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Localized Spillovers and Knowledge Flows: How Does Proximity Influence the Performance of Plants?

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Localized Spillovers and Knowledge Flows: How Does Proximity Influence the Performance of Plants?[i]

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Abstract: By means of a unique longitudinal database with information on all plants and employees in the Swedish economy, this paper analyzes how geographical proximity influences the impact of spillovers and knowledge flows on the productivity growth of plants. Concerning the effects of spillovers, we show that the density of economic activities as such mainly contributes to plant performance within a very short distance and that the composition of economic activities is more influential further away. Regarding the influence of local industrial setup, proximity increases the need to be located near different, but related, industries whereas increased distance implies a greater effect of intra-industry spillovers. The analyses also demonstrate that knowledge flows via the mobility of skilled labor is primarily a sub-regional phenomenon. Only inflows of skills that are related to the existing knowledge base of plants and come from less than 50 kilometers away have a positive effect on plant performance. Concerning outflows of skills, the results indicate that it is less harmful for a dispatching plant if a former employee remains within the local economy as compared to leaving for a job in another part of the national economy.

Keywords: Agglomeration economies, knowledge spillovers, labor mobility, plant performance, geographical proximity, related variety

JEL-codes: R11, Q12, O18

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1. Introduction

Following the early contributions by Marshall (1890), Weber (1929) and Hoover (1937), economic geographers and related scholars have been trying to empirically demonstrate whether regional specialization or diversification best contributes to the performance of agglomerated plants (e.g. Glaeser *et al.*, 1992; Henderson *et al.*, 1995; Malmberg *et al.*, 2000). Although recent contributions have brought this discussion forward by arguing that spillovers are promoted by sector-specific relatedness rather than by diversification *per se* (e.g. Frenken *et al.*, 2007; Boschma and Iammarino, 2009), the empirical support for whether relative specialization or diversification is more beneficial still varies. This can be attributed to many factors, for instance, relative differences across industries and plants, as well as different choices of study areas (Rosenthal and Strange, 2004; de Groot *et al*, 2009). Additionally, the effect of geographical proximity is often overlooked in this literature, despite a great consensus that proximity and co-location facilitates knowledge spillovers.

In order to take the analysis on agglomerations one step further, this paper argues that it is not sufficient to merely recognize that different agglomerations may induce different types of externalities unless paying particular attention to how the specialization of plants matches the territorial context in which they operate. We therefore distinguish between plant-specific routines and place-specific institutions (e.g. Boschma and Frenken, 2006; Nelson and Winter, 1982; Storper, 1995) to determine whether sector-specific similarity, relatedness and unrelatedness produce different effects for plants depending on if the external knowledge originates from the same territorial context or from another location. It is anticipated that high degrees of related (complementary) knowledge must be present near each plant for significant spillovers to occur. In addition, geographical proximity is expected to reduce potential communication problems associated with being located in a territory characterized by very different (unrelated) activities due to greater similarities in place-specific routines and technologies, whereas the inclusion of other sets of place-specific knowledge may increase the need for sector-specific similarity.

In order to control for the robustness of the above-presented propositions, these ideas are also transferred to labor mobility, which increasingly is regarded a key mechanism through which embodied knowledge diffuses between plants (e.g. Breschi and Lissoni, 2009; Eriksson and Lindgren, 2009). In this respect, institutions are likely to influence both the quantity and quality of knowledge flows due to the path-dependent production and reproduction of local labor skills (Storper, 1995). Since the effects of knowledge flows are not likely to be revealed without considering how the new skills match the existing knowledge base of plants (Boschma *et al.*, 2009), the degree of relative local specialization or diversification is expected to shape the availability of local skills that can bring in different but complementary pieces of knowledge to the plant rather than mainly producing pure knowledge externalities.

Embedded in the literature on related variety, the aim of this paper is to analyze how the impact of intra- and inter-industry spillovers is influenced by geographical proximity. By also considering the impact of proximity on skills brought in to plants via labor mobility, the paper will add to the theoretical discussion on the benefits of agglomeration in two ways. First, by more thoroughly accounting for the ways geographical proximity influences spillovers and knowledge flows. This is not carried out via regional aggregates but rather through creating plant-specific agglomeration measurements to estimate the impact of spillovers and knowledge flows for every plant in the economy. Second, by exploring the combined effect of both local and non-local knowledge flows, which is done by elaborating on inter-plant distances in more detail to also reveal the sub-regional dimension of knowledge flows. This is made possible by means of a unique micro-database that connects attributes of individuals (e.g. education and working experience) to features of plants (e.g. spatial coordinates, sector and productivity) and is empirically tested by estimating the productivity growth of 8,313 plants in Sweden between the years 2001 and 2003.

The paper is structured as follows: The next section presents the main theoretical ideas, and is followed by a presentation of data and the research design in Section 3. In Section 4 the empirical results are presented and, finally, Section 5 provides some concluding remarks and suggestions for further research.

