

## The Dynamics of Agglomeration Externalities along the Life Cycle of Industries

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## The Dynamics of Agglomeration Externalities along the Life Cycle of Industries

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# The Dynamics of Agglomeration Externalities along the Life Cycle of Industries

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## ABSTRACT

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This paper investigates the changing roles of agglomeration externalities along the industry life cycle. We argue that industries have different agglomeration needs in different stages of their life cycles because their mode of competition, innovation intensity, and learning opportunities change over time. For 12 Swedish manufacturing industries, we determine for each year between 1974 and 2004 whether the industry is in a young, intermediate, or mature stage. Whereas MAR externalities steadily increase with the maturity of industries, effects of local diversity (Jacobs' externalities) are positive for young industries but decline and even become negative for more mature industries.

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Keywords: Industry Life Cycle, agglomeration, externalities, evolution, MAR, Jacobs

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Classification: O18, R11, R12

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3 1. Introduction  
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8 A classical question in economic geography and regional economics is how geographic  
9 agglomerations contribute to the economic performance of firms. In the externalities  
10 literature, it is commonly understood that diversified cities offer different benefits as  
11 compared to specialized cities. A host of empirical studies have focused on the trade-off  
12 between diversification and specialization. However, so far, the empirical evidence on  
13 agglomeration externalities remains surprisingly inconclusive. The main question we seek to  
14 answer is whether the life-cycle stage of an industry determines which type of agglomeration  
15 externalities generates the highest benefits for local firms. Although the proposed framework  
16 is compatible with theoretical notions like “nursery cities” (DURANTON and PUGA, 2001)  
17 and in line with the oft-stated conjecture that externality estimates for high-tech industries  
18 differ from those for low-tech industries, to our knowledge, no study has yet systematically  
19 investigated the observed divergence in empirical outcomes by linking the concepts of  
20 agglomeration externalities to theories of industrial dynamics.  
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37 In doing so, we do not treat agglomeration externalities as static, and we will claim that the  
38 industry life-cycle framework can greatly help us to understand the changing nature of the  
39 effects of the local environment on the efficiency of local industries. Hypotheses are tested  
40 with data that cover industry life cycle (ILC) stages for twelve manufacturing industries in a  
41 panel of 70 Swedish cities over the period 1974-2004. The proposed statistical framework  
42 addresses many of the difficulties that arise in empirical work in the field of agglomeration  
43 externalities. Most importantly, we make an effort to reduce the arbitrariness in the choice of  
44 spatial units by the use of distance decay functions, and we address the problem of time-  
45 invariant regressors in panel data fixed effects models. We start from a production function  
46 inspired approach, with value added as the dependent variable. In order to disentangle the  
47 effects of factor costs and knowledge spillovers, we use both agglomeration indices and  
48 variables capturing differences in factor costs across cities. Our estimates show that young  
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3 industries benefit from being located in high-cost, high-diversity locations. When moving  
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5 towards more mature industries, however, the benefits shift gradually to plants located in  
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7 low-cost, specialized locations.  
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11 The structure of the article is as follows. First, in section 2, we briefly discuss the literature on  
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13 agglomeration externalities. Next, in section 3, we turn to the ILC concept and show how it  
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15 may be used to structure our expectations about the strength of different types of  
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17 agglomeration externalities. In section 4, we describe the Swedish dataset and explain how  
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19 we determine the life-cycle stages of the twelve industries. In section 5, we discuss the  
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21 econometric specification. Section 6 describes the data and presents the main results of our  
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23 regression analyses. In section 7, we summarize the main conclusions and research  
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25 challenges.  
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## 33 2. Agglomeration externalities<sup>i</sup> 34 35 36 37

