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WHICH AGGLOMERATION EXTERNALITIES MATTER MOST AND WHY?

Henri L.F. de Groot*

VU University Amsterdam
Tinbergen Institute
Ecorys

Jacques Poot

University of Waikato

Martijn J. Smit

VU University Amsterdam
Utrecht University

Abstract. This paper revisits the ongoing discussion on the importance of agglomeration externalities – specifically specialization, diversity and competition effects – that may contribute to innovation, productivity and urban employment growth. Previous meta-analyses suggested that the evidence on agglomeration externalities is strongly context-specific. Expanding an earlier analysis of 31 articles, we seek to draw in this paper more robust conclusions by means of the statistical evidence for agglomeration externalities presented in 73 scientific articles, all building on the seminal work of Glaeser *et al*. (1992). Our results confirm that the heterogeneity among studies is huge and can only be partially accounted for by means of an ordered probit analysis. Additionally, some evidence of publication bias is found. We conclude that the conventional lines of inquiry in this literature may now have reached strongly diminishing returns. New lines of inquiry, using rich micro-level data on firms and workers, dynamic general equilibrium models at the macro level, more attention for spatial and temporal variation in the impacts of agglomeration, and further investigations into the spatial scope of externalities are promising avenues for further research that can enhance our understanding of how agglomeration externalities continue to fuel our increasingly urbanized world.

Keywords. Agglomeration; Competition; Diversity; Meta-analysis; Specialization; Urban growth

1. Introduction

Researchers, and the general public alike, are fascinated by the ever-increasing urbanization of the world's population. It is well known that the world's urban population has exceeded half of the total population since 2008 and that two thirds of the world population are expected to live in cities by the middle of this century. Of course not all cities are prospering everywhere: population ageing and

*Corresponding author contact email: h.l.f.de.groot@vu.nl; Tel: +31 20 598 6168.

deindustrialization in parts of the developed world have led to some cities facing demographic and economic decline. Nonetheless, the emergence of many new mega cities in the developing world and the increasing economic and demographic dominance of many large cities in developed nations are generally seen as major drivers of global economic prosperity and wellbeing. This has prompted authors such as Glaeser (2011) to refer to this global transformation as the "triumph of the city". Urban agglomeration – in which economic benefits are reaped from production and consumption activities taking place in dynamically diverse, geographically concentrated, and fiercely competitive, urban spaces – appears to be one of the key drivers of growth and well-being in the 21st century.

But how important are such agglomeration effects? The seminal contribution by Glaeser *et al.* (1992) sparked a large volume of empirical research that has tried to identify the roles of industrial concentration and specialization (Marshall-Arrow-Romer or 'MAR' externalities, originating from Marshall, 1890), economic and social diversity leading to cross-sectoral spillovers (Jacobs externalities, after Jacobs, 1969), and the intensity of competition (Porter externalities, after Porter, 1990). However, this research endeavour has only been partially successful. Glaeser (2000) concluded that the relative importance of such externalities remains largely unresolved and more recently Glaeser and Gottlieb (2009) concluded that estimating the magnitude of agglomeration economies is difficult.

Given the large number of empirical estimates of agglomeration externalities reported in the literature, it is not surprising that this prompted several surveys and meta-analyses. Beaudry and Schiffauerova (2009) reviewed 67 articles and found, based on simple frequency counts of the different types of evidence, that about 70% of these studies show evidence of MAR externalities (a positive impact of specialization) whereas about 75% suggest that Jacobs externalities matter (a positive impact of diversity). A much smaller set of studies informed additionally on the benefits of competition. Beaudry and Schiffauerova conclude that the wide range of results that they find can be attributed to several measurement and methodological issues.

However, to see how such issues matter quantitatively requires a formal meta-regression analysis, for which several econometric procedures have now become widely known and applied; see, for example, Stanley and Doucouliagos (2012), Ringquist (2013) and Poot (2014). Melo *et al.* (2009) apply OLS and random effects meta-regression analysis to 729 elasticities (from 34 studies) of urban outcomes with respect to agglomeration measures. They find an average density elasticity of 0.058, which is consistent with Rosenthal and Strange's (2004) prediction that doubling urban population increases productivity by between 3% and 8%. Nonetheless, Melo *et al.* (2009) conclude that the size of the agglomeration externality is rather context specific. Additionally, their study does not inform on the differential impacts of specialization, competition and diversity in these agglomeration effects. To address the latter issue, we applied in De Groot *et al.* (2009) meta-regressions in the form of ordered probit models to estimate what determines the statistical significance of the different types of agglomeration externalities. We used 393 different estimates from 31 articles in the 'growth in cities' literature that emerged following the publication of the seminal paper by Glaeser *et al.* (1992).

We found, consistent with other surveys and meta-analyses, that there is considerable temporal, sectoral and spatial heterogeneity in the effects of specialization, competition and diversity on urban growth. The question therefore arises whether a larger sample would provide more definitive answers, or at least give some indication of what kind of evidence would inform policies concerned with urban growth. In the present paper we seek to draw more robust conclusions from this literature by means of the statistical evidence for agglomeration externalities presented in such a larger sample: 73 scientific articles that yielded 787 estimates of the statistical significance of agglomeration externalities on growth. These are referred to as 'effect sizes' in meta-analysis. These cover not only more recent results, but also a wider range of cases in terms of sectors and (developing and developed) countries.

For each type of externality we identify how various aspects of primary study design, such as the adopted proxy for growth, the data used, and the choice of covariates influence the outcomes. Given the heterogeneity of the 73 studies in this non-experimental literature, there is no common dimensionless measure such as an elasticity that can be used to identify between-study variation for each type of agglomeration externality. We therefore gauge the strength of the evidence by means of the reported statistical significance and link these effect sizes to study characteristics by means of an ordered probit analysis. There have been several other precedents for such an approach, including our earlier paper (De Groot *et al.*, 2009) but also the study by Card *et al.* (2010) on the effectiveness of active labour market policies and Koetse *et al.* (2009) on the impact of uncertainty on investment behaviour. However, additionally we run meta-regressions of reported t-statistics, and of the corresponding Fisher's z-statistics, on study characteristics. This constitutes a useful robustness check of our main findings. The statistical significance of various study characteristics in the meta-regressions highlights again the heterogeneity of the empirical research in this field and the impact of the observed heterogeneity on the findings.

Broadly speaking, our effect sizes are most supportive of the positive impact of competitive forces in the urban economy when we simply measure the share of studies that yield positive and statistically significant results. With respect to the impact of specialization, positive and negative impacts appear to be equally prevalent. A sizeable amount of evidence also points to the positive impact of diversity. Thus, our meta-analysis of nearly a quarter-century of research on this topic appears to reinforce the conclusion of Glaeser *et al.* (1992), as we find that up to 50% of the literature concludes that local competition and urban variety rather than regional specialization encourage employment growth in industries. The aim of this meta-analysis is to replace these observations based on simple vote counting by formal statistical analyses that enable us to identify the sources of heterogeneity and disparate conclusions in previously obtained results.

Our results suggest that specialization impacts more positively on lower density places, which are likely to be mid-sized manufacturing-oriented cities; and that the specialization effect is stronger when growth is measured in terms of output. In regressions that focus on patents or innovations, the positive effect of specialization is stronger, while for competition it is the opposite. Diversity externalities impact positively on urban growth throughout the world especially in more recent times, and particularly in Asia (as compared to Europe). Studies that were published more recently tend to be more supportive of specialization externalities and less of diversity externalities. We will argue that this suggests the presence of publication bias among more recent studies.

We conclude that the conventional lines of inquiry in this literature may now have reached strongly diminishing returns. New lines of inquiry, using rich micro- and multi-level data on firms and workers (e.g., Van Oort *et al.*, 2012), dynamic general equilibrium models at the macro level (Davis *et al.*, 2014), more attention for spatial and temporal variation in the impacts of agglomeration, and further investigations into the spatial scope of externalities are promising avenues for further research that can enhance our understanding of how agglomeration externalities continue to fuel our increasingly urbanized world.

In the next section, we concisely review the research strategies that have been adopted in the empirical literature to estimate the impact of agglomeration externalities on (urban) growth and development. Section 3 describes the dataset underlying our meta-analysis. Section 4 provides a descriptive summary of the studies and discusses the results of the meta-regression analyses. The final section sums up and suggests ways in which this literature can be fruitfully developed further.

2. Measuring the Growth Impact of Agglomeration Externalities

Glaeser *et al.* (1992) posited that the composition of labour inputs in a city provides proxies of measures that might be indicative of MAR, Porter and Jacobs externalities. Urban growth is in their model measured by employment growth. It is assumed that labour mobility is costless and therefore represents the force that leads to spatial equilibrium. In each region, industry-specific measures are constructed for specialization and competition. Glaeser *et al.*'s diversity measure also varies across industries: they use the fraction of region r's employment in the five largest industries other than industry i. Most subsequent studies, however, do not measure diversity in an industry-specific way. It should also be noted that in this model spatial dependence is not explicitly taken into account by means of spatial econometrics. Some later studies model spatial dependence more explicitly (e.g., Duranton and Overman, 2005; Jofre-Monseny, 2009).