2. Proximity, spillovers and knowledge flows

There is a general consensus in the literature on agglomerations and clusters that geographical proximity and co-location is beneficial. This is because proximity is argued to foster competition, mutual trust, enable the development of a specialized labor pool, and facilitate occasional knowledge spillovers (e.g. Glaeser et al., 1992; Henderson et al., 1995; Porter, 1998; Storper and Venables, 2004; Malmberg and Maskell, 2002; Boschma, 2005; Jacobs, 1969). Although a general debate concerning whether spillovers are most frequent and substantial within industries (localization or MAR-externalities), between industries (diversification or Jacob's externalities) or mainly are a product of absolute size and population density (urbanization), many empirical studies appear to be more interested in mapping the presence of different spillovers than to determine how the degree of proximity may influence their impact or how different plants are potentially affected by their co-located neighbors. Thus, proximity is often treated as a fixed definition rather than a specific characteristic of agglomerations (Martin and Sunley, 2003; Phelps, 2004; Oerlemans and Meeus, 2005)[ii]. To overcome this potential drawback and to determine how geographical proximity influences the economic impact of relative specialization and diversification, this paper will make an analytical distinction between cognitive proximity and geographical proximity (c.f. Boschma, 2005).

The empirical section is therefore based on the literature advocating the impacts of related variety on economic growth (e.g. Frenken *et al*., 2007, Boschma and Iammarino 2009). This makes it possible to more readily consider how the composition of sectors (i.e. the cognitive distance between sectors) influences spillovers and how the cognitive dimension may be influenced by geographical proximity. This literature argues that intra-industry spillovers may result in incremental innovations within a sector and therefore have positive effects on productivity, but it also stresses the importance of more thoroughly conceptualizing the impacts of diversification (i.e. inter-industry spillovers). This is because Jacob's externalities not only reflect relative density but also the composition of sectors within a local economy. These externalities are therefore expected to have different impact on local growth dependent on whether growth is measured in productivity or employment (see for instance Frenken *et al*., 2007; Essletzbichler, 2007; Pasinetti, 1993).

In this respect it is essential to make a distinction between related and unrelated variety. Whereas unrelated variety is unlikely to produce significant knowledge spillovers due to communication problems between very different types of activities, plants embedded in related variety are more likely to benefit from spillovers resulting in radical innovations due to the availability of different but complementary pieces of knowledge. This is because firms can only absorb, implement and utilize external knowledge that is close to their own knowledge base (Cohen and Levinthal, 1990). In order to secure an effective transfer of non-standardized tacit knowledge, the cognitive distance between the existing and new knowledge can therefore not be too great as this may make an effective inter-firm communication difficult (Nooteboom, 2000). Nooteboom *et al.* (2007) empirically support this notion by showing evidence of an inverted U-shape function related to the cognitive distance between technology-based partners and innovative performance. Their findings show that effective interactive learning and innovation are best facilitated when existing knowledge is combined with new, complementary knowledge that is neither too similar nor too different. When the cognitive distance between two partners is too similar it does not contribute to a recombination of different pieces of knowledge, while if it is too different it may be difficult to absorb and implement. This relationship is also found at the regional level. Both Frenken *et al.* (2007) and Boschma and Iammarino (2009) demonstrate that a high degree of related variety among industries in a region is crucial for explaining regional growth in the Netherlands and Italy, respectively. However, in contrast to the findings on aggregated regional data, Bishop and Gripaios (2009) show that the effects of either related or unrelated variety depend on the particular sector of interest. Their findings also indicate that the spatial range of externalities differs substantially between different sectors (see also Bishop, 2008). Thus, to gain further knowledge about the impact of externalities it is necessary to both consider the sector-specific knowledge of plants and to more properly address the effect of geographical proximity.

[ii] For recent studies on knowledge spillovers overcoming the issue of spatial biases by using spatial econometrics, see for example Rodríguez-Pose and Crescenzi (2008) and Sonn and Storper (2008).

We will address the proximity effect by arguing that knowledge is both plant-specific and place-specific, which, in turn, will influence how intra- and inter-industry knowledge can diffuse between both co-located and more geographically dispersed plants. In this sense, it is necessary to distinguish between organizational routines and institutions[iii]. In short, knowledge is not a public good but plant-specific and accumulated within employees as skills and collectively in firms as routines (e.g. Gertler, 2003; Nelson and Winter, 1982; Boschma and Frenken, 2006). Additionally, as labor and labor skills are produced and reproduced through the path-dependent evolution of the local industrial setup (Storper and Walker, 1989, Storper, 1995), the institutional context is likely to influence the availability of local skills and the formation of local routines and practices. Therefore, knowledge has also a place-specific distinctiveness in the sense that routines of firms tend to share many characteristics within the same institutional system but differ across institutions (Gertler, 1997; Storper and Scott, 2009). This, in turn, may influence the routines and technologies of plants operating in similar sectors but within different locations. For example, by studying regional variations in production techniques in the US machine tool industry, Essletzbichler and Rigby (2005) and Rigby and Essletzbichler (2006) show that the between-region variation of techniques is greater than the within-region variation. This sustained territorial variety of routines may provide intangible and non-tradable place-specific assets based on a unique knowledge and institutional base which in some cases can become difficult to access for non-local firms (Boschma, 2004). Empirical studies also confirm that knowledge is transferred and utilized within a close distance from where it was first created, and that spillovers tend to become weaker the greater the distance from the source (Audretsch and Feldmann, 1996; Jaffe *et al.*, 1993; Rodríguez-Pose and Crescenzi, 2008). Sonn and Storper (2008) even show that this localized effect is manifested despite recent improvements in information and communication technologies which is argued to have increased the importance of more temporal forms of proximity (e.g. Rallet and Torre, 1999; Torre, 2008; Bathelt and Schuldt, 2008).