38 Agglomeration externalities can be defined loosely as the benefits a firm derives from being  
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40 located close to other economics actors (see, for an extensive overview, ROSENTHAL and  
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42 STRANGE, 2004). Often, a distinction is made between three types of externalities:  
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44 Marshall-Arrow-Romer (MAR) <sup>ii</sup>, Jacobs', and urbanization externalities.<sup>iii</sup> These types of  
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46 externalities can be linked to opportunities for learning and the level of factor costs in a city.  
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51 Urbanization externalities are benefits experienced by firms located in large cities. On the  
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53 one hand, these cities often offer access to large markets (either locally, or because they are  
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55 hubs in international infrastructure networks), highly educated employees, and strong R&D  
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57 centres and business services. On the other hand, large cities are high cost environments,  
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59 with congestion, expensive labour, and high land prices.  
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3 MAR externalities arise when firms benefit from a strong local specialisation in their own  
4 industry. In the Marshallian tradition (MARSHALL, 1890), MAR externalities can be attributed  
5 to three sources: labour market pooling, input-output linkages and intra-industry knowledge  
6 spillovers. A large local industry is able to grow and sustain a highly skilled specialised labour  
7 force, and has lower matching costs between employers and employees (DURANTON and  
8 PUGA, 2004). It will also attract many specialised supplier and customer firms, resulting in  
9 lower transport costs and inventories. Moreover, spatial proximity to suppliers and customers  
10 facilitates joint innovation efforts along the value chain. Between competitors, knowledge  
11 spillovers occur through imitation and skill transfers that are greatly facilitated by face-to-face  
12 contacts between geographically proximate actors (STORPER and VENABLES, 2004).  
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27 In contrast to MAR externalities, Jacobs' externalities arise when firms benefit from the  
28 presence of a high level of industrial diversity. Local diversification gives rise to opportunities  
29 for combining knowledge across industries (JACOBS, 1969). Frequently, industries face  
30 problems in their production processes that have close analogues in other industries.  
31 Solutions that are applied in one industry can, in these cases, often be readily adapted to  
32 solve problems in other industries. Moreover, a diversified regional economy increases the  
33 likelihood of serendipitous inter-industry knowledge and product combinations to arise.  
34 Industrial diversity also results in more stable demand conditions and allows firms to choose  
35 from a wide range of local input substitutes, which reduces their exposure to price  
36 fluctuations in inputs. A formalization of this notion can be found in the love-of-variety models  
37 that use Dixit-Stiglitz (DIXIT and STIGLITZ, 1977) production or consumption functions (see  
38 for example DURANTON and PUGA, 2004).  
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55 Although congestion and high factor costs in large diversified cities may give rise to negative  
56 externalities, as argued above, diversity itself is thought to benefit local industries. However,  
57 in some empirical studies, diversity appears to have a negative effect on local economic  
58 performance. In fact, DE GROOT et al. (2009) report negative Jacobs' externalities in over  
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3 half the studies they review. Examples can be found in some of the industries studied by  
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5 HENDERSON (2003), and in COMBES (2000) for heavy manufacturing industries. Both  
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7 authors make note of these findings, but they do not probe their meaning or causes. We  
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9 argue that, in fact, Jacobs' externalities should be expected to become negative if they lead  
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11 to a lack of focus in the provision of a number of local endowments, such as infrastructure,  
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13 institutions, local services, and other facilities that are shared by all local industries.  
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18 In order to produce efficiently, industries draw on a wide variety of local resources, ranging  
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20 from professional services to infrastructure and institutions. Although many of these  
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22 resources are shared across the entire local economy, they can also be customized to a  
23  
24 certain degree. For example, business service providers, like legal offices, accountants, and  
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26 marketing agencies, can specialize their services to clients from a limited number of  
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28 industries and thereby focus on the specific needs of these clients. Similarly, the literature on  
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30 regional innovation systems (e.g. COOKE and MORGAN, 1998) has stressed that local  
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32 (government) institutions and vocational training institutes can become increasingly adapted  
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34 to the needs of specific local industries. However, the degree to which such local  
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36 endowments can be customized depends on how many different industries make use of  
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38 them. For example, although law agencies provide their services to firms in a number of  
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40 different industries, they will try to gain a specific expertise in the part of the legal code that is  
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42 relevant to their most important clients. Similarly, the physical infrastructure in a city is shared  
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44 among all industries, but one can think of many examples where infrastructure was  
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46 constructed with a particular industry in mind. However, the more heterogeneous the  
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48 industrial mix of a city, the harder it is to offer tailor-made solutions. Controlling for the size of  
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50 a city, the degree to which the provision of general (i.e., non industry-specific) local  
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52 endowments can be adjusted to meet the needs of individual industries depends on the  
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54 number of different industries that must share these endowments. Therefore, cities with little  
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56 industrial variety are likely to provide a stronger focus on these general endowments and  
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58 therefore better meet the specific demands of their local industries. To illustrate this, Figure 1  
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3 shows two cities of equal size that can generate just enough demand to sustain two law  
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5 firms.  
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10 - Figure 1 about here -  
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14 The law firms are depicted in the lower part of the figure. The upper part of the figure shows  
15 the client firms. In city A, there are only four industries, as indicated by the four different  
16 shadings for the client firms. Consequently, if we assume that the law firms specialize on  
17 clients in specific industries, each of them can focus on the legal code that is relevant for two  
18 different industries and still have enough clients to remain in business. By contrast, city B  
19 hosts eight different industries. In this city, the size of the local economy is the same as in  
20 city A, and we assume total turnover for both law firms to be equal as well. In city B,  
21 however, each law firm has to become proficient in the part of the legal code that is specific  
22 to four different industries. Therefore, the level of customization offered by the law firms in  
23 city B is likely to be lower than in city A. Similarly, services rendered by the infrastructure and  
24 institutions in city B may be expected to be less well-adapted to specific local industries.  
25 Particularly when an industry's requirements for such local resources do not change too  
26 much over time and the local environment therefore has time to adapt to its needs, the lack  
27 of such a local focus may represent an important locational disadvantage for such an  
28 industry.  
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50 In fact, some empirical support for this line of reasoning can be found in an article by  
51 COMBES et al. (2004). Combes and his co-authors use two different measures for local  
52 diversity simultaneously: a Herfindahl index that assesses how equally employment is  
53 distributed across local industries, and a simple count of industries active in a region. They  
54 find that "The most favorable local industrial structure would consist in a small number of  
55 industries but of roughly the same size ..." (p. 237). In other words, local diversity is  
56 beneficial to a region, as long as it is not too spread out across too many different industries.  
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3 This is fully in line with our claim that a lack of local focus may be harmful for local industries.  
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5 Although Combes and his colleagues do not elaborate on this finding, this regularity may  
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7 help explain why some studies find negative Jacobs' externalities.  
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11 Table 1 summarizes the different sources of urbanization, MAR, and Jacobs' externalities,  
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13 differentiating between knowledge spillover effects and the effects of factor costs.  
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21 -Table 1 about here-  
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27 Since the seminal articles by GLAESER et al. (1992) and HENDERSON et al. (1995), the  
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29 empirical literature investigating the impact of MAR, Jacobs', and urbanization externalities  
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31 has expanded rapidly. Unfortunately, though, these efforts have not yet resulted in a  
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33 complete understanding of agglomeration externalities. FELDMAN's (2000) literature review  
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35 about the connections between innovation and location notes that there is wide divergence in  
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37 the empirical results on the importance of MAR economies. GLAESER (2000) reaches  
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39 similar conclusions when it comes to the difference between the impacts of concentration  
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41 and diversity, respectively. Also, NEFFKE (2008) finds that the outcomes reported in seven  
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43 leading articles show considerable differences, even for studies that focus exclusively on the  
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45 United States. As noted by COMBES et al. 2004, there are many possible explanations for  
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47 these contradictory findings. For example, studies differ widely in their methodologies: plant-  
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49 level versus regional studies, panel data versus cross-section analyses, and productivity  
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51 versus employment regressions. Moreover, samples are drawn from different periods in  
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53 history and relate to different geographic areas in the world. DE GROOT et al. (2009)  
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55 reviewed 31 studies containing over 200 parameter estimates. In a meta-analysis, the  
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57 authors find that both sample issues and methodological issues affect outcomes. However,  
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59 COMBES (2000), on the basis of a single dataset and a uniform methodology, still finds  
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3 considerable differences in the externalities that are experienced by different industries. This  
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5 suggests that another important factor causing divergence of outcomes is industrial  
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7 heterogeneity.  
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11 Referring to a Vernonian product life-cycle view of regional development, it is often  
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13 hypothesized that product development takes place in large, diversified cities, whereas  
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15 production takes place in smaller-yet-specialized cities (e.g. HENDERSON, 2003).  
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17 DURANTON and PUGA (2001) formalize this conjecture in their “nursery cities” concept. We  
18  
19 agree that specialized cities may be attractive for different industries than are diversified  
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21 cities. Indeed, we will argue that this can best be understood by drawing from the literature  
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23 on industry life cycles.<sup>iv</sup>  
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### 31 3. Industry life cycles and agglomeration externalities 32 33 34

35 The industry life-cycle framework (ILC) (GORT and KLEPPER, 1982; ABERNATHY and  
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37 CLARK, 1985; KLEPPER, 1997) is a stylized description of the evolution of an industry from  
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39 infancy to decline. The archetypical evolution of the output in an industry follows a logistic (or  
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41 S-) curve, starting with the introduction of a new product, followed by a period of strong  
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43 expansion of production, which then levels off and eventually leads to a decline. The ILC  
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45 literature has grown into an extensive body of work with many detailed descriptions and  
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47 subtleties. In this paper, we restrict the discussion to three aspects of industry life-cycle  
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49 stages: type of innovation, innovation intensity, and mode of competition. Table 2  
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51 summarizes how an industry changes when moving from a young to a more mature stage.  
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-Table 2 about here-

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3 The birth of a new industry typically follows from radical innovations that result in new  
4 products. The young stage is characterised by the development of an immature technology.  
5 Innovation intensity is high, as there are many unexplored technological opportunities.  
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7 Because standardization has yet to set in, large discontinuities in a technological sense are  
8 not uncommon. Therefore, as argued by GORT and KLEPPER (1982), information about  
9 innovation(s) can come from a wide range of sources in these stages, often from outside the  
10 young industry's population of firms. Inter-industry knowledge spillovers associated with  
11 Jacobs' externalities should be of utmost importance to these young industries. These  
12 industries need – and can accommodate – a large variety of knowledge to build superior  
13 products.  
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27 Another characteristic of young industries is that firms tend to compete on the basis of quality  
28 characteristics of their new products as opposed to their price. Therefore, they are not very  
29 sensitive to factor-cost differentials between regions. Given their volatility and age, young  
30 industries are usually insufficiently embedded in the local environment to begin to  
31 successfully lobby local business service providers and the local government. For this  
32 reason, they will be largely unaffected by the lack of focus that may arise in Jacobs'  
33 environments. Typically, the scale of non-standardized production in young industries is  
34 small. As a consequence, urbanization benefits should not be expected from access to a  
35 large market. However, access to a highly qualified labour force and the lead users that can  
36 be found in large cities should be beneficial.  
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51 After a period of experimentation, disruptive technological jumps become less likely and the  
52 industry reaches more mature stages. A 'dominant design' (UTTERBACK and SUAREZ  
53 1993) allows for standardization of production. This opens up opportunities to exploit division  
54 of labour and economies of scale. Products get more homogenous, output volumes go up,  
55 and firms engage increasingly in price competition. This leads to a sharp drop in prices,  
56 enlarging the client base from early adopters to a wider general public. The importance of  
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3 factor costs rises, whereas the mechanization of the production process lowers the demand  
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5 for highly-educated labour. However, access to large markets and international infrastructure  
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7 networks is a prime concern in these industries, suggesting a significant effect of  
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9 urbanization externalities.  
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13 As technological opportunities become exhausted, R&D efforts shift towards process  
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15 innovation in order to increase efficiency. Process innovations often require specialized,  
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17 industry-specific machines, skills, and knowledge. Such know-how is often of a strong tacit  
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19 nature and best acquired through processes of the learning-by-doing and imitation that is  
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21 typical for traditional industrial districts (AMIN, 2003). Inter-industry spillovers become less  
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23 likely. The value of a local focus increases as the possibilities to tailor the local education  
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25 system, infrastructure, and many other aspects of the local environment grow (GRABHER,  
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27 1993). This may penalize high-diversity environments. Both tendencies lead to lower Jacobs'  
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29 externalities. Standardization supports the development of a common language and  
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31 technology framework across firms, facilitating the orchestration of innovation efforts along  
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33 the value chain. Similarly, industry-specific knowledge can now be carried more easily across  
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35 firm boundaries by labour mobility. Therefore, opportunities for intra-industry (MAR)  
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37 spillovers rise.  
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44 The ILC description of industry development is highly stylized. In practice, industries could  
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46 rejuvenate after a radical innovation that has far-reaching consequences for the industry, and  
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48 casts the industry back into more infant stages. Moreover, at a higher level of industrial  
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50 aggregation, various technological trajectories are often stacked and overlap with one  
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52 another. This may obfuscate the life cycle and prevent an industry from progressing through  
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54 each of the stages in the described order. However, the basic characteristics in each stage  
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56 are still the same, whether an industry really is new or just rejuvenated. Table 3 merges the  
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58 elements of tables 1 and 2 to summarize this discussion of the interaction between  
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60 agglomeration externalities and life cycle dynamics. In the rows, externality types and their