Glaeser *et al*. (1992) argue that the way in which specialization, competition and diversity affect urban growth depends on the externality theory considered. For example, specialization has under MAR-type theories of agglomeration externalities a positive impact on productivity. Moreover, in these theories innovation is typically undertaken by large and dominant firms that can internalize the knowledge externalities. The impacts of competition and of diversity on growth are then negative. Porter (1990) views specialization and competition as positive agglomeration forces, but not diversity, as it reduces the benefits from industrial clustering. In contrast, Jacobs (1969) emphasized the positive impact of competition and diversity, while downplaying the benefit of specialization.

Glaeser *et al*. (1992) assume a simple Cobb-Douglas production function, and wages that are set equal to the value of the marginal product, and such that they equilibrate labour markets spatially. These assumptions can be easily shown to lead to a regression equation in which the growth in employment in industry i and region r is a function of national real wage growth (a negative effect), national trends in technology and prices, industry fixed effects and measures of specialization, competition and diversity (see, for example, De Groot *et al*., 2009).

In order to test the empirical relevance of various agglomeration externalities, a dataset was constructed of growth rates of employment in a range of US Metropolitan Statistical Areas (MSAs) and mature industries. Overall, the results of the Glaeser *et al.* study appear particularly consistent with the Jacobs perspective. The effect of specialization as proxied by the location quotient of the city-industry was significantly negative.

The study by Glaeser *et al*. (1992) was extended in many directions. It has been applied to different countries and time periods, at different levels of spatial aggregation. Moreover, different proxies for the externalities have been used, growth has been operationalized in different ways, different estimation techniques have been used, etc. Not surprisingly, these different approaches have led to different conclusions on the relevance of the various externalities in explaining growth. This literature has been previously summarized qualitatively and quantitatively by Beaudry and Schiffauerova (2009), De Groot *et al*. (2009), Melo *et al*. (2009) and Combes and Gobillon (2014). The aim of the remainder of this paper is to provide an updated quantitative synthesis of all of the studies we could retrieve, representing most of the studies conducted (even including some from the non-English literature). We report robust findings on the sources of variation in the observed outcomes and draw conclusions regarding the research agenda that can push this literature forward.

3. Selection and Characterization of Studies

As noted in the introduction, the present paper expands substantially an earlier meta-analysis (De Groot *et al*., 2009), which incorporated only 31 papers instead of the current 73. The much larger sample was achieved by inclusion of papers that became available after the analysis for the 2009 paper was completed, and also because other researchers kindly notified us by e-mail of further studies that had been missed out.[1] Additionally, we improve the analysis by removing a type of heterogeneity that had not been addressed in the previous paper, namely the extent to which effect sizes came from broadly or very narrowly defined industries. Some studies performed separate regressions for one specific sector or a set of sectors. These include highly specific cases, such as the knitwear, apparel or aerospace industries. The heterogeneity among sector-specific regressions is large because these sectors cover a wide range of sizes and different stages of the industry development cycle (Neffke *et al*., 2008). Comparing them could lead to imprecise results with respect to identifying salient factors that influence study outcomes. Of course such heterogeneity can be partially controlled for by introducing sector dummies in meta-regressions. Even though some of these dummies were not statistically significant at the 5% significance level in such regressions,[2] their presence may influence the precision of the coefficients of other explanatory variables (referred to as moderator variables in this literature). Fortunately, the expanded dataset that we compiled for this paper allows us to combine a relatively large number of more homogeneous effect sizes obtained from primary studies that used economy-wide or total manufacturing data. Results for the more heterogeneous set of effect sizes are available in an online Appendix[3] and can be directly compared with the previous results obtained with the smaller dataset in De Groot *et al.* (2009).

In conducting the meta-analysis, we followed the guidelines laid down in Stanley *et al.* (2013). In order to acquire a systematic and representative set of journal articles, we used Web of Science (www.isiknowledge.com) to select all articles that cited either Glaeser *et al.* (1992) or both Porter (1990) and Jacobs (1969).[4] This selection method resulted in a well-defined list, collected in a quick, efficient, and reproducible manner. A consequence of this selection procedure is that it resulted in a list containing only journal articles. Hardly any (as yet) unpublished articles, books or book chapters were included. Furthermore, Web of Science has a bias towards journals written in the English language. To reduce these two disadvantages of our selection method, we used the technique of snowballing, viz. carefully scanning through the references of the articles included, to find additional studies, and we made use of notifications by colleagues of relevant papers to be added to our earlier analysis.

We chose to include in our database only those articles which adopted a quantitative approach and included (equivalents of) the three variables for specialization, diversity and competition that Glaeser *et al.* (1992) introduced. In some cases one or two of the three variables were omitted from a regression; most often this was a competition measure. In total, 73 articles were found to match Glaeser *et al.*'s methodology to a sufficient degree, yielding 787 different estimates.[5] The subset of studies using economy-wide or total manufacturing data is of course smaller but still contains 384 estimates from 188 regressions in 45 articles. We included articles with different dependent variables, and our approach implicitly builds on the assumption that all studies – regardless of the exact definition of their dependent variable – are informative on how agglomeration externalities impact on urban growth. However, we control for the type of dependent variable in the primary regression (growth in employment, output, productivity, patents, etc.) to test whether the choice of dependent variable mattered for statistical significance.

The studies use a wide range of proxies for measuring specialization, competition and diversity. Many studies follow Glaeser *et al.* (1992) in their choices, at least partly, but some other trends can be observed as well. For example, a large number of studies follow Henderson *et al.* (1995) in using a Hirschman-Herfindahl index for diversity. Beaudry and Schiffauerova (2009) give excellent overviews of the different types of proxies used in the literature. We capture the main variants through a series of dummies, to test whether different proxies lead to different outcomes.

The studies show considerable variation in the direction and statistical significance of the effects found. Table 1 provides information on the studies included, the country and spatial unit to which the analysis pertains, the number of regressions provided by each study, whether the study uses sectoral or economy-wide data, and the definition of the dependent variable. It also shows the conclusions found for each of the three agglomeration variables. We see a great variety of results and it is certainly not clear from simple inspection of Table 1 whether the empirical literature is more supportive of MAR, Jacobs or Porter externalities. We therefore turn to a formal meta-analysis in the next section.

4. Meta-Analysis

Following, for example, Card *et al.* (2010) we first categorize all the available effect sizes into three classes, viz. significantly negative, insignificant and significantly positive (adopting a significance level of 10% throughout). These frequency tabulations are depicted in Figure 1. The top half refers to the

Table 1. List of Included Studies and Study Features.

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
Acs and Armington, 2004	full	3	—	○	n.a.	USA	LMAs [2]	employment
Almeida, 2005	full	8	○	+	○	Portugal	concelhos	4× employment, 4× productivity
Andersson *et al.*, 2005	both	12	n.a.	+	++	Sweden	LMAs	patents or innovations
Baltzopoulos, 2009	full	2	++	—	○	Sweden	functional regions	other
Baptista and Swann, 1998	full	9	–	n.a.	+	UK	CSO regions	patents or innovations
Baptista and Swann, 1999	sector	4	+	○	–	2× UK, 2× USA	CSO regions, states	employment
Baten *et al.*, 2005	full	1	+	n.a.	—	Germany	districts	patents or innovations
Batisse, 2002	sector	6	—	○	+	China	provinces	output
Beaudry and Breschi, 2003	full	2	—	n.a.	○	UK, Italy	counties, provinces	patents or innovations
Beaudry, 2009	sector	2	++	n.a.	+	UK	counties	1× patents or innovations, 1× employment
Boix and Trullén, 2007	sector	4	—	n.a.	++	Spain	municipalities	employment

Table 1. *Continued.*

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
Boschma and Weterings, 2005	sector	5	○	n.a.	–	Netherlands	NUTS3	patents or innovations
Bradley and Gans, 1998	sector	1	n.a.	n.a.	—	Australia	cities	employment
Brülhart and Mathys, 2008	full	4	++	n.a.	n.a.	Europe	NUTS3	productivity
Burger *et al.*, 2010	sector	18	○	n.a.	○	Netherlands	NUTS3, LMAs, municipalities	employment
Cainelli and Leoncini, 1999	full	4	++	++	++	Italy	provinces	employment
Carlino *et al.*, 2007	both	18	+	++	–	US	SMAs [1]	patents or innovations
Chen, 2002	full	10	○	○	++	Taiwan	cities	2× productivity, 8× employment
Cingano and Schivardi, 2004	full	3	++/–	–/++	–/++	Italy	LMAs	2× productivity/ 1× employment
Combes, 2000	full	4	—	–	○	France	LMAs	employment
Combes *et al.*, 2004	full	6	n.a.	○	+	France	LMAs	other
Condliffe *et al.*, 2008	full	3	+	n.a.	–	US	counties, states	productivity
Das and Finne, 2008	sector	4	○	n.a.	–	Norway	LMAs	patents or innovations
De Lucio *et al.*, 2002	full	1	–	–	+	Spain	provinces	productivity