Consequently, certain sectors are likely to be characterized by different types of technologies, organization forms, norms and routines that are only applicable in particular sectors of the economy (Simpson, 1992). In addition, co-located activities tend to be characterized by similar practices as compared to more spatially dispersed firms which may influence to what extent knowledge can diffuse across greater spatial distances. Since geographical proximity often enables co-located firms to monitor each other constantly with almost no effort or cost (Malmberg and Maskell, 2002), spillovers can on the one hand be expected to be more frequent and substantial between close neighbors. For spillovers across greater spatial distances it is on the other hand reasonable to expect that a greater share of absorptive capacity and complementarities are required for external knowledge to be integrated into the organization and to have an effect on performance.

Similar to the notions put forward by Boschma (2005) we therefore expect that geographical proximity neither is a necessary nor a sufficient condition for spillovers to occur, but that geographical proximity is likely to influence to what extent plants can absorb and utilize similar, related or very different (unrelated) external knowledge from the sector in which the plant operates. It is anticipated that spillovers between co-located plants in related sectors will have the most substantial effects on plant performance since this allows a recombination of different but complementary pieces of knowledge. However, since the routines of firms are likely to share many characteristics within the same territory but differ from one place to another, we expect geographical proximity to reduce potential communication problems associated with being located in a very diverse local setting. We also expect increased distance between plants to increase the need for having access to similar sector-specific knowledge that can be easily absorbed into the organization.

These ideas on how proximity influences the impact of spillovers are also applied when accounting for the impact of knowledge flows. A general assumption in the literature is that the mobility of personnel is crucial for the transfer of spatially sticky and locally embedded tacit knowledge between firms and regions as well as for the sustained competitiveness of clustered activities (Almeida and Kogut 1999; Cooper 2001; Maskell and Malmberg 1999; Rodríguez-Pose and

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[iii] For a more detailed discussion on the difference between routines and institutions, see MacKinnon et al, 2009 and Boschma and Frenken, 2009.

Vilalta-Bufi 2005; Malmberg, 2003; Power and Lundmark 2004; Pinch and Henry 1999). Recent empirical work has also demonstrated that the partial effects of local labor mobility are far greater than the impact of co-location as such. This positive relationship seems to be evident in both high-tech industries, where the mobility of inventors is investigated (Breschi and Lissoni, 2009), and in more traditional sectors including many different types of labor and competences (Eriksson and Lindgren, 2009). Since the mobility of labor is regarded to create linkages between firms through the social ties of former employees (Granovetter, 1973), mobility may strengthen the social cohesion between plants and thereby facilitate knowledge flows between the inter-linked firms (Breschi and Lissoni, 2003). Due to the predominantly local process of labor mobility, these social networks are primarily formed locally and are therefore expected to further enhance local knowledge accumulation and increase the performance of plants (Dahl and Pedersen, 2003; Malmberg and Power, 2005). However, as demonstrated by Agrawal *et al.* (2006) these social relationships can also extend over great geographical distances which signifies the relevance of recent contributions advocating the value of also addressing the impact of non-local linkages (e.g. Boschma and Iammarino, 2009; Bresnahan *et al.* 2001; Asheim and Isaksen 2002; Bathelt *et al.* 2004; Faggian and McCann 2006).

It should though be noted that labor mobility is not always beneficial. McCann and Simonen (2005), for instance, demonstrate a negative relationship between job mobility and the innovative performance of plants. Since workers employed in certain firms, sectors and locations will accumulate certain types of skills that are not necessarily applicable everywhere in the space economy and therefore may become a sunk-cost in case of changing job (e.g. Becker, 1962; Simpson, 1992; Fischer *et al.*, 1998), it is also necessary to distinguish between the cognitive distance between sectors and the geographical distance of knowledge flows. Boschma *et al.* (2009) empirically demonstrate the need to distinguish between different types of skills and between local and non-local dimensions. Their analysis on the impact of knowledge flows on the performance of plants indicates that the sectoral background of newly recruited labor plays an important role in whether or not the new skills can be implemented and utilized within a new organization. Inflows bringing in different, but related, skills contributed the most to performance whereas the more different the skills were, the greater the need was for geographical proximity.

