	16	0.07	0.13	-0.01	0.53	-0.04	-0.10	0.03
Vakhitov (2008)	4	-0.10	0.32	-0.54	0.15	0.03	-0.07	0.12
Verstraten et al. (2019)	39	-0.01	0.12	-0.59	0.14	-0.03	-0.09	0.03
C.-Y. Wang and Haining (2017)	9	0.28	0.20	0.01	0.65	0.08	0.03	0.12
Wetwitoo and Kato (2017)	27	0.05	0.23	-0.42	0.94	-0.08	-0.13	-0.04
Wheeler (2001)	5	0.02	0.01	0.00	0.04	-0.02	-0.04	-0.00
Wibowo and Kudo (2019)	7	-0.41	0.37	-0.80	0.02	-0.06	-0.16	0.03

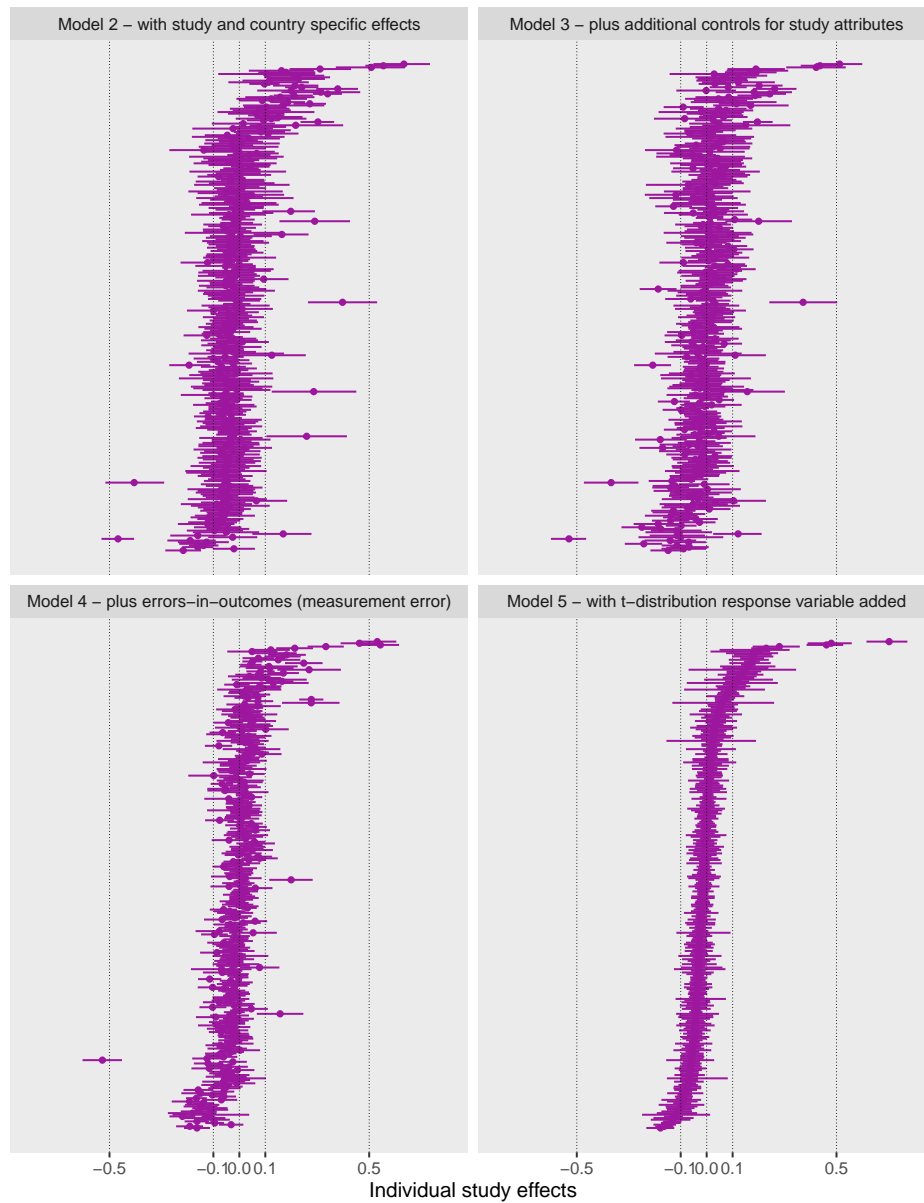
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Authors	n	$\bar{y}_s$	SD	$y_s^{\min}$	$y_s^{\max}$	$\zeta_s$	$\zeta_s^{\min}$	$\zeta_s^{\max}$
Widya et al. (2019)	4	0.22	0.32	-0.06	0.60	-0.02	-0.12	0.10
Williamson et al. (2008)	3	0.09	0.01	0.09	0.10	-0.03	-0.09	0.03
Wixe (2015)	2	0.03	0.01	0.02	0.03	0.06	0.01	0.11
Yang (2018)	58	0.02	0.05	-0.08	0.15	-0.10	-0.13	-0.06
Ženka et al. (2015)	3	0.09	0.03	0.06	0.11	0.01	-0.08	0.09
Zhang (2016)	20	-0.12	0.10	-0.33	0.02	-0.18	-0.24	-0.13
Zheng et al. (2009)	4	0.07	0.03	0.04	0.11	-0.01	-0.05	0.04
Zierahn and Michaelis (2012)	1	0.12		0.12	0.12	0.02	-0.04	0.07
Ziv (2015)	2	0.01	0.00	0.01	0.01	-0.07	-0.09	-0.04