Table 1. *Continued.*

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
De Vor and De Groot, 2010	full	3	–	+	n.a.	Netherlands	industrial areas	employment
Deidda *et al.*, 2006	full	2	—	++	+	Italy	LMAs	employment
Dekle, 2002	sector	8	—	○	○	Japan	prefectures	4× employment, 4× productivity
Drucker and Feser, 2007	sector	9	n.a.	+	○	USA	LMAs	output
Feldman and Audretsch, 1999	full	4	—	+	++	USA	SMAs	patents or innovations
Fritsch and Slavtchev, 2007	full	2	n.a.	—	++	Germany	Raumordungs–regionen	patents or innovations
Fu and Hong, 2008	full	2	○	n.a.	○	China	cities	productivity
Gao, 2004	full	5	○	++	+	China	provinces	provinces
Glaeser and Kerr, 2008	full	2	++	n.a.	—	USA	SMAs	patents or innovations
Glaeser *et al.*, 1992	full	4	—	+	+	USA	SMAs	employment
Greunz, 2004	full	4	++	n.a.	++	Europe	NUTS2	patents or innovations
Gustavsson, 2003	full	8	+	○	○	Sweden	counties	4× employment, 4× productivity
Hanson, 1998	full	6	—	+	○	Mexico	states	employment

Table 1. *Continued.*

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
Harrison *et al.*, 1996	sector	7	○	n.a.	n.a.	USA	counties	patents or innovations
Henderson, 2003	sector	4	+	n.a.	+	USA	counties	employment
Henderson *et al.*, 1995	sector	5	+	n.a.	○	USA	SMAs	employment
Henderson *et al.*, 2001	both	2	+	n.a.	○	South Korea	cities	output
Jofre-Monseny, 2009	sector	7	+	○	—	Spain	municipalities	other
Kameyama, 2004	sector	6	○	n.a.	○	Japan	LMAs	employment
Ketelhöhn, 2006	sector	1	++	++	++	USA	counties	patents or innovations
King *et al.*, 2003	sector	7	–	++	○	USA	states	employment
Lee *et al.*, 2005	full	5	—	++	++	South Korea	regions/counties	productivity
Lu *et al.*, 2009	both	8	○	++	○	China	cities	6× patents or innovations, 2× output
Malpezzi *et al.*, 2004	full	4	n.a.	n.a.	++	USA	SMAs	other
Mano and Otsuka, 2000	sector	15	—	n.a.	○	Japan	prefectures	employment
Martin *et al.*, 2008	full	2	++	–	—	France	LMAs	output

Table 1. *Continued.*

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
Massard and Riou, 2002	sector	4	–	n.a.	–	France	départements	patents or innovations
Mendoza Cota, 2002	full	2	–	n.a.	+	Mexico	(unclear)	employment
Mody and Wang, 1997	sector	6	—	+	n.a.	China	counties/ provinces	productivity
Mukkala, 2004	sector	6	+	n.a.	n.a.	Finland	NUTS4	productivity
Neffke, 2009	full	4	○	n.a.	—	Sweden	municipalities/	2× output,
Ouwersloot and Rietveld, 2000	full	3	–	○	○	Netherlands	municipalities	output
Paci and Usai, 1999	full	6	++	n.a.	++	Italy	LMAs	patents or innovations
Paci and Usai, 2000	full	1	—	–	++	Italy	LMAs	employment

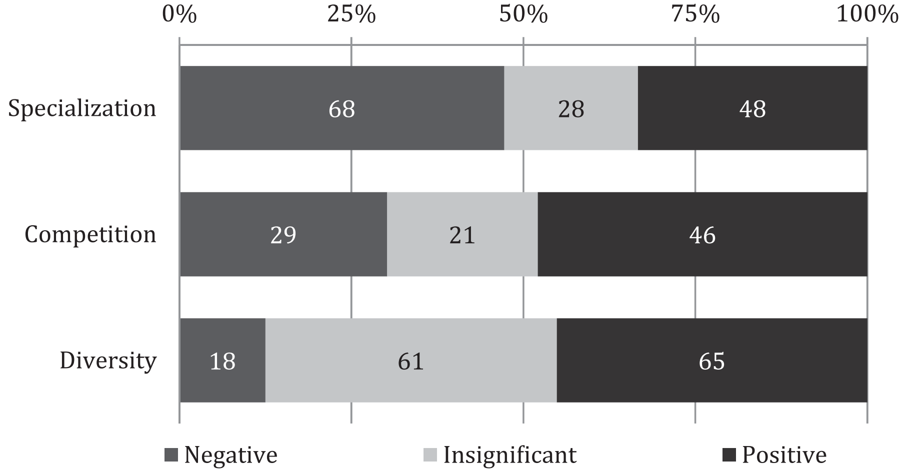
Table 1. *Continued.*

Study	Full or sector	# est. eqs	Conclusions: Specialization	Conclusions: Competition	Conclusions: Diversity	Characteristics: Country	Characteristics: Regions	Characteristics: Dependent
Paci and Usai, 2001	full	2	—	+	++	Italy	LMAs	employment
Paci and Usai, 2006	full	2	++	n.a.	++	Italy	LMAs	patents or innovations
Partridge and Rickman, 1999	sector	5	+	n.a.	+	USA	states	productivity
Rosenthal and Strange, 2003	sector	18	+	○	—	USA	ZIP regions	12× empl., 6× other
Serrano and Cabrer, 2004	both	22	–	n.a.	○	Spain	provinces	productivity
Sjöholm, 1999	full	6	○	○	++	Indonesia	3× districts, 3× prov.	2× prod., 4× other
Sonobe and Otsuka, 2006	sector	18	○	n.a.	○	Taiwan	townships	9× empl., 9× other
Staber, 2001	sector	3	++	n.a.	—	Germany	circles of 10 km	other
Suedekum and Blien, 2005	full	2	—	—	n.a.	Germany	NUTS3	employment

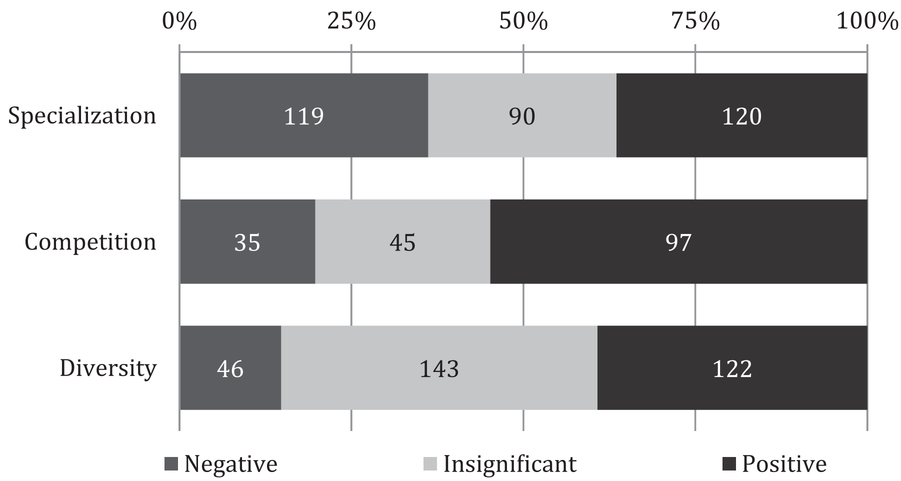
Table 1. *Continued.*

			Conclusions			Characteristics		
Study	Full or sector	# est. eqs	Specialization	Competition	Diversity	Country	Regions	Dependent
Van der Panne, 2004	full	3	++	—	○	Netherlands	ZIP regions	patents or innovations
Van Oort and Atzema, 2004	sector	3	+	+	+	Netherlands	municipalities	other
Van Oort and Stam, 2005	sector	2	++	+	++	Netherlands	municipalities	employment
Van Oort, 2002	full	4	○	—	+	Netherlands	municipalities	patents or innovations
Van Soest *et al.*, 2002	full	4	—	++	++	Netherlands	cities, ZIP regions	employment
Viladecans-Marsal, 2004	sector	6	++	n.a.	n.a.	Spain	cities	employment

Notes: [1] Statistical Metropolitan Areas
[2] Labour Market Areas
Note 1: the numbers in the third column indicate the number of estimated equations from which estimates for the externalities have been derived.
Note 2: The symbols in the next three columns summarize the conclusions and have the following meaning:
— significantly negative in all cases;
– negative in all cases, but not always significantly so;
○ inconclusive;
+ positive in all cases, but not always significantly so;
++ significantly positive in all cases; and
n.a. no estimates available.