However, similar to the studies on spillovers, many previous studies on knowledge flows tend to downplay the impact of more proximate flows than those bounded within functional regions. Yet this is an important aspect, as labor is widely acknowledged to be the most immobile factor of production and job moves seldom take place between local labor markets. Hence, if the majority of all labor flows are defined into a single intra-regional category, the real features of local knowledge flows are not likely to be elucidated. This is also indicated in previous case studies on the relationship between labor mobility and clustered firms. Power and Lundmark (2004), for instance, show that the mobility of personnel within the spatially concentrated Stockholm ICT cluster is significantly higher than in the rest of the urban economy due to a higher sub-regional availability of appropriate skills. Accordingly, in parallel with the need to account for plant-specific potential to benefit from spillovers, it is not reasonable to assume that there is not only one local labor market that affects knowledge flows for all plants in a region. Rather, it is more pertinent to assume that each plant has its own local labor market characterized by factors such as specialization, location and industrial affiliation of neighboring plants. Together, these patterns are likely to influence the potential to acquire new knowledge and therefore generate plant-specific geographies of knowledge flows.

3. Research design

The theoretical propositions above are tested by analyzing changes in productivity among 8,313 plants within the entire Swedish economy. We use data retrieved from a unique longitudinal micro-database, ASTRID, which is a compilation of several administrative registers at Statistics Sweden and contains annual information on all people, firms and workplaces in Sweden. In ASTRID, attributes of individuals (working experience) are connected to features of plants (spatial coordinates at hectare squares and sector). The high resolution of socio-economic data makes it possible to both create plant-specific neighborhoods and analyze flows of employees at various distances. Before we turn to the variables used in the analyses, some notes on the sampling procedure need to be discussed.

The database contains no variable directly indicating job mobility. Therefore, this variable had to be created based on a number of conditions. In order to confirm that the selection only measures the impact of job movers established on the labor market and working full-time, individuals had to meet the following income and age criteria: Job movers had to (i) earn more than USD 20,500 annually (SEK 200,000 in 2001 monetary values), (ii) be aged 25 to 64 and (iii) have a registered change in both workplace identity and workplace coordinates (hectare grid) between the years 2000 and 2001. The first and second conditions are set to exclude part-time workers (e.g. students) or people not yet established on the labor market. The third condition is set so as to check for an actual job move having taken place. Due to the widespread idea that knowledge transfers between workplaces are mainly the result of mobility of key persons (e.g. Power and Lundmark 2004), a fourth criterion was added: (iv) individuals must have obtained at least a Bachelor's degree or belong to the top 20% of income earners. Two indicators for key persons are used since these individuals do not automatically have higher academic training.

At the initial stage, all workplaces with information on industrial affiliation and performance indicators were selected (256,985). All the indicators for both agglomeration economies and knowledge flows were then based on this first sample. To be able to control for the relative effect of different types of inflows and not only address the relationship between mobility and performance, only workplaces with inflows of skilled labor were selected from the original sample, which resulted in a sample of 17,098 workplaces. A final selection was made to only include manufacturing units and knowledge-intensive service sectors (e.g. financial services, R&D and creative industries like marketing, design and software production) because knowledge spillovers are assumed to be the strongest in these sectors (e.g. Frenken *et al.* 2007). By only modeling the performance of workplaces within manufacturing and knowledge-intensive service sectors with skilled inflows, we end up with a final sample of 8,313 workplaces[iv].

After having selected the workplaces and job moves to be included in the analysis, the next step is to define plant-specific neighborhoods. Although there are no obvious ways of defining geographical proximity because knowledge spillovers and externalities derived from market size are likely to work at different spatial scales (Martin 1999), the analysis applies three different distances similar to those used by Li *et al.* (2009). The areas include economic activities from every single plant within radii of 0.5, 5 and 50 kilometers, respectively. The closest range is defined to cover the location of economic activities within the same business park or urban district. Each plant and its employees are likely to be aware of the whereabouts of other economic activities, since they are practically carried out within arm's length and within sight of the workplace. Employees are therefore likely to cross each other's paths on several occasions during a working week, and firms able to monitor each other. Moreover, according to Fischer *et al.* (1998), about 50% of all mobility in Sweden is less than 5 kilometers, whereas 83% is less than 50 kilometers. This insight makes it reasonable to define the two other plant-specific surroundings accordingly, as they are likely to reflect both the local labor market of each plant and the potential for collaboration and socialization. For instance, it is no major problem to regularly travel 5 kilometers to another urban district for business meetings, and this distance is also likely to cover many of the small- and medium-sized urban regions in Sweden. Finally, a plant is less likely to actually have close relations with other plants up to 50 kilometers away, since daily interactions are more difficult to maintain. In addition, in order to more accurately asses the effects of relaxing administrative borders, agglomeration measurements were also calculated for each municipality (n=290, average size=1,420 km^2), which is the main local administrative division for economic activities in Sweden.

3.1 Dependent variable: Labor productivity

[iv] Since the sampling procedure may influence the parameter estimates, the empirical models have also been run, respectively, on all plants in the original sample and on manufacturing plants only. While the estimates on the entire population implied that the relative effect of inflows as such increased on the one hand, on the other hand it also resulted in a relative lower effect of the different types of inflows. When only manufacturing units were modeled, the outcome of the key variables was not affected. Taken together, this implies that the models show signs of being relatively robust.