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3 different sources are listed. In the columns, we describe how the influence on the  
4 competitiveness of local industries changes between negative, neutral, and positive when  
5 moving from young to more mature industries.  
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12 -Table 3 about here-  
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#### 18 4. Data and industry life-cycle stages 19

##### 20 Data 21 22

23 The data used in this study cover all Swedish manufacturing plants with five employees or  
24 more without further restrictions in the period 1968-1989 and all manufacturing plants with at  
25 least five employees that belong to *firms* employing at least 10 people in the period 1990-  
26 2004.<sup>v</sup> All plants in the dataset are classified according to the Swedish SNI-code system at  
27 the five-digit level (similar to the SIC classification). Due to a change in this system, we had  
28 to merge some five digit industries. For these industries, the classes correspond roughly to  
29 the three- or four-digit level.<sup>vi</sup> The geographical location of plants is known at the municipality  
30 level (there are 277 in our dataset). This provides us with a high-quality database containing  
31 detailed information about the development of the Swedish economy from the late 1960s up  
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##### 50 Calculation of potentials

51 As the unit of our analysis is the local industry, we aggregate plant-level data into spatial  
52 units. A classical problem occurs when simply summing micro-level data up to regional units:  
53 outcomes of analyses based on such data are often subject to change when borders of units  
54 are redrawn. Moreover, there are many qualitative differences between regional units. For  
55 one, some regions are larger in terms of area than are others. Another issue is that some  
56 regions are multi-core regions, whereas other regions are dominated by one large city. In this  
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3 study, we argue that agglomeration externalities are primarily found in cities. Swedish  
4 municipalities are, in many cases, too small in terms of population to exhibit the kind of  
5 agglomeration externalities discussed in the literature (e.g GLAESER et al., 1992). For these  
6 reasons, we construct metropolitan-area data around 70 Swedish labour market regions (so-  
7 called functional or A-regions). Most regions are dominated by a single large city, but some  
8 harbour two or more equally sized cities. Agglomeration externalities in multi-core regions  
9 should be weaker than their combined size suggests, but stronger than what may be  
10 expected from each city separately. Simply attributing all economic activity to a single point in  
11 space would therefore overstate the size of externalities, whereas focusing only on the  
12 largest city would understate them. Instead of committing ourselves to one of these  
13 extremes, we calculate potential measures for the largest cities in each of the regions. The  
14 lowest spatial level we can distinguish is the municipality. Typically, this consists of a town  
15 and some surrounding hamlets or villages. Therefore, it is not too restrictive to assume that  
16 all economic activity takes place at the location of the central town. Using a road-distance  
17 matrix, we construct a spatially weighted sum of the contributions from all municipalities in  
18 Sweden to the largest town in each A-region. This gives us a potential measure for each of  
19 the 70 major cities in Sweden. Take as an example the number of plants. Let:

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42  $P_{mit}$  : number of plants in municipality  $m \in M$  in industry  $i$  at year  $t$ .

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44  
45  $d_{ma}$  : distance by road between the municipality core,  $m$ , and the A-region core,

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47  
48  $a \in A$

49  
50  $M$ : set of all municipalities in Sweden

51  
52  $A$ : set of all A-region cores in Sweden

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56 Now the “plant-potential” in industry  $i$  for A-region-core  $a$  is calculated as follows:

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$$P_{ait}^{pot} = \sum_{m \in M} f(\delta, d_{ma}) P_{mit}$$

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5  $f(\delta, d_{ma})$  is a distance decay function.<sup>vii</sup> Analogously, we can calculate a population-  
6  
7 potential, an employment-potential and a valued added-potential for each of the 70 cities.  
8  
9 However, if we were to apply the potential calculations as described above to the dependent  
10  
11 variable in a regression analysis, we would artificially create spatial autocorrelation.  
12  
13 Therefore, when calculating potentials for the dependent variable and the employment  
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15 variable (which captures the scale of the inputs), we set the contributions of municipalities  
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17 outside the A-region equal to zero. For all other variables, contributions from all Swedish  
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19 municipalities are used.  
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26 Next, we add data on house prices, acquired from Statistics Sweden.<sup>viii</sup> The house price  
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28 indicators, however, are not spatially weighted and reflect the house prices in the 70 core  
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30 cities.  
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#### 34 Industries and lifecycles

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36 In total, our dataset distinguishes between 102 different industries that can be followed  
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38 consistently over time. Most of the industries are small and are present in only a handful of  
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40 labour market regions. As this would cause additional estimation problems, we focus on 12  
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42 major industries. These 12 account for some 44% of total Swedish manufacturing output in  
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44 1974 and for 42% of such output in 2004.  
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50 A major challenge is to find an adequate way to determine the life-cycle stages of each  
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52 industry over time. Traditionally, life-cycle stages have been described using entry-exit  
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54 patterns (e.g. GORT and KLEPPER, 1982). However, in a small country like Sweden, the  
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56 number of plants in a single industry and, hence, the number of entrants and exits, is very  
57  
58 small.<sup>ix</sup> This means that just a few entries or exits are sufficient to mark the transition  
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60 between two life-cycle stages. AUDRETSCH and FELDMAN (1996) suggest an alternative  
approach to identify life-cycle stages. They classify industries into different life cycle stages

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3 by looking at the innovation intensity of small firms compared to large firms by drawing on a  
4 product announcements database. Young industries are characterized as industries with a  
5 high innovation intensity that takes place predominantly in small firms. If large firms  
6 undertake the bulk of the innovation effort, industries are said to be either in the growth stage  
7 or in the mature stage, depending on whether the overall innovation intensity is high or low.  
8 Declining industries are supposed to exhibit little innovation, but that which does exist will be  
9 carried out predominantly by small firms. Data on innovation intensity were not available for  
10 this study. However, the way we define life-cycle stages has some commonalities with the  
11 work by Audretsch and Feldman. Instead of innovation intensity, we look at the market share  
12 of young plants in an industry. The logic behind this is that young plants will, in general, use  
13 newer production technologies than will mature plants. After all, technology is to a large  
14 degree embedded in machinery, which is costly to replace. Moreover, new technologies  
15 require new routines and skills, the acquisition of which is costly and time consuming (e.g.,  
16 NELSON and WINTER, 1982). If an industry is in a stage of strong technological renewal –  
17 i.e., if the industry is young or recently rejuvenated – mature plants struggle to respond to a  
18 situation where both physical and human capital are becoming obsolete, allowing young  
19 plants to capture large shares of the market. In contrast, if the industry is in a stage with a  
20 stable technological trajectory, older plants are less threatened by new entrants and will  
21 retain a larger share of the market.  
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46 Defining old plants as plants that are 10 years or older, we calculate the market share of old  
47 plants for all industries in our dataset. To control for changes in the overall plant turnover  
48 over the years, we divide the old-plant market shares of each industry by the market share of  
49 old plants in the economy as a whole. This yields the over- or underrepresentation of old  
50 plants compared to the national level. Next, we normalize this index by subtracting the mean  
51 and dividing by the standard deviation across all industries. Let the maturity index be:  
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$$I_{it} = \frac{VA_{it}^{old} / VA_{it}^{tot}}{VA_t^{old} / VA_t^{tot}}$$

where:

$VA_{it}^{old}$  : value added in old plants in industry  $i$  at year  $t$

$VA_{it}^{tot}$  : value added in all plants in industry  $i$  at year  $t$

$VA_t^{old}$  : value added in all old plants in Sweden at year  $t$

$VA_t^{tot}$  : value added in all plants in Sweden at year  $t$

The normalized maturity index is now:

$$I_{it}^{norm} = \frac{I_{it} - \text{mean}(I_{it})}{\text{stddev}(I_{it})}$$

We distinguish between three levels of maturity: young, intermediate, and mature. In order to obtain a roughly equal number of observations for each type, we use the mean  $-0.3$  times the standard deviation and  $+0.3$  times the standard deviation as demarcation values. Using a five-year moving average to control for business cycle volatility, table 4 shows, for each year, the life-cycle stages for the twelve industries in our study. Industries may move through several stages, such as “other plastics,” which progresses through young as well as intermediate and mature stages. However, please note that industries close to the maturity threshold may shift repeatedly between categories.<sup>x</sup> The general picture shows, in line with our intuition, that textiles, sawmilling, carpentry, furniture, paper, and chemicals have been rather mature industries over the entire course of the past three decades. Publishing and communication underwent rejuvenation in the 1990s. Electric motors had entered a young stage already in the 1980s. Other plastics, in contrast, slides into maturity. To a lesser

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3 degree, the same holds for metal ware. The instruments industry has been classified as a  
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5 young industry for all years in our sample.  
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12 -Table 4 about here-  
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20 5. Econometric specification  
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22 In order to measure the size of externalities, we estimate a Cobb-Douglas inspired  
23 production function for city-industries. Output is measured by value added. Due to a lack of  
24 capital data, the only inputs in the production process at our disposal are employment data.  
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29 This gives rise to the following multiplicative model:  
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32

33 (1) 
$$VA_{cit} = T_{cit} L_{cit}^{\alpha} \varepsilon_{cit}$$
  
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38 where:  
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42  $VA_{cit}$  : Value-added potential produced by city c in industry i at year t  
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45  $L_{cit}$  : Labour potential employed by city c in industry i at year t  
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48  $T_{cit}$  : Technology term. This term contains the externality effects for city c in industry i  
49  
50 at year t.  
51  
52  
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54 The omission of a variable that captures the size of capital inputs is potentially problematic.  
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56 For example, it may be particularly expensive to use capital intensive production technology  
57  
58 in large cities, where transport and storage of capital goods is costly. In this case, the  
59 urbanization externalities parameter would suffer from a downward bias: the negative effect  
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3 of a lower capital intensity in big cities reduces the parameter estimate for urbanization  
4 externalities.  
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9 A satisfactory solution would require the estimation of a full Total Factor Productivity (TFP)  
10 model as in CINGANO and SCHIVARDI (2004). Such models enable the researcher to  
11 quantify the overall efficiency improvements that can be attributed to agglomeration  
12 externalities. Without data on capital, this strategy is unavailable. However, concerns about  
13 omitted variable bias should be limited as long as the estimate of  $\alpha$  stays close to 1. The  
14 reason for this is that we can think of labour as a proxy for the total amount of inputs that  
15 went into the production process. If we now assume that there are constant returns to scale –  
16 which is not unreasonable at the level of regional aggregates – and that there is no  
17 confounding with the other variables in the model, we should expect that all effects of the  
18 scale of production are captured in  $\alpha$ . Therefore, a finding of  $\alpha = 1$ , although strictly  
19 speaking not a proof, suggests that labour inputs are also a solid proxy for capital inputs and,  
20 as a consequence, that the externality estimates are not confounded by omitted variable  
21 bias.  
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40 We will now turn to the elements that make up the technology term. Urbanization  
41 externalities are measured by the population potential:  
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$$46 \quad POPULATION_{ct} = \sum_{m \in M} f(\delta, d_{mc}) pop_{mt}$$

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51 We would like to disentangle, however, the different aspects of a big city implicit in  
52 urbanization externalities. We therefore control for two other factors. The first is the overall  
53 wage level in the city. For this purpose, we construct, for each industry, the relative wage  
54 level in a city compared to the corresponding national level. We next construct a weighted  
55 average, using local employment in each industry as a weight:  
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$$WAGE_{ct} = \sum_i \frac{L_{cit}}{L_{ct}} \frac{w_{cit}}{\bar{w}_{it}}$$

where:<sup>xi</sup>

$w_{cit}$  : average local wage paid in industry  $i$ .

$\bar{w}_{it}$  : average Swedish wage paid in industry  $i$ .

The resulting index is equal to one if average wages in the city are equal to average wages in the whole of Sweden, keeping constant the composition of industries. As this index is calculated across all 102 manufacturing industries in the economy, the influence of the wage level of a single industry is negligible. The problem of using a wage index is that the wage level in a city reflects both variations in the cost of living across cities and differences in the premium that is paid for the quality of the local workforce. We would like to distinguish between the cost and quality-of-labour effects. As rents account for a large portion of household expenditures, the higher costs of living in big cities are to a large degree accounted for if we control for housing prices ( $HOUSE_{ct}$ ). We will assume that if we keep housing prices constant, the remaining variation in the wage index is due to differences in quality of labour.

MAR externalities have been modelled in various ways in the literature. Levels or shares of own industry employment are widely used indicators (e.g., GLAESER et al., 1992, HENDERSON et al., 1995, HENDERSON, 1997). However, these indicators do not differentiate between plant-internal and plant-external economies of scale. In the extreme case, where all the employment in a city-industry is located in a single plant, the effects of local employment are fully attributable to internal economies of scale. The number of plants, in contrast, can only give rise to external economies of scale.<sup>xii</sup> HENDERSON (2003) argues that the number of plants is a good measure for capturing MAR externalities. His reasoning is

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3 that each plant can be interpreted as an experiment with a specific variation on the industry's  
4 production process. The potential of intra-industry knowledge spillovers depends, therefore,  
5 on the local number of those experiments, not so much on the number of the local industry's  
6 employees. Moreover, workers acquire more industry-specific skills if they can become  
7 employed and educated in different local firms. The number of plants also measures the  
8 number of potential innovation partners in the own industry. For these reasons, we measure  
9 the scope for knowledge spillovers in MAR externalities as the number-of-plants potential in  
10 the local industry:  
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$$22 \quad MAR_{cit} = \sum_{m \in M} f(\delta, d_{mc}) P_{mit}$$

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28 where:

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32  $P_{mit}$  : the number of plants in municipality  $m$ , industry  $i$  at year  $t$ .  
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37 Jacobs' externalities result from the presence of a large diversity of industrial activity in a city.  
38 To quantify this, many authors use an index that measures the evenness of the distribution of  
39 economic activity across different local industries, like the Hirschman-Herfindahl index (HHI)  
40 or the entropy index of local employment shares. However, these measures are not very  
41 informative, as constellations with very different spillover potentials may yield the same  
42 HHI.<sup>xiii</sup> The number of significant industries in a city, by comparison, is a more adequate  
43 measure. We call an industry's presence in a region significant if its size reaches a certain  
44 threshold. As we argued that spillovers are related to the number of experiments in different  
45 plants, we base the Jacobs' externalities indicator on the number of plants potential.<sup>xiv</sup>  
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$$59 \quad JACOBS_{ct} = \sum_i g \left( \sum_{m \in M} f(\delta, d_{mc}) P_{mit} \geq 10 \right)$$

where:

$g(\cdot)$ : indicator function that evaluates to 1 if its argument is true and 0 otherwise.