(a) Economy-wide and total manufacturing studies



(b) All studies

Figure 1. Characterization of Study Findings.

studies using economy-wide or total manufacturing data, the bottom half includes also studies that run regressions for specific sectors only. The relative frequencies tell the same story across the two datasets. Because our main meta-regressions concern the more homogeneous studies that use economy-wide or all manufacturing data, we will focus more closely on those.

Several results emerge. First, regarding specialization there is no clear-cut evidence in the literature regarding its impact on the growth of cities. Although only 20% of the available estimates are statistically

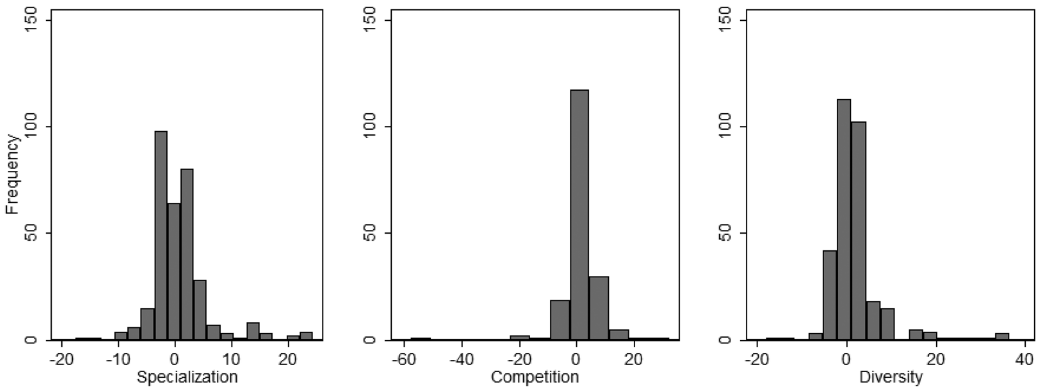


Figure 2. Distribution of *t*-values.

insignificant, the significant results are strongly divided between negative and positive effects (and almost equally so for the case of "all studies"). Regarding competition, we see that close to 50% of the estimated effect sizes are positive and significant in the case of Figure 1a and more than 50% in the case of Figure 1b. For diversity, finally, a little less than half of the estimates are statistically insignificant. Out of the significant ones, however, a large majority points at a positive effect of diversity on urban growth. Overall, the support for Jacobs' hypotheses is relatively most convincing and Glaeser *et al.*'s (1992) overall conclusion of the importance of competition and diversity has not been overturned.

Ideally, we would have used an effect size that measures "economic significance", such as an elasticity, rather than "statistical significance" to gauge the relative effects of specialization, competition and diversity. In the research under consideration, however, the heterogeneity in terms of both the dependent variable as well as the proxies used for our key variables of interest is so large that it is not feasible to construct a common metric to characterize the available empirical evidence (as doing so in homogeneous subcategories would result in rather small samples). Instead, we have chosen to focus on the reported or calculated *t*-values.[6] The distribution of these *t*-values is given in Figure 2, again excluding studies that focused on one narrow sector only. Note how the values for competition and diversity centre around zero.[7] For specialization, there appears to be some density "missing" around zero, which may be indicative of publication bias in which insignificant results are less likely to be published.

Before we consider the extent to which study heterogeneity impacts on these frequency distributions, it should be noted that sample size is of course an important determinant of statistical significance. Allowing for between-study unspecified heterogeneity, the hypothesis of the mean weighted effect size being zero is only rejected for diversity. This again confirms the importance of diversity. Statistical details and the associated funnel plots can be found on the website.[8]

Taken together, the descriptive results of our meta-analysis tend to re-confirm the conclusions in Glaeser *et al.* (1992). The literature supports the presence of positive effects of diversity and competition on urban growth, whereas the results regarding the effects of specialization are more ambiguous. This conclusion was also drawn by Beaudry and Schiffauerova (2009) in a much more detailed form of "vote counting" (based on frequency distributions of results) than we have reported above. However, the question arises in what ways the distribution of results is driven by the design of the primary studies. Meta-regression techniques can identify differences between studies that can have a discernible impact on the results.

Some of these differences are listed in Table 1. They relate to the way in which the dependent variable in the analysis has been measured (viz. employment growth, output growth, productivity growth, patents or innovations, or other measures), the level of regional aggregation and the country covered in the analysis.

In our meta-analysis, we operationalize the characteristics of the dependent variable by means of several dummies, which indicate whether the dependent variable is measured in terms of patents/innovations, output, or productivity (employment is the omitted category). Some heterogeneity is also still present in the sectoral coverage in the analysis, as we included both studies that cover the whole economy and studies that cover only the manufacturing sector. We therefore include a dummy that indicates whether the analysis includes the services sector.[9] Thirdly, we add two variables that are not obtained from the studies themselves but inform on the kind of cities that yielded the data in the primary studies. These variables are the average population density and average GDP per capita of the geographical units of observation of the primary analysis.[10]

A second set of factors that might affect the outcomes of the analyses concerns the regression specification with respect to the key variables of interest, viz. specialization, competition and diversity. If all three variables have separate impacts on urban outcomes, the omission of any of these creates specification bias, which can be remedied in meta-analysis by the introduction of dummies that indicate the presence or absence of variables (e.g., Koetse *et al.*, 2010). The exact empirical operationalization can matter. Considering specialization, it is likely to matter whether specialization is measured as a location quotient (viz. the share of a sector in regional employment relative to the national average) or as a share in regional employment, or absolute regional employment in a sector. For competition, different measures are used as well, among which the number of establishments in a sector and the reciprocal of average firm size in a sector feature most prominently. Regarding diversity, the crucial distinction is between studies that use the share of the five largest sectors (as done in Glaeser *et al.*, 1992), and studies that use more continuous variables such as a relative diversity index, a Herfindahl index or a Gini coefficient. All these differences are captured by simple dummy variables.

Other factors that we consider relate to other data and study characteristics and the presence of additional control variables. These are the period covered by the analysis (captured by the mean year of the analysis to which the data pertain), the length of the period covered (to distinguish between long-run and short-run effects), the part of the world covered in the analysis,[11] the inclusion of control variables for urbanization, educational variables, wages or GDP, as well as the presence of regional dummies of some kind.[12] Moreover, we add two dummies for the estimation technique, distinguishing firstly between panel and cross-sectional approaches, and secondly between static and dynamic approaches.[13] We also check whether the use of micro-data (using data on individual firms or on employees) makes a difference, as Van Oort *et al.* (2012) suggest and as evidenced by, for example, Combes *et al.* (2008) and Groot *et al.* (2014). Finally we include the year of publication of the study, and a dummy whether the study is a working paper.[14]

We are not able to test for publication bias in the regular way, viz. by checking whether significant results suspiciously dominate the literature through formal statistical tests (as suggested by, e.g., Stanley, 2005). This is because we are not estimating one common metric for our three dependent variables, and because our ordered probit estimation does not allow the type of tests commonly performed. However, our prior is that our effect sizes will not be affected much by publication bias, since we tackle three variables at the same time, from studies where the variable of interest was sometimes yet another variable; this would make it less likely that an unexpected result would not be published, and disappear in a file drawer. However, we do include a dummy for working papers, and we control for the year of publication separately from the year of the data, as in Koetse *et al.* (2009), to see whether there is no publication bias at all.[15] Finally we already noted that, with respect to specialization, Figure 2 suggested an unusually low frequency of *t*-statistics in the neighbourhood of zero, possibly indicating publication bias.

We first estimate an ordered probit model, distinguishing between the three ordered categories that were introduced at the beginning of this section. We use weights to take into account that studies report different numbers of estimates (Stanley and Doucouliagos, 2013). Results are given in Table 2, which shows explanations for the variation in the effects of specialization, competition and diversity.[16] Although the significance of the results can be interpreted 'as is', it is important to note that the interpretation of the

Table 2. Ordered Probit Meta-Regression Analysis.