To measure how the performance of plants is affected by attributes in the local economy and by knowledge flows, labor productivity at the plant level is used as dependent variable. As it is reasonable to expect that external knowledge will not instantly materialize at the plant but perhaps needs several rounds of modification before productivity increases are attained, change in labor productivity between 2001 and 2003 is used. While this time dimension can be regarded as too short to actually reveal learning processes with effects in productivity, Eriksson and Lindgren (2009), for example, show that the immediate short-term sunk costs associated with integrating new staff into an organization is turned into a positive effect on productivity on a three-year basis. This insight implies that a change between 2001 and 2003 may be an appropriate time span. However, productivity is mainly an indicator of relative efficiency and not of knowledge output, which would require information on, for instance, patent citations (e.g. Breschi and Lissoni, 2009). Nevertheless, productivity proxies both the relative degree of learning and the relative degree of efficiency within plants. According to Schumpeter (1939), firms constantly recombine existing pieces of knowledge. While this can result in either incremental or radical innovations, it also implies learning processes within plants by making the production of consumer goods and services more effective. Innovative and competitive firms can thus be considered able to use their resources more efficiently which also makes them more productive than less innovative firms. It is therefore reasonable to expect that plants acquiring external knowledge via either spillovers or labor flows may show greater productivity increases than other similar plants. Moreover, while patent citations are a direct measure of knowledge transfer, this is only viable for a small share of all economic activities and would not reveal how non-high-technology sectors benefit from potential spillovers and knowledge flows.

Because the database does not contain information on employees' hours of work, labor productivity has been defined as the value added per employee[v]. However, value added in our dataset is reported for firms and not for workplaces. For about 25% of the firms in this sample, with more than one plant, value added was distributed to the workplaces in the same proportion as the distribution of the sum of wages across workplaces (Wictorin 2007). Thereafter, the calculated sum of value added was divided by the number of employees at the workplace. This procedure potentially takes into account both education and experience when measuring labor productivity at the plant level. This aspect would be neglected if value added were distributed only according to the share of firm employees at the workplace[vi]. Finally, the unique identification number associated with each workplace makes it possible to follow workplaces over time. This allows us to measure growth by subtracting the level of productivity in 2001 from the level in 2003. All numbers were adjusted to 2001 price levels. In the model, log values are used to reduce the impact of skewed distributions.

3.2 Independent variables

To assess the impacts of being co-located with similar, related or very different industries, all independent variables are measured at the beginning of the period (i.e. 2001) and are based on the entire population of plants within all sectors. For estimating the effects of agglomeration externalities on firm performance, entropy measurements similar to Frenken *et al.* (2007) and Boschma and Iammarino (2009) are used. Briefly, this calculation compares the industrial affiliation (SNI codes) of all plants with the sectoral belonging of all other plants within their respective neighborhoods. The SNI nomenclature consists of 753 different five-digit categories nested within 224 different three-digit categories and 10 different one-digit categories related to the specific output of different plants. While this division indicates the specialization of the plants, using the industrial categories of each plant to measure relative similarity, relatedness or difference, we implicitly assume that plants belonging to one industrial (sub-)category are more similar than those belonging to different categories. However,

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[v] To control for part-time work and increased efficiency, which would have been possible with information on hours of work, a proxy controlling for this was created. It held information on the per capita social benefits received for all employees at each workplace (including parental leave, unemployment insurances and sick leave), which implicitly account for the relative share of absence from work during 2001 (Eriksson and Lindgren 2009). This variable did not affect the estimates and was omitted from the final model.

[vi] The two groups with either observed or estimated productivity were estimated separately to check for the robustness of this indicator. The outcomes of the key variables did not differ substantially, which means that they can be interpreted with confidence.

this is not necessarily the case in real life (for instance, two sub-contractors can share similar technologies but produce quite different products, for different markets) but this type of analysis requires the use of industry codes since the data do not contain information on input-output relationships. Nevertheless, the standard industrial classification does reveal the type of local setting plants are located in and how this influences their performance. To begin with, following the findings in Frenken *et al.* (2007) and Boschma and Iammarino (2009) demonstrating that related variety at the regional level contributes to regional growth, three measurements of the average regional composition of sectors within municipalities are calculated to address the influence of regional externalities on plant performance before calculating the plant-specific externalities.

The degree of regional similarity (i.e. the degree of regional specialization) is used to measure the extent of intra-industry spillovers and is measured as the inverted entropy at the five-digit industrial level. Although this measurement is not a direct indicator of localization economies, it captures the main ideas in the literature by addressing the relative impact of intra-industry concentrations as compared to externalities associated with diversity. Let p_i^V be the share of plants within five-digit industry *i* and let N^V be the number of five-digit classes. The similarity measurement is then calculated as:

$$\text{Similarity} = 1 / \sum_{i=1}^{N^V} p_i^V \log_2 \left(\frac{1}{p_i^V} \right), \tag{1}$$

where the higher the score, the higher the concentration of similar or exactly the same industries within regions.