Assuming that all externalities and control variables enter the technology term in a multiplicative way, we arrive at the following log-transformed estimation equation:

$$(2) \quad \log(VA_{cit}) = cst + \alpha \log(L_{cit}) + \beta_1 \log(POPULATION_{ct-2}) + \beta_2 \log(WAGE_{ct}) + \beta_3 \log(HOUSE_{ct}) + \beta_4 \log(MAR_{cit-2}) + \beta_5 \log(JACOBS_{ct-2}) + \log(\varepsilon_{cit})$$

The effects of local learning will only be felt after a certain amount of time. We therefore use a two-year lag for all variables that mainly capture knowledge spillovers.<sup>xv</sup> To meet the aim of the study, we must discover how externalities differ across ILC stages. We therefore pool observations across all industries and make coefficients dependent on the particular ILC stage. Taking the lag 2 into consideration, we end up with a panel of 70\*12 city-industries for 34 years. Adding city-industry fixed effects and year dummies, we get:

$$(3) \quad \log(VA_{cit}) = cst + \alpha^s \log(L_{cit}) + \beta_1^s \log(POPULATION_{ct-2}) + \beta_2^s \log(WAGE_{ct}) + \beta_3^s \log(HOUSE_{ct}) + \beta_4^s \log(MAR_{cit-2}) + \beta_5^s \log(JACOBS_{ct-2}) + \eta_{ci} + \delta_t + \log(\varepsilon_{cit})$$

where:

$\eta_{ci}$ : city-industry fixed effects

$\delta_t$ : year fixed effects

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3 .<sup>s</sup> : superscript indicating industry life-cycle stage: young / intermediate / mature  
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## 7 6. Empirical results

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11 Table 5 shows the main descriptive statistics for our dependent variable, log(VA), and for the  
12 six regressors. Table 6 contains the correlations between the regressors.  
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18 -Table 5 about here-

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22 -Table 6 about here-

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26 As a baseline, we estimate the effects of externalities without distinguishing between life-  
27 cycle stages using a fixed effects (FE) estimation. The outcomes are shown in column (1) of  
28 table 7. The estimate for employment (L) is very close to 1, indicating constant returns to  
29 scale. In fact, this finding is replicated in all the estimations of this article. As argued before,  
30 this is an indication that the omitted variable bias due to a lack of data on capital inputs is  
31 limited. MAR externalities are positive and have an elasticity of about 2%, meaning that a  
32 doubling of the number of own-industry plants leads to efficiency gains of 2%. As a  
33 comparison, this estimate ranges from 2% to 8% in HENDERSON (2003). Jacobs'  
34 externalities seem to be absent. The point estimate for urbanization externalities, as  
35 measured by population, is high, but the standard error is large as well. The reason for this is  
36 apparent in table 5. The population of a city changes only very slowly over time, which gives  
37 rise to a very low within standard deviation. However, the between standard deviation is high,  
38 as, cross-sectionally, population potentials vary widely. In FE models, this leads to imprecise  
39 estimates. Including the extra information on wages and housing prices (column 2, table 7)  
40 unfortunately does not solve the problem.  
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3 One way to improve the precision of the estimates is using random effects (RE). However,  
4 RE models assume that the unobserved city-industry fixed effects are uncorrelated with the  
5 regressors. Theoretically, there is little reason for this assumption. Column 3 (table 7)  
6 presents the results. The population estimate is small but negative, and the standard error  
7 drops tremendously. The other parameter estimates have remained more or less the same.  
8 However, a Hausman test on the adequacy of the RE model rejects the RE specification at  
9 any conventional level.  
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20 This leaves us with a dilemma: on the one hand, FE will not allow us to get precise estimates  
21 on one of our core variables; on the other hand, RE has not passed the Hausman test.  
22 Theoretically, the Hausman-Taylor procedure (HAUSMAN and TAYLOR, 1981) could be  
23 applied. However, the fact that, for this method, one must find variables that can be  
24 convincingly thought of as a priori uncorrelated with the city-industry effects makes this  
25 method problematic (ARELLANO, 2003, p. 44).  
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35 A different solution has been developed by PLÜMPER and TROEGER (2007). These  
36 authors use a procedure originally proposed by HSIAO (2003).<sup>xvi</sup> In their “Fixed Effects  
37 Vector Decomposition” (FEVD) method, variables can be modelled as either time-varying or  
38 (predominantly) time-invariant. The time-varying variables can be estimated without bias.  
39 However, the estimates of the effect of time-invariant and slowly changing variables are  
40 biased, as already noted by HSIAO (2003). This bias can be interpreted as a between-  
41 groups (cross-sectional) omitted variable bias and therefore depends on the correlation  
42 between the time-invariant variables and the unexplained city-industry effect. As the city-  
43 industry effects are unobserved, it is impossible to assess this correlation. However, Plümp  
44 er and Troeger show that, for a wide range of values, in small samples, the FEVD estimator  
45 outperforms the FE, RE, and Hausman-Taylor estimators in terms of the Root Mean Squared  
46 Error (RMSE). In other words, the increased efficiency more than offsets the modest bias in  
47 our estimates.  
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5 In our study, the superiority of the FEVD depends on two variables: first, the correlation  
6 between the city-industry effects and the regressors that we regard as slowly changing and,  
7 second, the ratio of between to within standard deviations of the slowly changing variables.  
8 Looking at tables 5 and 6, population is clearly a slowly changing variable, with a between-to-  
9 within ratio of over 17. As POPULATION is strongly correlated with JACOBS, and a large  
10 part of the variation in JACOBS is actually cross-sectional, omitting JACOBS from the  
11 residuals would give rise to a large omitted variable bias in the second step of the FEVD  
12 procedure.  
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25 Column (4) in table 7 shows the estimates for the FEVD specification, where POPULATION  
26 and JACOBS are modelled as slowly changing variables. The estimates are similar to the RE  
27 estimates. The parameter estimates for the time-varying variables, L, MAR, HOUSE, and  
28 WAGE, are all indistinguishable from their FE estimates in column (2). However, the  
29 standard errors of FEVD estimates are considerably lower. Jacobs' externalities are  
30 significant and negative. The point estimate for population is positive and, for the first time,  
31 significant (though very close to the RE estimate). Finally, the estimate for WAGE is positive  
32 and significant.  
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46 The ILC and agglomeration externalities

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48 Having arrived at a satisfactory econometric specification, we now turn to our research  
49 question: how do externalities change with life-cycle stages. Column (5) of table 7 shows the  
50 outcomes of the final model. Parameters are allowed to vary depending on the life-cycle  
51 stage of the industry. Economies of scale for industries in all stages are more or less  
52 constant, as indicated by the employment parameter estimates that are very close to 1. MAR  
53 externalities are positive in all industries. The elasticity estimates, however, clearly rise from  
54 hardly significant (0.8%) in young industries to 1.3% in intermediate industries and to 2.2% in  
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3 mature industries. The pattern for Jacobs' externalities runs opposite to this. Young  
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5 industries benefit from local diversity (doubling diversity leads to a rise in efficiency of 1.9%),  
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7 whereas mature industries experience large negative effects (-5.3%). Both estimates are  
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9 highly significant. The estimate for intermediate industries is small and insignificant. These  
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11 outcomes support our hypothesis that young industries, with their low levels of  
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13 standardization, are open to knowledge from very diverse sources, but do not benefit much  
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15 from specialized, industry-specific knowledge. Mature industries, on the other hand, benefit  
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17 far more from intra-industry knowledge spillovers, but experience difficulties in diversified  
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19 cities, in line with our hypothesis that these industries would benefit from a focused local  
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21 environment.  
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27 As explained in section 2, the size of the local population can benefit or harm a local industry  
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29 in various ways. The higher costs of living and the higher quality and level of education in  
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31 large cities are controlled for by the variables WAGE and HOUSE. Even so, access to large  
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33 and sophisticated markets gives rise to positive effects, whereas congestion has negative  
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35 consequences. According to our estimates, the net benefit derived from locating in large  
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37 cities is positive for mature and intermediate industries, but negative for young industries.  
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39 This is surprising, but suggests that big city amenities and immediate market access only  
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41 play a role for intermediate and mature industries.  
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47 Young industries need a highly educated labour force to cope with the volatile nature of this  
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49 part of the technological trajectory. In mature industries, production processes have become  
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51 more standardized and mechanized. For these, the quality of labour plays a smaller role.  
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53 This is reflected in the WAGE estimates. The benefits of high wages are indeed limited to  
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55 young industries. Column (6) shows outcomes when housing prices are omitted. The positive  
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57 effect for young industries has decreased sharply, supporting the claim that housing prices  
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59 effectively control for the factor-cost component in the WAGE variable.  
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3 High housing prices should harm all industries alike. For mature and intermediate industries,  
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5 this is confirmed, although more so for intermediate than for mature industries. Surprisingly,  
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7 however, young industries benefit from higher housing prices. One reason for this could be  
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9 that housing prices are, to some extent, correlated with factors affecting the quality of life in a  
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11 city. Given the negative effect of POPULATION in young industries, this suggests young  
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13 industries thrive in smaller but highly-developed, expensive cities.  
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18 Robustness: endogeneity