Dependent: categorical	Specialization	Competition	Diversity
Characteristics of dependent variable			
Data measure patents or innovations	2.643***	−1.329**	0.529
	(0.887)	(0.647)	(0.409)
Data measure productivity	0.658	0.588	0.0752
	(0.692)	(0.744)	(0.564)
Data measure output	2.941***	−0.673	−0.0655
	(0.938)	(1.015)	(0.590)
Data include the service sector	0.348***	−0.329**	−0.130
	(0.108)	(0.164)	(0.0898)
Specification of key variables			
Specialization included		−0.528*	−0.474
		(0.288)	(0.373)
Specialization as a location quotient	−0.567		
	(0.427)		
More specialization variables included	−0.407		
	(0.485)		
Competition included	−1.251***		0.400
	(0.448)		(0.304)
Competition is measured in est. per employee		2.000***	
		(0.666)	
Competition is measured in establishments		0.604	
		(0.938)	
More competition variables included		0.380	
		(0.595)	
Diversity included	1.731***	0.0570	
	(0.600)	(0.429)	
Diversity estimated using largest five			2.499**
			(1.234)
More diversity variables included			1.794***
			(0.585)
Other data characteristics			
Population density (log)	−0.436**	0.0879	0.0969
	(0.174)	(0.144)	(0.212)
GDP per capita (log)	0.434*	−0.181	0.339
	(0.231)	(0.445)	(0.304)
Standardized mean year to which the data pertain#	0.0400	−0.437	1.267***
	(0.154)	(0.940)	(0.447)
Length of period covered by the data (in years)	−0.617*	0.457	−0.0593
	(0.365)	(0.510)	(0.359)
Data are from Asia	0.201	2.839**	0.452
	(0.716)	(1.297)	(0.714)
Data are from the USA	1.575*	−0.359	−2.147*
	(0.877)	(0.679)	(1.100)

Table 2. *Continued.*

Dependent: categorical	Specialization	Competition	Diversity
Presence of additional control variables			
Urbanization included	−1.081*	1.901***	−0.511
	(0.634)	(0.667)	(0.430)
Educational variables included	−1.626***	1.205*	1.851***
	(0.601)	(0.640)	(0.488)
Wages or GDP also included	0.672	0.167	1.378***
	(0.620)	(0.598)	(0.394)
Geographical variables also included	1.745***	−0.0658	−0.538
	(0.637)	(0.492)	(0.390)
Other study characteristics			
Estimated using panel data or similar	1.090**	1.473	0.466
	(0.544)	(0.964)	(0.568)
Static estimation	−2.795***	2.439*	−0.480
	(0.981)	(1.300)	(0.840)
Estimated using microdata	−1.431***	−0.173	0.681
	(0.551)	(0.540)	(0.451)
Working paper	0.240	2.208**	−1.094
	(0.620)	(0.958)	(0.675)
Standardized year of publication#	1.168***	−0.552	−0.754**
	(0.273)	(0.736)	(0.358)
Limit point 1	1.416	2.578	−0.361
Limit point 2	2.185	3.511	1.586
Number of observations	144	96	144
Pseudo-R^2	0.369	0.339	0.450

Notes: # The non-dummy variables are standardized in such a way that their mean is 0 and a value of +1 represents a value one standard deviation above the mean. For the mean year to which the data pertain, one standard deviation is 9.15 (average 1989.5); for the year of publication, it is 3.57 (average 2003.2). The regression uses weights which are reciprocal to the number of estimates that were obtained from the same study. Standard errors are in parentheses. Statistical significance is indicated with stars: ***, ** and * means statistically significant at the 1, 5 and 10 percent significance level, respectively.

estimated coefficients of an ordered probit analysis is not straightforward (see Greene, 2000, p. 878).[17] We therefore also estimate a weighted least squares regression model in which we take *t*-values for the estimates of interest from the studies, again weighted inversely proportional to the number of estimates obtained from each study.[18] The results can be found in Table 3.[19]

One result that stands out immediately is something that may be referred to as a paradigm cycle, which can lead to a form of publication bias. More recent studies, as shown by the "Standardised year of publication" near the bottom of the table, are significantly more likely to yield negative results for diversity, i.e. contradicting the finding of Glaeser *et al*. (1992), and more likely to yield positive results for specialization. This is a common pattern in the paradigm cycle: new insights and methods, such as those of Glaeser *et al*. (1992), are first confirmed by other scientists, and journal editors have a tendency to publish these confirmations. Then, as the new views become generally accepted, publishing evidence that confirms them becomes less interesting, and in a true Popperian fashion evidence to the contrary is favoured by both researchers and journal editors. Our results also show that working papers, which

Table 3. WLS Meta-Regression Analysis.

Dependent: *t*-values	Specialization	Competition	Diversity
Characteristics of dependent variable			
Data measure patents or innovations	2.576	−3.176	1.811*
	(3.210)	(2.167)	(0.925)
Data measure productivity	−2.682	0.353	0.190
	(2.872)	(4.348)	(0.755)
Data measure output	−6.219	4.514	−1.129
	(3.999)	(4.396)	(1.057)
Data include the service sector	0.339	−0.341	−0.0154
	(0.419)	(0.493)	(0.108)
Specification of key variables			
Specialization included		−2.914**	−0.133
		(1.218)	(0.515)
Specialization as a location quotient	2.266		
	(1.951)		
More specialization variables included	−4.578**		
	(2.108)		
Competition included	−4.763**		−0.423
	(2.183)		(0.353)
Competition is measured in est. per employee		−3.323	
		(3.501)	
Competition is measured in establishments		2.455	
		(2.937)	
More competition variables included		2.921	
		(2.136)	
Diversity included	9.467***	−1.882	
	(2.573)	(1.754)	
Diversity estimated using largest five			2.904***
			(0.691)
More diversity variables included			2.466***
			(0.731)
Other data characteristics			
Population density (log)	−1.895*	4.570**	−0.733*
	(1.055)	(1.733)	(0.366)
GDP per capita (log)	−0.0664	−3.811	0.178
	(1.674)	(3.575)	(0.399)
Standardized mean year to which the data pertain[#]	0.410	−3.298	0.916***
	(0.707)	(3.881)	(0.178)
Length of period covered by the data (in years)	−0.0843	0.701	0.569
	(1.612)	(1.620)	(0.469)
Data are from Asia	3.111	−6.307	3.659***
	(4.772)	(8.562)	(1.223)
Data are from the USA	7.803*	−6.530*	−0.585
	(4.632)	(3.654)	(1.172)

Table 3. *Continued.*

Dependent: *t*-values	Specialization	Competition	Diversity
Presence of additional control variables			
Urbanization included	−0.639	5.002*	0.595
	(1.986)	(2.702)	(0.713)
Educational variables included	−5.794*	8.388**	1.646**
	(3.224)	(3.216)	(0.644)
Wages or GDP also included	−1.447	5.989	1.437**
	(2.015)	(3.954)	(0.595)
Geographical variables also included	1.989	−0.741	−0.586
	(2.212)	(1.779)	(0.502)
Other study characteristics			
Estimated using panel data or similar	3.595	1.617	1.445
	(2.776)	(4.062)	(0.977)
Static estimation	−4.587	7.333*	1.222
	(3.585)	(3.873)	(0.838)
Estimated using microdata	−4.144*	−3.915	0.582
	(2.179)	(2.650)	(0.700)
Working paper	4.177	0.126	0.735
	(3.252)	(2.966)	(1.014)
Standardized year of publication[#]	1.743	0.747	−0.966**
	(1.240)	(3.183)	(0.464)
Constant	−5.182	17.39	−4.460*
	(7.709)	(14.60)	(2.497)
Number of observations	144	96	144
R^2	0.400	0.526	0.499
Adjusted R^2	0.285	0.365	0.403

Note: All notes of Table 2 apply.

have not (yet) been published, are more likely to show favourable effects of competition, which up to now has often been the neglected third in the debate (Van der Panne and Van Beers, 2006; Beaudry and Schiffauerova, 2009); however, the regression on *t*-values does not confirm this.

Let us next turn to the results regarding the characteristics of the dependent variable. Here, we test whether measures of urban growth other than employment, which Glaeser *et al*. (1992) used, lead to significantly different results. We note that studies on patents or innovations are more likely to find significantly positive results for specialization and higher *t*-values for diversity, and less likely to find positive significant results for competition. In the case of diversity, this underlines the theory of Duranton and Puga (2001), who argue that innovation benefits from diversified or 'nursery' cities. On the other hand, rents and profits that boost R&D and thereby innovation are more likely in monopolistic and oligopolistic (i.e., less competitive) and specialized sectors.

A third set of results relate to the specification of the key variables of interest. The inclusion of other agglomeration externalities sometimes has an impact on the estimated effects of the key variable of interest; we were able to measure this because many studies either include only two out of the three key variables, or present their results in different stages, as Glaeser *et al*. (1992) did. Our results thus point out the importance of studying agglomeration effects together, in order to avoid omitted variable bias. This holds, for example, for competition in the specialization case. The in- or exclusion of the former does significantly influence the results in this case. This is important because the debate in the literature often boils down to Marshall vs. Jacobs (Van der Panne, 2004; Beaudry and Schiffauerova, 2009). As for the specification, we note that *t*-values for diversity are influenced by the inclusion of secondary variables that also measure related phenomena (such as related variety).