After constructing a measure for intra-industry spillovers, the effect of being surrounded by complementary activities is addressed. This is measured by calculating the weighted sum of entropy at the five-digit level within each three-digit industrial category[vii]. Thus, we assume that plants belonging to different five-digit categories nested within the same three-digit category share different but complementary pieces of knowledge and can therefore understand each other. For instance, we expect that an automobile production plant will be able to absorb and utilize knowledge spilling over from co-located plants specialized in subsectors of automobile production but not from plants specialized in pulp production because the cognitive distance between them is expected to be too great. The higher the variety within the three-digit level, the more beneficial it is expected to be for the performance of plants due to a higher degree of local complementarities. The degree of related variety is calculated as follows: All five-digit sectors p_i^V belong to a three-digit category S_j^{III}, where $j=1,\dots,N^{III}$. Therefore, we can derive the three-digit shares p_j^{III} by adding the shares of all five-digit sectors nested within S_j^{III}:

$$p_j^{III} = \sum_{i \in S_j^{III}} p_i^V . \tag{2}$$

Related variety is then defined as the weighted sum of entropy within each three-digit industry category, given by:

$$\text{RelVar} = \sum_{j=1}^{N^{III}} p_j^{III} H_j \tag{3}$$

where:

$$H_j = \sum_{i \in S_j^{III}} \frac{p_i^V}{p_j^{III}} \log_2 \left(\frac{1}{p_i^V / p_j^{III}} \right) \tag{4}$$

Finally, the degree of unrelated variety within regions is calculated in order to assess how relative regional diversification affects the performance of plants. This variable is measured as the

[vii] It should be noted that the entropy within each two-digit category has also been calculated, but this did not change the effect of related variety in any of the models.

entropy at the one-digit level, where a high variety symbolizes that a region is characterized by very different activities[viii]. Let p_l^I be the share of one-digit industrial sector $S_l^I \in S_1^I,...,S_{N^I}^I$. We now get:

$$\text{UnrelVar} = \sum_{l=1}^{N^I} p_l^I \log_2 \left(\frac{1}{p_l^I} \right) \tag{5}$$

where the higher the score, the more diversified the region.

However, as asserted in Section 2, the use of regional aggregates for focusing on the geography of knowledge spillovers may create biased estimates as regional aggregates probably conceal the effects of different micro-clusters within regions and do not consider the plant-specific geography. In order to address the potential impact of geographical proximity, each plant is ascribed a unique plant-specific measurement of similarity, related variety and unrelated variety, repeatedly calculated for each of the distances. This is done to capture the different types of externalities surrounding each plant. By adopting modified entropy measurements considering both the plant-specific industry and all other co-located activities, it is possible to determine how similar, related or unrelated the local environment is in relation to every single plant. The degree of similarity (i.e. the degree of surrounding plants with exactly the same SNI code) was calculated as follows (where p_{ip}^V is the share of neighboring plants belonging to exactly the same five-digit industry I and p_u^I the total share of plants belonging to the same one-digit category):

$$\text{SimilarityMod} = (p_u^I * p_{ip}^V) * \log_2 \left(\frac{1}{p_{ip}^V} \right). \tag{6}$$

Plants scoring high on this measurement are located in an environment with many identical industries and are assumed to benefit from spillovers due to a high level of available-for-all sector-specific knowledge that can easily and almost without cost be absorbed into the organization and lead to incremental improvements and higher productivity. However, as hypothesized in Section 2, we expect that the positive effect arising from being located in such a setting will only be prevalent within some distance from the plant. This is because the plant can absorb this knowledge but it will not be different enough to induce learning processes. In such a case, other types of place-specific knowledge are required to create a sufficient distance between the existing and the new knowledge.

Thus, while spillovers from similar industries can be absorbed but some differences between them are needed to induce an economic effect, we expect that knowledge will spill over more easily between co-located plants and generate enhanced firm performance as the complementarity of the territory increases. This is measured for each plant by calculating the entropy at the five-digit level within its three-digit industrial category. The degree of related variety is defined as the entropy within each three-digit industry category p_{ip}^{III}, except for those plants belonging to exactly the same industry (i.e. similar industries: p_{ip}^V), by also considering the total share of industries within both the same one-digit category (p_u^I) and the same three-digit category, which is given by:

$$\text{RelVar Mod} = (p_u^I * p_{ip}^{III}) * H_{ip} \tag{7}$$

where:

$$H_{ip} = \sum_{i \in S_j^{III}} \frac{p_{ip}^V}{p_{ip}^{III}} \log_2 \left(\frac{1}{p_{ip}^V / p_{ip}^{III}} \right). \tag{8}$$

We expect that the impacts of related variety will occur particularly within a short distance from each plant, and fade away as distance increases. This is because proximity is likely to facilitate the re-

[viii] Because of the decomposable nature of the entropy measure, differentiating variety at various digit levels, this variable should not be interpreted as the inverse of the similarity variable (see Frenken 2007 for more details).

combination of complementary knowledge while the inclusion of other types of place-specific pieces of knowledge may result in a greater effect of intra-industry spillovers at greater distances.