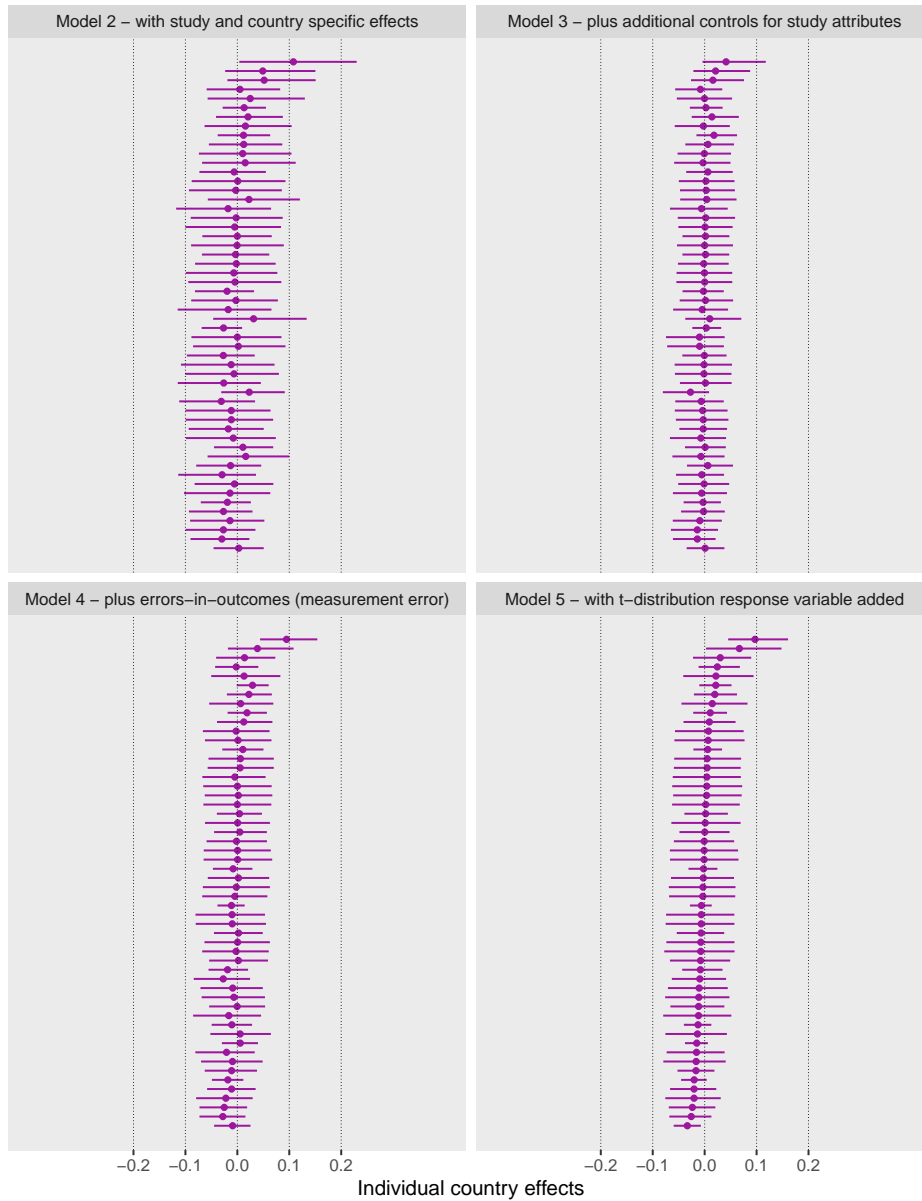
## C. Individual Study and Country Effects