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20 A potential problem in the interpretation of our outcomes is the presence of endogeneity.  
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22 Highly productive cities may attract people and firms just as much as a high number of local  
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24 plants or inhabitants may cause local industries to be more productive. Moreover, wages and  
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26 housing prices may rise because of productivity increases in local industries. The statistical  
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28 association between VA and these variables may therefore also be a result of a reverse  
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30 causality. Such an argument builds largely on feedback loops through effective local  
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32 demand.  
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38 The standard econometric approach to accommodate such problems is instrumental variable  
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40 estimation. For this technique to work, instruments are needed that are correlated with the  
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42 regressors, yet uncorrelated with VA. We do not know of any variables that qualify for this  
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44 task.<sup>xviii</sup> In panel data, the time-series dimension often provides the researcher with suitable  
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46 instruments, which can be used in General Method of Moments (GMM) estimation. In this  
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48 approach, first-differenced equations are estimated using lagged independent variables as  
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50 instruments. The applicability of this method critically depends on the strength of the  
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52 variables (i.e., on the correlation between lagged regressors and first-differenced  
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54 regressors). In our case, experiments with GMM led to highly unstable coefficients. This is  
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56 not surprising, as, for our independent variables, the variation in lags explained typically  
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58 about as little as 5% of the variation in first-differences. Such values suggest that the GMM  
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60 approach is indeed unlikely to yield any interpretable results. Instead of IV estimation, we

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3 therefore tried to make sure that reverse causality is likely to be an order of magnitude  
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5 smaller than modelled causality.  
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10 First, we measure the dependent variable at the city-industry level, whereas most regressors  
11  
12 - population, house prices, diversity, and wages - are measured at the city level. The 12  
13 industries in the study together make up under 45% of all manufacturing employment.  
14  
15 Manufacturing as a whole accounts for roughly one third of Swedish employment. Therefore,  
16  
17 the variation in local demand as a consequence of the variation in VA in one of the  
18  
19 investigated industries – the feedback loop causing reverse causality – will be negligible  
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21 when compared to the modelled causality.  
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27 Second, for our externality indicators, we use a lag-2 specification. Take, for example, the  
28  
29 MAR externalities.<sup>xviii</sup> MAR is measured two years before high productivity is manifest.  
30  
31 Assuming that firms are unable to anticipate high productivity, but rather react to it, new  
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33 plants should become operational after the high productivity is realized, not before. Again,  
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35 this should weaken reverse causality.  
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40 The third reason we are not too concerned about endogeneity is that, in some cases, our  
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42 estimates should be regarded as cautious estimates because we would expect reverse  
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44 causality to run in the opposite direction of modelled causality. Housing prices, for example,  
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46 should rise as a reaction to an increase in VA. For two out of three industry stages, however,  
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48 we find a negative relation between housing prices and VA. The same argument holds for  
49  
50 the influence of wages in mature and intermediate stages.  
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55 Finally, we are not interested in the level of the parameter estimates per se, but rather in their  
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57 changes across industry life-cycle stages. There is no compelling reason to expect that, for  
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59 instance, housing prices will react differently if the VA increase is generated in a young  
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industry or in a mature industry. The increase in local demand as a consequence of a local

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3 VA surge should have the same impact on the regressors regardless of the industry in which  
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5 the VA is produced. Moreover, as we will show below, if we move between different cut-offs  
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7 for our ILC stage definitions, coefficients behave exactly as implied by our theoretical  
8  
9 framework. Any effective reverse-causality charge to our findings must also have an  
10  
11 adequate explanation for this observation. Taking all this together, we deem it unlikely that  
12  
13 endogeneity invalidates the main results of this article.  
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18 Robustness: changing period definition  
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20 The results above obviously depend on the definition of the industry stages. Therefore, we  
21  
22 rerun model (5) in table 7 for two alternative life-cycle stage definitions. Column (5a) in table  
23  
24 8 shows the results when the category of intermediate industries is narrowed and the line  
25  
26 demarcating mature and young industries gets thinner. Column (5b) uses the same limits as  
27  
28 in table 7, and, in column (5c), the intermediate category is widened at the expense of the  
29  
30 young and the mature categories. As we move from (5a) to (5b) to (5c), industries classified  
31  
32 as mature become increasingly older, and industries classified as young become  
33  
34 increasingly younger. If our hypotheses are correct, the parameter estimates for young and  
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36 mature industries should lie closer together in column (5a) and further apart in column (5c).  
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42 Indeed, the patterns for both MAR and Jacobs' externalities are amplified when moving from  
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44 column (5a) to (5b) and then to (5c). Also, the variables that measure urbanization  
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46 externalities get more pronounced. For all variables – POPULATION, HOUSE, and WAGE, -  
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48 the difference between the estimates for mature and young industries increases. This  
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50 strongly supports the robustness of our analyses.  
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55 -Table 8 about here-  
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## 7. Conclusions

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3 In this paper, we conjectured that industries have different agglomeration needs in different  
4 phases of their life cycles. To test this, we set up a framework that describes the evolution of  
5 agglomeration externalities along the life cycle of industries.  
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11 In all, our results show that the benefits industries derive from their local environment are  
12 strongly associated with their stage in the industry life cycle. Moving from young to  
13 intermediate to mature industries, the benefits derived from local specialization steadily  
14 increase. In contrast, the benefits from local diversity for young industries are positive, then  
15 turn insignificant for intermediate industries, and finally become negative for mature  
16 industries. These findings support our hypothesis that with increasing levels of maturity,  
17 industries experience rising benefits of intra-industry spillovers, but declining inter-industry  
18 spillovers. Moreover, we have argued that the relative stability of mature industries would  
19 allow them to take advantage of more specialized environments and make them more  
20 vulnerable to a lack of local focus that is more common in diversified cities. This could  
21 explain the negative Jacobs' externalities we found in these industries. We also show that, in  
22 line with our ILC framework, factor costs and quality of labour have very different effects on  
23 the efficiency of young and mature industries. Whereas the former thrive in expensive,  
24 medium-sized cities with highly qualified and costly labour, the latter are better off in low-cost  
25 cities with a relatively large local market.  
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46 Instead of treating agglomeration externalities as static, our results show that the study of  
47 agglomeration externalities demands a dynamic, long-term perspective. The industry life-  
48 cycle framework can greatly help us understand the changing nature of effects of the  
49 environment on the efficiency of local industries.  
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56 In terms of methodology, we used a procedure that solves some of the main issues  
57 encountered in empirical research in this field. For instance, the use of city-potentials  
58 smoothes regional borders and reduces arbitrariness in the choice of regional units. Another  
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3 improvement was the FEVD methodology to estimate the impact of population, which  
4 typically shows very little time-variation. Finally, we disentangled many of the different  
5 aspects of urbanization externalities by using information on local housing prices and wages.  
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11 There are, however, still some open questions. Although we have argued that endogeneity  
12 issues are of no great concern, an analysis at the plant level could solve the issue in a more  
13 theoretically satisfactory way. Moreover, replication of our results in other countries and  
14 industries, especially in service industries, is necessary. Finally, juxtaposing diversity and  
15 specialization unnecessarily dichotomizes the local economic environment into a similar,  
16 MAR-externalities-generating component and a dissimilar, Jacobs'-externalities-generating  
17 component. In fact, as argued by FRENKEN et al. (2007): "Analogous to economies of scope  
18 at the firm level, one expects knowledge spillovers within the region to occur primarily among  
19 related sectors, and only to a limited extent among unrelated sectors." (p. 688). By  
20 implication, quantifying the relatedness linkages between industries in the economy, as for  
21 instance in NEFFKE and SVENSSON HENNING (2008), is necessary to arrive at a more  
22 complete understanding of the agglomeration effects that occur as a consequence of a  
23 specific set of industries at the regional level.  
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## Tables