The direction or strength of agglomeration effects is not much influenced by the development stage of a region (as proxied by GDP per capita for the period concerned). Average population density plays a more convincing role for specialization, which seems to be stronger in less populated regions. Whether this is a causal effect is still an open question, but the result is in line with the 'nursery cities' theory (Duranton and Puga, 2001). Studies using data from Asia are more likely to find positive effects for competition, perhaps pointing to a relationship with industrial life cycles; Table 2 also shows that US data are less likely to find positive effects for diversity, compared to the reference category (Europe, Australia).

A fifth set of results points at the potential importance of the time dimension. We control for the mean year to which the data of an estimate pertain, and this provides us with a rough estimate whether an effect is stable over time. Besides this variable, also the effect of the length of the period covered in the analysis as well as the use of panel techniques (as opposed to pure cross-section techniques) are indicative in this respect. For diversity, we see that the use of more recent data (in both probit and *t*-value regressions) tends to increase the chances of finding significantly positive effects. This can be interpreted as a trend for diversity effects to become stronger over time, as well as an indication of a long-run portfolio effect of diversity. The use of panel data, which accounts for unobserved cross-sectional heterogeneity in the primary regression, results in a higher probability to find positive effects for specialization.

The inclusion of proxies for human capital has a downward effect on statistical significance for specialization, and positive effects on competition and diversity, whereas the inclusion of wages or GDP (per capita) in the source studies has a consistent effect on the results found for diversity. This is consistent with popular notions that diverse urban areas that are attractive for high-skilled persons flourish. Finally, we see that estimations using micro-data are less likely to find significant results for specialization. We believe this result shows that specialization effects might be less important at the firm level, and that the use of aggregated data can result in false positives, confusing pure agglomeration effects with sorting mechanisms (Combes *et al*., 2008; Groot *et al*., 2014). Van Oort *et al*. (2012) therefore advocate the use of hierarchical or multilevel modelling.

5. Conclusions

This paper has revisited the available empirical evidence on the importance of three externalities in explaining urban growth, viz. MAR externalities, Porter externalities and Jacobs externalities by means of a meta-analysis of econometric studies that capture these effects by proxies of specialization, diversity and competition. The overall evidence of the meta-analysis based on a simple counting of conclusive effect sizes reveals that relatively many primary studies conclude in favour of significantly positive effects of both competition and diversity on growth. For diversity we also found the smallest share of significantly negative findings but a large number of statistically insignificant results. The latter finding suggests that much more needs to be done, both theoretically and empirically, to identify exactly how a diversified urban economy yields, for example, more innovation and employment growth. No clear-cut favourite was found for the effects of specialization, where significantly positive and significantly negative estimations are roughly of equal number. Apparently, both effects exist, but under different circumstances. This underlines the value of conducting a meta-analysis that delves deeper into the sources of heterogeneity in study outcomes.

Our main results can be summarized as follows. First, we found quite strong indications for sectoral, temporal and spatial *heterogeneity* of the effects of specialization, competition and diversity on regional growth. For example, more recent data find stronger effects for diversity, and studies using data from less densely populated areas find specialization to be a more important factor than elsewhere. Such heterogeneity typically remains unnoticed in primary studies, which tend to focus the analysis on a specific region, sector or time period. It underlines, for example, the need for research focusing on the dependency of the strength of agglomerative forces on the stage of development of the region, but also of the sector (see, e.g., Neffke *et al*. 2008). Overall, our results appear consistent with those of Marrocu *et al*. (2013) who find that the positive effect of diversity is particularly noticeable in the knowledge-intensive services sector in the "old" European urban areas, while the specialization effect still impacts positively in low-tech manufacturing in the "new" Europe.

An important question remains whether in the knowledge-driven post-industrial economy of producer and consumer services characterized by many young and small firms, Jacobs externalities are the most important. However, we also point out some aspects of studies which appear not to influence the outcomes, making heterogeneous studies still comparable. This is the case for stages of development (GDP per capita), and studies that use long or short time periods.

It is also clear that the level of regional *aggregation* matters for the strength with which the agglomeration forces are operational. We therefore reiterate the conclusion of Van Oort *et al*. (2012) that because the fundamental causes of agglomeration are microeconomic, micro and macro levels ought to be modelled simultaneously. The fact that for specialization, population density (typically city scale effects) has a negative influence on the results found, gives rise to interesting questions regarding the transmission mechanisms through which the externalities function and it is consistent with Duranton and Puga's (2001) theory of "nursery cities". More theoretical as well as empirical work investigating these issues is warranted. We also found that including *control variables* on wages or GDP and education has effects on our key variables of interest. Similar effects may be expected from factors such as social capital and trust, risk-taking and entrepreneurship, R&D policies and institutions. More research on the role of the latter factors in determining the strength with which agglomerative forces are operating is warranted. Our results also suggest that more attention needs to be paid to the *specification* of the key variables of interest.

We conclude that the conventional lines of inquiry in this literature may now have reached strongly diminishing returns. New lines of inquiry, using rich micro-level data on firms and workers, dynamic general equilibrium models at the macro level, more attention for spatial and temporal variation in the impacts of agglomeration, and further investigations into the spatial scope of externalities are promising avenues for further research that aims to enhance our understanding of how agglomeration externalities continue to fuel our increasingly urbanized world.

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Online resources

The dataset and syntax files for this paper can be downloaded from the website (http://www.henridegroot.net/datasets). An online Appendix with additional results can be downloaded as well. The online Appendix contains:

- an ordered probit analysis of the more heterogeneous full dataset, which can be directly compared with the previous results obtained with the smaller dataset in De Groot *et al.* (2009);
- marginal effects for the three estimations reported in Table 2;
- Fixed Effect and Random Effect average weighted effect sizes of Fisher z-statistics and the corresponding 95% confidence intervals, where weights have been applied according to the number of observations in the primary study;
- funnel plots for the effect sizes used in Table 3.

Notes

1. Foremost among these were Catherine Beaudry and Andrea Schiffauerova, who kindly sent us an unpublished appendix to their survey article (Beaudry and Schiffauerova, 2009).
2. This was shown by running a meta-regression on the full dataset, with several sectoral dummies covering subsectors.
3. See http://www.henridegroot.net/datasets.
4. After we agreed on the coding scheme and coded a first set of papers collectively, the remainder of the coding was done by Martijn Smit, with help from Marten Kamphorst, whom we thank for his contribution.
5. These estimates were derived from 398 regressions, whereby most regression equations provided information on more than one externality. The number of estimated equations per study included in the database varies between 1 and 22, with an average 5.5 estimates per study (see Table 1). In our regressions a few of these estimates disappear because of missing values on some study characteristics, resulting in a maximum of 787 observations.
6. Some studies report z-values, which we also include; some report significance levels, where we use the threshold value to recalculate a (conservative) t-score, using the number of observations reported.
7. For some studies, exact t-values could not be calculated, for example when only significance stars for certain p-values were given; we assumed 0.01, 0.005 or 0.001 as the adopted significance levels in these cases. This is a conservative approach; an alternative would be to establish a median p-value informing about the most probably p-value in view of the range within which the significance level should be on the basis of the information provided by the stars.
8. See http://www.henridegroot.net/datasets.
9. Our broader analysis, available online, also includes a dummy whether the analysis is focused on high-tech sectors.
10. The variable describing the mean population density of the spatial units of a study was collected mainly from national statistical offices. We also considered the average surface area and population size separately, but that did not lead to different results. Data for GDP are from a World Bank dataset on Real Historical GDP, in turn compiled from World Development Indicators, International Financial Statistics of the IMF, HIS Global Insight, Oxford Economic Forecasting, and the Economic Research Service, all converted by the World Bank to 2005 dollars. We calculated GDP per capita using population figures from Angus Maddison's work.
11. We mark Asia and the USA by means of dummies, with Europe and the rest of the world as the omitted category.
12. Regional dummies are sometimes included for exceptional regions, such as more developed parts of a country (e.g., northern Italy) or capital regions. Fixed effects for all regions are rarely present; these

would be incompatible with the diversity measures, which are based on the sectoral composition of a region but normally do not (or hardly) vary by sector observed.

13. Glaeser *et al*. (1992) estimated employment dynamics over a long time period, but many of the patent count analyses consider a static situation in one year, or an average situation over a few years.
14. We standardize the year of publication and the mean year of the data (so that the data for these variables have mean 0 and standard deviation 1); for population density, GDP per capita and the length of the period covered we take logs.
15. We also performed robustness tests to check whether specific studies overly influence the estimated coefficients. Results are available upon request.
16. A risk in meta-analysis is that dummies for a specific specification apply only to one or two studies, so that the dummy starts to function as a dummy for those studies as a whole. To counter this effect, we have included only dummies that yielded a value of one in at least five different studies.
17. In order to facilitate the interpretation of the ordered probit regressions, marginal effects have been computed, and are available in our online Appendix. These represent the change in the probability of finding an estimate in one of the three categories in response to a change of one of the explanatory variables. Interpretation of those results does not lead to different conclusions than those we will draw based on the estimated coefficients reported in Table 3, and we will be looking mainly at sign and statistical significance. Note, however, that the actual economic significance should be assessed from relevant primary studies before drawing policy-related conclusions (cf. Ziliak and McCloskey, 2008).
18. An alternative method is to perform a transformation of the t statistics into Fisher's z statistics and to account for the number of observations in the primary estimates in the weights as well. This method yields some differences in results, as there is substantive variation in the number of observations in the primary estimates. Results are available in our online Appendix.
19. In both tables, standard errors are assumed to be cluster correlated at the study level and calculated with the Huber-White sandwich estimator.