### C.1. Individual Study Effects



**Figure 9:** Individual study effects for **Model (2)** (top-left panel), **Model (3)** (top-right panel), **Model (4)** (bottom-left panel), and **Model (5)** (bottom-right panel).

## C.2. Individual Country Effects



**Figure 10:** Individual country effects for **Model (2)**, top-left panel; **Model (3)**, top-right panel; **Model (4)**, bottom-left panel; and **Model (5)**, bottom-right panel. For **Model (5)**, countries listed from largest to smallest country effects are: South Korea, Germany, Romania, Ireland, Indonesia, Sweden, U.S., Ukraine, Russia, Asia / Latin America, Guatemala, OECD-5, New Zealand, Italy, Norway, Hungary, Czechia, Mexico, EU-26, EU-27, EU-16, Africa, EU-20, Brazil, Belgium, Ecuador, EU-new (2004), Australia, France, Japan, EU-11, U.K., Colombia, Africa / Asia / Latin America, EU-14, EU-17, Spain, EU-5, Chile, South Africa, China, EU-15, EU-21, Netherlands, Poland, Canada, Iran, South America, Finland, Turkey, Greece, India, EU-25, and Morocco. For further details on the studies associated with combinations of countries, please contact the authors.

## D. Additional Sensitivity Tests

Table D: Meta-analysis regression results—Additional sensitivity tests

Attribute	Level	Model (5)	Column 2	Column 3	Column 4	Column 5
Intercept		0.112*** (0.012)	0.108*** (0.010)	0.112*** (0.012)	0.109*** (0.013)	0.113*** (0.012)
Sector	Manufacturing	-0.006** (0.002)	-0.006*** (0.002)	-0.006*** (0.002)	-0.006** (0.002)	-0.007** (0.003)
	Service	-0.000 (0.002)	-0.000 (0.002)	-0.000 (0.002)	0.000 (0.002)	0.004 (0.002)
Published	Yes	-0.021* (0.013)	-0.013 (0.010)	-0.021* (0.012)	-0.025* (0.013)	-0.024* (0.013)
Micro-data	Yes	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003 (0.002)	-0.002 (0.002)
Panel data	Yes	0.000 (0.002)	-0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	-0.000 (0.002)
Dependent variable	Lab. Prod.	-0.011*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)	-0.010*** (0.003)	-0.011*** (0.003)
	Wages	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.000 (0.002)
	Output	-0.000 (0.011)	0.001 (0.011)	-0.000 (0.011)	0.001 (0.014)	-0.003 (0.012)
	Rents	0.107 (0.068)	0.107** (0.052)	0.109 (0.068)	0.106 (0.072)	0.105 (0.067)
Agg. indicator	Monetary	0.017*** (0.004)	0.019*** (0.004)	0.017*** (0.004)	-0.004 (0.003)	0.017*** (0.004)
Agg. measure	Density	0.003** (0.001)	0.003** (0.001)	0.003** (0.001)	0.006*** (0.001)	0.003** (0.001)
	Isochrone	-0.008*** (0.003)	-0.008*** (0.003)	-0.008*** (0.003)	0.000 (0.002)	-0.008*** (0.003)
	Potential	-0.007*** (0.002)	-0.008*** (0.002)	-0.007*** (0.002)	0.001 (0.002)	-0.007*** (0.002)
Secondary measure	Yes	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
	Magnitude	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)	-0.040*** (0.003)
Worker effects	Yes	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)	-0.011*** (0.001)
Firm effects	Yes	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.005* (0.003)	-0.003 (0.003)
Sectoral controls	Yes	-0.002* (0.001)	-0.002* (0.001)	-0.002* (0.001)	-0.003** (0.001)	-0.002* (0.001)
Occ. controls	Yes	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)
Time controls	Yes	-0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Geo. controls	Yes	0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)