Table 1: Externalities and their origins

	Costs of production	Knowledge & skills	Other
Urbanization	land rents wage premium congestion	highly-skilled employees knowledge infrastructure	market access
MAR	matching costs labour market minimize inventories	specialized labour force intra-industry knowledge spillovers	access to specialized clients and suppliers
Jacobs'	transportation costs within the value chain low-risk environment love of variety lack of focus	joint innovation efforts within the value chain inter-industry knowledge spillovers	

Table 2: Industry characteristics and life-cycle developments

	Life cycle stage of industry	
	Young	→ Mature
Innovation intensity	high	→ low
Type of innovation	product	→ process
Mode of competition	product	→ price

Table 3: Agglomeration externalities and life-cycle dynamics

			Life-cycle stage of industry		
			Young	→	Mature
Urbanization	factor costs	high land rents	0	→	-
		high wages	0	→	-
		congestion	0	→	-
	knowledge	highly-skilled labour force	+	→	0
		knowledge infrastructure	+	→	+
	market conditions	access to large market	0	→	+
		access to sophisticated market	+	→	0
MAR	factor costs	low matching costs labour market	0	→	+
		low inventories	0	→	+
		low transportation costs within the value chain	0	→	+
	knowledge	large specialized labour force	0	→	+
		high intra-industry knowledge spillovers	+	→	+
		easy joint innovation efforts within the value chain	0	→	+
	market conditions	easy access to specialized clients and suppliers	0	→	+
Jacobs'	factor costs	large variety of services and goods	+	→	0
		lack of focus	0	→	-
	knowledge	high inter-industry knowledge spillovers	+	→	0
	market conditions	reduced volatility in demand and supply	+	→	0

+: expected effect is positive, 0: no important effects expected/effects cancelling out; -: negative effect expected.

Table 4: Definition of life-cycle stages

	textiles	sawmilling	carpentry	furniture	paper	publishing	chemicals	other plastic	metalware	electric motors	communication	instruments
1974												
1975												
1976												
1977												
1978												
1979												
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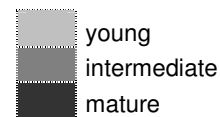


Table 5: General descriptive statistics of variables.

				standard deviation		
	mean	min	max	between	within	ratio
log(VA)	10.15	-3.77	17.82	2.13	0.98	2.17
log(L)	4.55	-9.36	10.04	1.97	0.73	2.71
log(MAR)	0.48	-34.86	5.76	2.38	1.12	2.12
log(JACOBS)	0.75	0.00	3.33	0.67	0.26	2.54
log(POPULATION)	10.95	9.08	13.80	0.73	0.04	17.45
log(HOUSE)	6.09	4.56	8.31	0.28	0.50	0.55
log(WAGE)	0.01	-0.60	0.26	0.04	0.03	1.29

Variables as defined in section 5. Final column contains ratio of between to within standard deviation.

Table 6: Correlation table of regressors.

	log(L)	log(MAR)	log(JACOBS)	log(HOUSE)	log(WAGE)	log(POPULATION)
log(L)	1.000					
log(MAR)	0.663	1.000				
log(JACOBS)	0.283	0.351	1.000			
log(HOUSE)	0.054	0.062	0.168	1.000		
log(WAGE)	0.123	0.176	0.408	0.082	1.000	
log(POPULATION)	0.263	0.323	0.764	0.359	0.641	1.000

Variables are as defined in section 5.



Table 7: Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
log(L)	0.999 *** (0.004)	0.998 *** (0.004)	1.015 *** (0.004)	0.998 *** (0.002)		
log(L_Y)					1.008 *** (0.004)	1.013 *** (0.004)
log(L_I)					0.998 *** (0.004)	0.998 *** (0.004)
log(L_M)					0.985 *** (0.003)	0.986 *** (0.003)
log(MAR)	0.019 *** (0.004)	0.019 *** (0.004)	0.017 *** (0.004)	0.019 *** (0.003)		
log(MAR_Y)					0.008 * (0.004)	0.015 *** (0.004)
log(MAR_I)					0.013 *** (0.005)	0.021 *** (0.005)
log(MAR_M)					0.022 *** (0.005)	0.027 *** (0.005)
log(JACOBS)	0.014 (0.011)	0.014 (0.011)	0.009 (0.010)	-0.017 *** (0.006)		
log(JACOBS_Y)					0.019 ** (0.009)	-0.004 (0.009)
log(JACOBS_I)					0.006 (0.009)	0.014 * (0.008)
log(JACOBS_M)					-0.053 *** (0.008)	-0.052 *** (0.008)
log(POPULATION)	0.138 * (0.079)	0.124 (0.090)	-0.002 (0.020)	0.018 ** (0.009)		
log(POPULATION_Y)					-0.029 *** (0.010)	0.009 (0.008)
log(POPULATION_I)					0.042 *** (0.010)	0.007 (0.008)
log(POPULATION_M)					0.038 *** (0.010)	0.023 *** (0.008)
log(WAGE)		0.149 (0.102)	0.144 (0.098)	0.149 ** (0.072)		
log(WAGE_Y)					0.522 *** (0.114)	0.341 *** (0.112)
log(WAGE_I)					-0.136 (0.116)	0.008 (0.113)
log(WAGE_M)					0.074 (0.102)	0.092 (0.100)
log(HOUSE)		0.000 (0.023)	0.008 (0.020)	0.000 (0.012)		
log(HOUSE_Y)					0.069 *** (0.014)	
log(HOUSE_I)					-0.063 *** (0.015)	
log(HOUSE_M)					-0.027 ** (0.014)	
Nobs	17424	17424	17424	17424	17424	17424
N	753	753	753	753	753	753
average T	23.10	23.10	23.10	23.10	23.10	23.10
Rsqr	0.873	0.873	0.873	0.970	0.970	0.970

\*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ . Dependent variable: log(VA). Variables as defined in section 5. \_Y: young industries, \_I: intermediate industries, \_M: mature industries. All models include time and city-industry effects. Models in column 1 and 2 use fixed effects. Model in column 3 uses random effects. Models in column 4, 5 and 6 are based on FEVD estimators.