References

Acs, Z.J. and Armington, C. (2004). Employment growth and entrepreneurial activity in cities. *Regional Studies* 38: 911–927.

Almeida, R. (2005). Local economic structure and growth. World Bank Policy Research Working Paper no. 3728.

Andersson, R., Quigley, J.M. and Wilhelmsson, M. (2005). Agglomeration and the spatial distribution of creativity. *Papers in Regional Science* 84: 445–464.

Baltzopoulos, A. (2009). Agglomeration externalities and entrepreneurship - Micro-level evidence from Sweden. CESIS Discussion Paper no. 190.

Baptista, R. and Swann, P. (1998). Do firms in clusters innovate more? *Research Policy* 27: 525–540.

Baptista, R. and Swann, G.M.P. (1999). A comparison of clustering dynamics in the US and UK computer industries. *Journal of Evolutionary Economics* 9: 373–399.

Baten, J., Spadavecchia, A., Yin, S. and Streb, J. (2005). Clusters, externalities and innovation: new evidence from German firms, 1878 to 1913. Universität Tübingen Discussion Paper no. 2005/4.

Batisse, C. (2002). Dynamic externalities and local growth – a panel data analysis applied to Chinese provinces. *China Economic Review* 13: 231–251.

Beaudry, C. (2009). Entry, growth and patenting in industrial clusters: a study of the aerospace industry in the UK. *International Journal of the Economics of Business* 8: 405–436.

Beaudry, C. and Breschi, S. (2003). Are firms in clusters really more innovative? *Economics of Innovation and New Technology* 12: 325–342.

Beaudry, C. and Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy* 38: 318–337.

Boix, R. and Trullén, J. (2007). Knowledge, networks of cities and growth in regional urban systems. *Papers in Regional Science* 86: 551–574.

Boschma, R.A. and Weterings, A.B.R. (2005). The effect of regional differences on the performance of software firms in the Netherlands. *Journal of Economic Geography* 5: 567–588.

Bradley, R. and Gans, J.S. (1998). Growth in Australian cities. *Economic Record* 74: 266–278.

Brülhart, M. and Mathys, N.A. (2008). Sectoral agglomeration economies in a panel of European regions. *Regional Science and Urban Economics* 38: 348–362.

Burger, M.J., Van Oort, F.G. and Van der Knaap, B. (2010). A treatise on the scale-dependency of agglomeration externalities and the modifiable areal unit problem. *Scienze Regionali* 9: 19–40.

Cainelli, G. and Leoncini, R. (1999). Esternalità e sviluppo industriale di lungo periodo in Italia. Una analisi a livello provinciale. *L'industria (New Series)* 20: 147–166.

Card, D., Kluve, J. and Weber, A. (2010). Active labour market policy evaluations: a meta-analysis. *Economic Journal* 120: F452–F477.

Carlino, G., Chatterjee, S. and Hunt, R. (2007). Urban density and the rate of invention. *Journal of Urban Economics* 61: 389–419.

Chen, H.P. (2002). Urban externalities and city growth in Taiwan. *Annals of Regional Science* 36: 531–550.

Cingano, F. and Schivardi, F. (2004). Identifying the sources of local productivity growth. *Journal of the European Economic Association* 2: 720–742.

Combes, P.P. (2000). Economic structure and local growth: France, 1984–1993. *Journal of Urban Economics* 47: 329–355.

Combes, P.P. and Gobillon, L. (2014). The empirics of agglomeration economies. CEPR Discussion Paper no. 10174.

Combes, P.P., Magnac, T. and Robin, J.M. (2004). The dynamics of local employment in France. *Journal of Urban Economics* 56: 217–243.

Combes, P.P., Duranton, G. and Gobillon, L. (2008). Spatial wage disparities: sorting matters! *Journal of Urban Economics* 63: 723–742.

Condliffe, S., Latham, W., LeBas, C. and Miribel, F. (2008). Agglomeration economies within IT-producing and IT-consuming industries in U.S. regions. Alfred Lerner College Working Papers no. 2008–24.

Das, S. and Finne, H. (2008). Innovation and co-location. *Spatial Economic Analysis* 3: 159–194.

Davis, M.A., Fisher, J.D.M. and Whited, T.M. (2014). Macroeconomic implications of agglomeration. *Econometrica* 82: 731–764.

De Groot, H.L.F., Poot, J. and Smit, M.J. (2009). Agglomeration, innovation and regional development: theoretical perspectives and meta-analysis. In R. Capello and P. Nijkamp (eds), *Handbook of Regional Growth and Development Theories*. Cheltenham: Edward Elgar.

De Lucio, J.J., Herce, J.A. and Goicolea, A. (2002). The effects of externalities on productivity growth in Spanish industry. *Regional Science and Urban Economics* 32: 241–258.

De Vor, F. and De Groot, H.L.F. (2010). Agglomeration externalities and local growth: the performance of industrial sites in the Amsterdam region. *Annals of Regional Science* 44: 409–431.

Deidda, S., Paci, R. and Usai, S. (2006). Spatial externalities and local economic growth. CRENoS Discussion Paper no. 02/06.

Dekle, R. (2002). Industrial concentration and regional growth: evidence from the prefectures. *Review of Economics and Statistics* 84: 310–315.

Drucker, J.M. and Feser, E. (2007). Regional industrial dominance, agglomeration economies, and manufacturing plant productivity. CES Discussion Paper no. 07–31.

Duranton, G. and Overman, H.G. (2005). Testing for localization using micro-geographic data. *Review of Economic Studies* 72: 1077–1106.

Duranton, G. and Puga, D. (2001). Nursery cities: urban diversity, process innovation, and the life cycle of products. *American Economic Review* 91: 1454–1477.

Feldman, M.P. and Audretsch, D.B. (1999). Innovation in cities: science-based diversity, specialization and localized competition. *European Economic Review* 43: 409–429.

Florax, R.J.G.M., De Groot, H.L.F. and De Mooij, R.A. (2002). Meta-analysis: a tool for upgrading inputs of macroeconomic policy models. Tinbergen Institute Discussion Paper no. 02–041/3.

Fritsch, M. and Slavtchev, V. (2007). Industry specialization, diversity and the efficiency of regional innovation systems. Jena Economic Research Papers no. 2007–018.

Fu, S. and Hong, J. (2008). Testing urbanization economies in manufacturing industries: urban diversity or urban size? MPRA Paper no. 10078.

Gao, T. (2004). Regional industrial growth: evidence from Chinese industries. *Regional Science and Urban Economics* 34: 101–124.

Glaeser, E.L. (2000). The new economics of urban and regional growth. In G.L. Clark, M.P. Feldman and M.S. Gertler (eds), *The Oxford Handbook of Economic Geography*. Oxford: Oxford University Press.

Glaeser, E.L. (2011). *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier*. Basingstoke: Macmillan.

Glaeser, E.L. and Gottlieb, J.D. (2009). The wealth of cities: agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature* 47: 983–1028.

Glaeser, E.L. and Kerr, W.R. (2008). Local industrial conditions and entrepreneurship: how much of the spatial distribution can we explain? Harvard Business School Discussion Paper no. 09–055.

Glaeser, E.L., Kallal, H.D., Scheinkman, J.A. and Shleifer, A. (1992). Growth in cities. *Journal of Political Economy* 100: 1126–1152.

Greene, W.H. (2000). *Econometric Analysis*. Upper Saddle River , NJ: Prentice-Hall.

Greunz, L. (2004). Industrial structure and innovation - Evidence from European regions. *Journal of Evolutionary Economics* 14: 563–592.

Groot, S.P.T., De Groot, H.L.F. and Smit, M.J. (2014). Regional wage differences in the Netherlands: micro-evidence on agglomeration externalities. *Journal of Regional Science* 54: 503–523.

Gustavsson, R. (2003). Industrial growth and dynamic externalities: the case of Sweden. *Journal of Economic Integration* 18: 607–625.

Hanson, G.H. (1998). Regional adjustment to trade liberalization. *Regional Science and Urban Economics* 28: 419–444.

Harrison, B., Kelley, M.R. and Gant, J. (1996). Specialization versus diversity in local economies: the implications for innovative private-sector behavior. *Cityscape* 2: 61–93.