Finally, if a plant-specific surrounding is characterized by very different types of industries, it is assumed that the plant will not be able to benefit from spillovers due to problems of absorbing and integrating new, very different, pieces of knowledge. Since co-located plants is expected to share similar technologies and routines, geographical proximity is assumed to reduce such problems whereby we anticipate that an increasing distance from the plant will make it more difficult to sustain effective communication due to greater dissimilarities in place-specific routines. Let p_{jp}^{I} be the share of co-located plants belonging to the same one-digit industry code but another three-digit sector than the specific plant. The measurement of unrelated variety is then defined in relation to the share of co-located plants in all other one-digit categories, p_{u}^{I}. The higher the score, the more difference there is as compared to the other co-located activities. This is in comparison to the variation within the same one-digit category as well as the activities in other one-digit categories:

$$\text{UnrelVar Mod} = 1/(p_{u}^{I} * p_{jp}^{I}) * \log_2 \left(\frac{1}{p_{jp}^{I}} \right). \qquad (9)$$

As mentioned in Section 2, increasing attention is given the impact of labor flows as compared to the effect of pure knowledge externalities. We therefore also create variables measuring the similarity, relatedness and unrelatedness of labor flows at different distances. However, ASTRID only provides information concerning the main output for each workplace, which implies that only one single five-digit sector code is available. This means that it is not possible to use entropy measures when estimating knowledge flows at the workplace level. Nevertheless, by comparing the background of new employees and summarizing the total number of different types of inflows, it is possible to obtain information on how different extra-firm linkages affect plant performance. The degree of similar inflows is measured as the total number of inflows originating from the same five-digit sector code, while the related inflows are defined as the number of new employees from the same three-digit code, excluding the inflows from the same five-digit code (i.e. similar inflows). Finally, unrelated inflows are defined as the number of employees with a background in all other five-digit industries. Similar to the findings in Boschma *et al.* (2009), we expect inflows similar to the plant specialization to be absorbable, but no new knowledge will be added. Therefore, this is not expected to increase performance unless such knowledge is combined with other place-specific routines obtained further away from the plant. Moreover, for high levels of unrelated inflows, the cognitive distance between the existing knowledge base and the new knowledge is expected to be too great and will therefore not improve plant performance due to problems of communication. However, due to the assumption that routines of co-located plants will share many characteristics although operating in different sectors we expect that the communication problems associated with inflows of unrelated skills will be reduced if recruited from the next-door neighbor. In contrast, high levels of related inflows will complement the existing knowledge base, which increases learning opportunities and potentially contributes to increased performance. This is an effect we expect to be particularly strong in combination with close proximity, but it will slowly decrease by including other place-specific knowledge from further distances.

However, it is not reasonable to assume that plants will constantly increase their numbers of employees by continually recruiting new skills that add to their existing knowledge. In order to determine the set of skills brought to the plant and its potential economic effects, it is also necessary to control for skills leaving the plant. Due to the mono-structure of the SNI codes, skills leaving the plant do not show any variation since the plant is only ascribed a single sector code. The constitution of data makes it impossible to draw any conclusions about the outflows of similar, related or unrelated skills leaving the plant (data can indicate which sector the former employee leaves for, but cannot tell anything about how the departing skill matches the knowledge base of the old plant). However, it is possible to take into account the number of employees leaving the plant and determine whether they go elsewhere in the local milieu or to jobs further away.

Irrespective of these data issues, it is possible to draw some general conclusions about the impacts of outflows. For instance, following the notion that job mobility will create linkages of weak occupational ties between the old and new workplaces (Granovetter 1973), Bienkowska (2007) argues that former employees may be regarded as 'ambassadors' for the previous firm, due to their role mediating connections with new customers and arranging the recruitment of new staff. This insight leads to the conclusion that the impacts of job mobility do not necessarily involve a relative gain for the receiving firm as compared to the dispatching firm's loss. However, the effect of outflows should be interpreted with some caution since it is reasonable to assume that the potential negative effect of outflows as compared to the positive effect of inflows works through different time spans. Whereas external knowledge may take some time to implement, the loss of skills is a more direct effect. Nevertheless, due to the primarily local dimension of job flows and social ties (Breschi and Lissoni, 2003; Dahl and Pedersen, 2003), we expect that it will be less damaging if employees change jobs to another employer within the local milieu since their embedded knowledge will remain within close proximity and remain available to the old plant, either indirectly via sustained spillovers or via the social link produced by the job move. If the former employee leaves for a new position far away, it may still be beneficial (e.g. Agrawal *et al.*, 2006), but is likely that more effort is needed to maintain the connection and benefit from his/her role as 'ambassador'.

In total, 18 different variables on similar, related and unrelated inflows within and outside the defined neighborhoods are constructed. Similarly, six variables measuring the distance of outflows within and outside the neighborhoods are calculated (see Table A1 in the Appendix for a full description of variables and descriptive statistics).