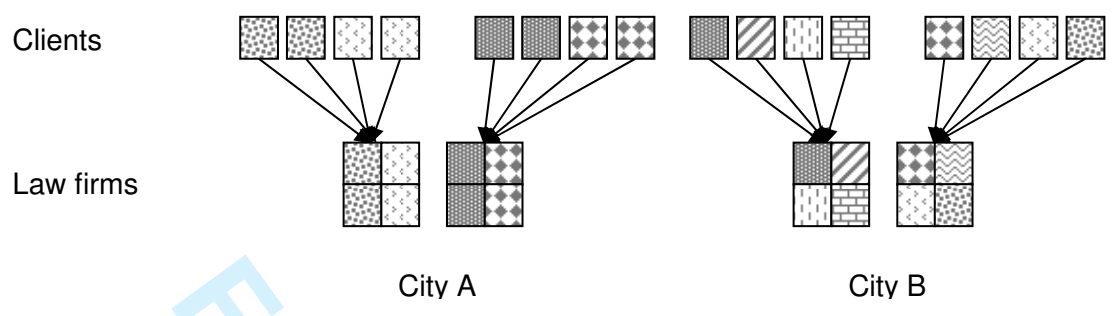
Table 8: Outcomes of alternative stage definitions

	(5a)	(5b)	(5c)
log(L_Y)	1.006 *** (0.004)	1.008 *** (0.004)	1.009 *** (0.006)
log(L_I)	0.991 *** (0.006)	0.998 *** (0.004)	0.997 *** (0.003)
log(L_M)	0.990 *** (0.003)	0.985 *** (0.003)	0.981 *** (0.005)
log(MAR_Y)	0.007 * (0.004)	0.008 * (0.004)	0.003 (0.006)
log(MAR_I)	0.025 *** (0.008)	0.013 *** (0.005)	0.019 *** (0.003)
log(MAR_M)	0.021 *** (0.004)	0.022 *** (0.005)	0.051 *** (0.010)
log(JACOBS_Y)	0.015 * (0.009)	0.019 ** (0.009)	0.026 * (0.014)
log(JACOBS_I)	0.011 (0.013)	0.006 (0.009)	-0.001 (0.006)
log(JACOBS_M)	-0.038 *** (0.007)	-0.053 *** (0.008)	-0.139 *** (0.013)
log(POPULATION_Y)	-0.010 (0.010)	-0.029 *** (0.010)	-0.059 *** (0.013)
log(POPULATION_I)	0.039 *** (0.013)	0.042 *** (0.010)	0.024 *** (0.009)
log(POPULATION_M)	0.037 *** (0.009)	0.038 *** (0.010)	0.058 *** (0.014)
log(WAGE_Y)	0.429 *** (0.106)	0.522 *** (0.114)	0.613 *** (0.174)
log(WAGE_I)	-0.507 *** (0.187)	-0.136 (0.116)	0.169 ** (0.081)
log(WAGE_M)	0.078 (0.091)	0.074 (0.102)	-0.445 *** (0.167)
log(HOUSE_Y)	0.038 *** (0.014)	0.069 *** (0.014)	0.126 *** (0.021)
log(HOUSE_I)	-0.039 * (0.02)	-0.063 *** (0.015)	-0.017 (0.013)
log(HOUSE_M)	-0.033 ** (0.013)	-0.027 ** (0.014)	-0.031 (0.021)

\*\*\*:  $p < 0.01$ , \*\*:  $p < 0.05$ , \*:  $p < 0.10$ . Dependent variable:  $\log(VA)$ . Variables as defined in section 5. \_Y: young industries, \_I: intermediate industries, \_M: mature industries. All models include time and city-industry effects. Models use the FEVD estimator. (5a) young:  $I_{it}^{norm} < 1 - 0.1$  std dev; intermediate:  $1 - 1$  std dev  $< I_{it}^{norm} < 1 + 0.1$  std dev; mature:  $I_{it}^{norm} > 1 + 0.1$  std dev; (5b) young:  $I_{it}^{norm} < 1 - 0.3$  std dev; intermediate:  $1 - 0.3$  std dev  $< I_{it}^{norm} < 1 + 0.3$  std dev; mature:  $I_{it}^{norm} > 1 + 0.3$  std dev; (5c) young:  $I_{it}^{norm} < 1 - 0.6$  std dev; intermediate:  $1 - .6$  std dev  $< I_{it}^{norm} < 1 + 0.6$  std dev; mature:  $I_{it}^{norm} > 1 + 0.6$  std dev

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Figure 1: Diversity and focus



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5 <sup>i</sup> For a concise exposition on the different research traditions on urban economic growth and  
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7 diversity, see QUIGLEY (1998). We focus on the empirical debate that began in the 1990s.  
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9 <sup>ii</sup> Another term for benefits of local specialization is “localization externalities”. The difference  
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11 is that MAR externalities are supposed to be dynamic or self-reinforcing, whereas localization  
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13 externalities are more of a static nature. We do not think this distinction has much merit in  
14  
15 this study, and will therefore call all benefits firms derive from local specialization MAR  
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17 externalities.  
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20 <sup>iii</sup> A fourth type of externality arises from a contest between local producers for excellence  
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22 and innovation (PORTER, 1990). However, the intensity of competition is difficult to quantify.  
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24 Therefore, it is not included here.  
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26 <sup>iv</sup> In the 1980s, the ILC approach was widely applied in economic geography to explain the  
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28 rise of new industries in new growth regions (STORPER and WALKER 1989; BOSCHMA  
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30 1997). AUDRETSCH and FELDMAN (1996) found evidence that the propensity for  
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32 innovative efforts to cluster spatially was shaped by the characteristics of life-cycle phases.  
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34 Also in GLAESER et al. (1992), mention is made of interactions between the maturity of an  
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36 industry and the agglomeration externalities it may experience. However, the authors’  
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38 suspicion that agglomeration externalities – regardless of type – are strongest in young  
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40 industries is only mentioned in passing and as a possible caveat that should be kept in mind  
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42 when interpreting their results.  
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45 <sup>v</sup> The data on which the databases are built were provided by Statistics Sweden. We have  
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47 run several algorithm-based data cleaning procedures and parts of the data were checked by  
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49 hand. Information can be obtained from the authors.  
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52 <sup>vi</sup> This was the case for chemicals, furniture, metal ware, paper, publishing, and textiles.  
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54 <sup>vii</sup> We choose an exponential decay that gives a 1% weighting to places 100 km away. Within  
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56 a circle of 10 km surrounding the A-region-core, decay was assumed to be zero. We also  
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58 experimented with distance decays that gave a 1% weighting to places 75 or 125 km away.  
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60 Results, available on request, were very similar to the ones presented in this text.

<sup>viii</sup> The data on housing prices are based on sales prices for smaller houses, available at the municipality level. Before 1981, only growth rates in housing prices at the province level and for major metropolitan areas (11 regions in total) were available. Between 1974 and 1981, our housing prices are therefore only estimates.

<sup>ix</sup> For example, our smallest industry, electric motors, consists (on average) of only 111.6 plants. Moreover, for over one third of all years, net entry into single industries is between just -5 and +5 plants.

<sup>x</sup> As the threshold is arbitrary, it is important to test the sensitivity of results to changes in this threshold. We come back to this issue in section 6.

<sup>xi</sup> In the analyses below, we use an unweighted average of plant wages to calculate  $w_{cit}$  and  $\bar{w}_{it}$ . As a robustness check, we also used weighted averages that use plant employment levels as weights. The outcomes are all but indistinguishable from the ones we present in this article.

<sup>xii</sup> The effect of the number of plants while holding local employment constant can also be interpreted as the effect of average plant size. However, average plant size is not very informative in our study, as plant sizes are very skewed. Therefore, we do not attribute any specific meaning to this interpretation.

<sup>xiii</sup> E.g., the HHIs for the employment sets {100,20,20,20} and {100,100,9,9} are about the same.

<sup>xiv</sup> We set this threshold at 10 plants, but also experimented with different threshold values and variants based on employment. This had virtually no impact on the outcomes.

<sup>xv</sup> Different lag structures have been tested and yielded very similar outcomes.

<sup>xvi</sup> In the first step, they estimate an FE model. The residuals of this equation now contain two components: the unobserved city-industry effects and a part that can be explained using variables with no or very little variation over time. In the next step, the authors regress these residuals on the time-invariant and slowly-changing variables, and then decompose them into two parts: an unexplained part and a part explained by the time-invariant and slowly-

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4 changing variables. In the final step, the complete model is rerun without fixed effects, but  
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6 this time with estimates of the unexplained part of the city-region effects obtained in the  
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8 second step.  
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11 <sup>xvii</sup> This is a common problem. In many studies, the only available instruments are weak and  
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13 yield such low efficiency that no conclusions can be drawn from the analyses (e.g.,  
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15 HENDERSON, 2003).  
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18 <sup>xviii</sup> Remember that due to the time-varying specification of MAR, the estimate depends only  
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20 on within-variation. Cross-sectional differences do not have any influence.  
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