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Attribute	Level	Model (5)	Column 2	Column 3	Column 4	Column 5
Own skills	Yes	−0.009*** (0.001)	−0.009*** (0.001)	−0.009*** (0.001)	−0.008*** (0.001)	−0.009*** (0.001)
Labour ( <i>L</i> ) inputs	Yes	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)	0.002 (0.002)
Capital ( <i>K</i> ) inputs	Yes	−0.001 (0.002)	−0.001 (0.002)	−0.002 (0.002)	−0.001 (0.002)	−0.002 (0.002)
<i>K/L</i> ratio	Yes	−0.024*** (0.005)	−0.021*** (0.005)	−0.024*** (0.005)	−0.024*** (0.005)	−0.024*** (0.005)
Human capital	Yes	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)
Social capital	Yes	−0.008*** (0.002)	−0.007*** (0.002)	−0.008*** (0.002)	−0.008*** (0.002)	−0.008*** (0.002)
Housing	Yes	−0.038*** (0.004)	−0.038*** (0.004)	−0.038*** (0.004)	−0.038*** (0.004)	−0.038*** (0.004)
Spatial scope	Metro	−0.019*** (0.002)	−0.019*** (0.002)	−0.019*** (0.002)		−0.019*** (0.002)
	Regional	−0.008** (0.003)	−0.007** (0.003)	−0.008** (0.003)		−0.008*** (0.003)
	National	0.012*** (0.004)	0.012*** (0.004)	0.012*** (0.004)		0.010*** (0.004)
	International	0.065*** (0.008)	0.067*** (0.008)	0.065*** (0.008)	0.070*** (0.007)	0.064*** (0.008)
Wages	Yes	−0.012*** (0.002)	−0.012*** (0.002)	−0.012*** (0.002)	−0.017*** (0.003)	−0.010*** (0.002)
Localisation	Yes	0.003 (0.002)	0.003* (0.002)	0.003* (0.002)	0.002 (0.002)	0.003** (0.002)
Input links	Yes	−0.021** (0.008)	−0.022*** (0.008)	−0.021** (0.008)	−0.021** (0.008)	−0.021** (0.008)
Innovation	Yes	−0.012** (0.006)	−0.012** (0.006)	−0.012** (0.006)	−0.014** (0.005)	−0.012** (0.006)
Diversity	Yes	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
Competition	Yes	−0.031** (0.012)	−0.030** (0.011)	−0.031** (0.012)	−0.031** (0.012)	−0.033** (0.012)
IV	Yes	−0.003*** (0.001)	−0.004*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
Hyper-parameters	Studies ( $\sigma_s^2$ )	0.092*** (0.005)	0.069*** (0.006)	0.092*** (0.005)	0.098*** (0.005)	0.093*** (0.005)
	Countries ( $\sigma_c^2$ )	0.034*** (0.009)	0.030*** (0.007)	0.035*** (0.009)	0.038*** (0.009)	0.035*** (0.009)
	DOF ( $\nu$ )	1.760*** (0.049)	1.720*** (0.047)	1.759*** (0.049)	1.745*** (0.049)	1.751*** (0.048)
Section reference			S. 4.2.2	S. 4.2.5	S. 5	S. 5
Model performance	PSIS-LOO	−22, 652	−22, 652	−22, 659	−22, 542	−22, 702
	$R^2$	0.262	0.360	0.263	0.263	0.263

Notes: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. All models use the benchmark sample, which has 6,684 observations.

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