Henderson, J.V. (2003). Marshall's scale economies. *Journal of Urban Economics* 53: 1–28.

Henderson, V., Kuncoro, A. and Turner, M. (1995). Industrial development in cities. *Journal of Political Economy* 103: 1067–1090.

Henderson, V., Lee, T. and Lee, Y.J. (2001). Scale externalities in Korea. *Journal of Urban Economics* 49: 479–504.

Jacobs, J. (1969). *The Economy of Cities*. New York: Random House.

Jofre-Monseny, J. (2009). The scope of agglomeration economies: evidence from Catalonia. *Papers in Regional Science* 88: 575–590.

Kameyama, Y. (2004). Dynamic externalities and the growth of manufacturing employment in Japanese cities: the roles of specialization and diversity. Conference presentation at Australian Conference of Economists, Sydney, 28 September 2004.

Ketelhöhn, N.W. (2006). The role of clusters as sources of dynamic externalities in the US semiconductor industry. *Journal of Economic Geography* 6: 679–699.

King, C., Silk, A.J. and Ketelhöhn, N.W. (2003). Knowledge spillovers and growth in the disagglomeration of the US advertising-agency industry. *Journal of Economics and Management Strategy* 12: 327–362.

Koetse M.J., De Groot, H.L.F. and Florax, R.J.G.M. (2009). A meta-analysis of the investment-uncertainty relationship. *Southern Economic Journal* 76: 283–306.

Koetse, M.J., Florax, R.J.G.M. and De Groot, H.L.F. (2010). Consequences of effect size heterogeneity for meta-analysis: a Monte Carlo study. *Statistical Methods and Applications* 19: 217–236.

Lee, B.S., Sosin, K. and Hong, S.H. (2005). Sectoral manufacturing productivity growth in Korean Regions. *Urban Studies* 42: 1201–1219.

Lu, Y., Ni, J. and Tao, Z. (2009). City-industry Growth in China. Discussion paper available at http://ssrn.com/abstract=1222182.

Malpezzi, S., Seah, K.Y. and Shilling, J.D. (2004). Is it what we do or how we do it? New evidence on agglomeration economies and metropolitan growth. *Real Estate Economics* 32: 265–295.

Mano, Y. and Otsuka, K. (2000). Agglomeration economies and geographical concentration of industries: a case study of manufacturing sectors in postwar Japan. *Journal of the Japanese and International Economies* 14: 189–203.

Marrocu, E., Paci, R. and Usai, S. (2013). Productivity growth in the old and new Europe: the role of agglomeration externalities. *Journal of Regional Science* 53: 418–442.

Marshall, A. (1890). *Principles of Economics: An Introductory Volume*. London: Macmillan.

Martin, P., Mayer, T. and Mayneris, F. (2008). Spatial concentration and firm-level productivity in France. CEPR Discussion Paper no. 6858.

Massard, N. and Riou, S. (2002). L'impact des structures locales sur l'innovation en France: Spécialisation ou diversité? *Revue Région et Développement* 16: 111–136.

Melo, P.S.C., Graham, D.J. and Noland, R.B. (2009). A meta-analysis of estimates of urban agglomeration externalities. *Regional Science and Urban Economics* 39: 332–342.

Mendoza Cota, J.E. (2002). *Agglomeration Economies and Urban Manufacturing Growth in the Northern Border Cities of Mexico*. s.l..

Mody, A. and Wang, F.Y. (1997). Explaining industrial growth in coastal China: economic reforms . . . and what else? *World Bank Economic Review* 11: 293–325.

Mukkala, K. (2004). Agglomeration economies in the Finnish manufacturing sector. *Applied Economics* 36: 2419–2427.

Neffke, F. (2009). *Productive Places: The Influence of Technological Change and Relatedness on Agglomeration Externalities*. Ph.D. dissertation, Utrecht University.

Neffke, F., Svensson Henning, M., Boschma, R., Lundquist, K.-J. and Olander, L.-O. (2008). Who needs agglomeration? Varying agglomeration externalities and the industry life cycle. Papers in Evolutionary Economic Geography no. 08.08.

Ouwersloot, H. and Rietveld, P. (2000). The geography of R&D: Tobit analysis and a Bayesian approach to mapping R&D activities in the Netherlands. *Environment and Planning A* 32: 1673–1688.

Paci, R. and Usai, S. (1999). Externalities, knowledge spillovers and the spatial distribution of innovation. *GeoJournal* 49: 381–390.

Paci, R. and Usai, S. (2000). The role of specialization and diversity externalities in the agglomeration of innovative activities. *Rivista Italiana degli Economisti* 5: 237–268.

Paci, R. and Usai, S. (2001). Externalities and local economic growth in manufacturing industries. CRENoS Discussion Paper no. 01–13.

Paci, R. and Usai, S. (2006). Agglomeration economies and growth: the case of Italian local labour systems, 1991–2001. CRENoS Discussion Paper no. 200612.

Partridge, M.D. and Rickman, D.S. (1999). Static and dynamic externalities, industry composition, and state labor productivity: a panel study of states. *Southern Economic Journal* 66: 319–335.

Poot, J. (2014). Meta-analysis of previous empirical research findings. In R.J. Stimson (ed.), *Handbook of Research Methods and Applications in Spatially Integrated Social Science*. Cheltenham: Edward Elgar.

Porter, M.E. (1990). *The Competitive Advantage of Nations*. Houndmills: Macmillan.

Ringquist, E.J. (2013). *Meta-Analysis for Public Management and Policy*. San Franciso: Jossey-Bass.

Rosenthal, S.S. and Strange, W.C. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics* 85: 377–393.

Rosenthal, S.S. and Strange, W.C. (2004). Evidence on the nature and sources of agglomeration economics. In J.V. Henderson and J.F. Thisse (eds), *Handbook of Regional and Urban Economics*, Vol. 4. Amsterdam: North Holland.

Serrano, G. and Cabrer, B. (2004). The effect of knowledge spillovers on productivity growth inequalities in Spanish regions. *Environment and Planning A* 36: 731–753.

Sjöholm, F. (1999). Productivity growth in Indonesia: the role of regional characteristics and direct foreign investment. *Economic Development and Cultural Change* 47: 559–584.

Sonobe, T. and Otsuka, K. (2006). The division of labor and the formation of industrial clusters in Taiwan. *Review of Development Economics* 10: 71–86.

Staber, U. (2001). Spatial proximity and firm survival in a declining industrial district: the case of knitwear firms in Baden-Württemberg. *Regional Studies* 35: 329–341.

Stanley, T.D. (2001). Wheat from chaff: meta-analysis as quantitative literature review. *Journal of Economic Perspectives* 15: 131–150.
Stanley, T.D. (2005). Beyond publication bias. *Journal of Economic Surveys* 19: 309–345.
Stanley, T.D. and Doucouliagos, H. (2012). *Meta-Regression Analysis in Economics and Business*. London: Routledge.
Stanley, T.D. and Doucouliagos, H. (2013). Neither fixed nor random: weighted least squares meta-analysis. Deakin Economics Series no. 2013/1.
Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R.S. and Rost, K. (2013). Meta-analysis of economics research reporting guidelines. *Journal of Economic Surveys* 27: 390–394.
Suedekum, J. and Blien, U. (2005). Local economic structure and industry development in Germany, 1993–2001. *Economics Bulletin* 15: 1–8.
Van der Panne, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics* 14: 593–604.
Van der Panne, G. and Van Beers, C. (2006). On the Marshall-Jacobs controversy: it takes two to tango. *Industrial and Corporate Change* 15: 877–890.
Van Oort, F.G. (2002). Innovation and agglomeration economies in the Netherlands. *Tijdschrift voor Economische en Sociale Geografie* 93: 344–360.
Van Oort, F.G. and Atzema, O.A.L.C. (2004). On the conceptualization of agglomeration economies: the case of new firm formation in the Dutch ICT sector. *Annals of Regional Science* 38: 263–290.
Van Oort, F.G. and Stam, E. (2005). Agglomeration economies and entrepreneurship: testing for spatial externalities in the Dutch ICT industry. Papers on Entrepreneurship, Growth and Public Policy no. 0905.
Van Oort, F.G., Burger, M.J., Knoben, J. and Raspe, O. (2012). Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys* 26: 468–491.
Van Soest, D.P., Gerking, S.D. and Van Oort, F.G. (2002). Knowledge externalities, agglomeration economies, and employment growth in Dutch cities. CentER Discussion Paper no. 2002–41.
Viladecans-Marsal, E. (2004). Agglomeration economies and industrial location: city-level evidence. *Journal of Economic Geography* 4: 565–582.
Ziliak, S.T. and McCloskey, D.N. (2008). *The Cult of Statistical Significance: How the Standard Error Costs us Jobs, Justice, and Lives*. Ann Arbor: University of Michigan Press.