3.3 Control variables

A number of other factors, such as sector, plant size and educational level, are likely to co-determine labor productivity at the plant level. These factors also need to be incorporated into the analysis. To control for industry-specific effects, a dummy variable separating manufacturing units from service sectors is included. To control for different labor and capital intensities, we added detailed industry dummies in the analysis, which did not alter the effects of the key variables or provided any additional explanatory value in terms of higher R^2 values. This made us decide to only include the manufacturing dummy as industry controller. Two additional controllers are plant size and ratio of workers with an education equivalent to, or higher than, a Bachelor's degree. While large plants are expected to show higher levels of productivity, they are not expected to show as high levels of relative productivity growth as smaller plants. We also expect that a greater share of formal human capital measured as educational level will have a positive effect on performance. Additionally, the more people who are clustered nearby each plant, the higher the expected probability for knowledge spillovers (Glaeser 1999). Since we expect that it is the composition of activities and not density as such that is important for creating spillovers, a general measure of population density was added to more accurately control for this effect. The uneven population distribution justifies a logarithmic transformation of the number of workers per square kilometer within each municipality and neighborhood. This transformation makes the measurements comparable over different spatial units. To control for non-linear relationships, a quadratic term of population density is also included. It should be noted that a variable controlling for the number of other co-located workplaces within the same corporate group was also included in the analyses, since this is likely to influence the impacts of agglomeration measurements as well as different types of labor flows. However, this variable did not have any effect on the estimation scores and was therefore excluded in the final analysis. Definitions of variables and descriptive statistics of all included variables are provided in the Appendix (Table A1).

Despite the potential risks of extensive multicollinearity, no such problems are identified[ix]. For the empirical analyses, ordinary least squares (OLS) models were applied. Additionally, the models are

[ix] For example, except for the correlation between PopDensKm^2 and PopDensKm^2^2, the only correlation higher than 60% and significant at the 5% level was between the similar and unrelated variety variables calculated for the municipalities (correlation = 0.74). This is confirmed by testing the Variance Inflation Factor (VIF) in all models, where only the two variables on population density show a tolerance below 0.2.

White corrected, since while plotting the residuals against the fitted values in our models we could not rule out the presence of heteroskedasticity.

4. Empirical results

The empirical estimates are presented in this section (Tables 1 and 2). The tables display the coefficients and the t-values (within brackets) to reveal the sign and the relative effect of each covariate. Table 1 presents the effects of agglomeration externalities on plant performance within administrative regions (Models B), within plant-specific surroundings of 0.5 kilometers (Models C), 5 kilometers (Models D) and 50 kilometers (Models E), respectively. In Model A, only estimating control variables, all variables show expected signs. A high share of employees with a university degree will increase performance, whereas plant size has the greatest effect on performance. In general, small plants show higher levels of productivity growth. As compared to knowledge-intensive service sectors, manufacturing units have a negative effect on productivity change during the period 2001 to 2003. It should be noted that we have not estimated a conventional productivity growth model; in such a case we would need information on capital/labor ratio for plants, which is not available in the database. Nevertheless, the base model fits the data reasonably well. Despite the high degree of unexplained heterogeneity involved in modeling micro-data, the model explains about 58% of the total variation. This implies that our aim to address how plant performance is influenced by the composition of economic activities and knowledge flows, on the one hand, and proximity on the other hand is possible to fulfill despite the absence of capital/labor ratio.

– Table 1 about here –

In Models B1 and B2 (the municipal level), the impacts of external factors such as density and composition of economic activities are presented by distinguishing between pure intra-industry spillovers (Model B1) and inter-industry spillovers (Model B2)[x]. The results show that high concentrations of plants within a municipality generally have a positive effect on performance (Model B1), but this effect weakens when variables on diversity are added in Model B2. When differentiating between the effects of intra- and inter-industry spillovers, the scores show expected signs. Both similar and related activities contribute to plant performance, but when comparing the t-values and the R^2-values, it is possible to conclude that the impact of related variety is greater. However, high degrees of very different activities do not have an effect on performance. In sum, these two models confirm the previous findings (e.g. Frenken *et al.* 2007; Boschma and Iammarino 2009), indicating that plants are more likely to benefit from spillovers if the region is characterized by complementary activities rather than very similar or very different activities.

By shifting the focus to Models C1 to E2 where the administrative borders are relaxed and the effects of the unique plant-specific agglomerations at 0.5 kilometers (Models C1 and C2), 5 kilometers (Models D1 and D2) and 50 kilometers (Models E1 and E2) are measured, the findings in Models B on regional aggregates are somewhat altered. Within all three radii, the scores on plant density indicate a non-linear relationship with increased productivity. When the influence of geographical proximity is assessed by comparing the estimate scores and the t-values through Models C1 to E2, the models indicate that in close proximity (within 0.5 kilometers), the composition of activities is subordinated to the effect of relative density. High concentrations of similar activities are strongly negatively correlated with productivity growth and neither related nor unrelated variety shows any significant effects. Thus, a general urbanization effect dominates within 'arm's length' of plants as compared to the qualitative composition of sectors. However, the influence of intra-industry spillovers grows stronger as the geographical distance increases and turns significantly positive when measured within 50 kilometers

[x] These effects have been separated for two main reasons: First, there is collinearity between the measurements of similarity and unrelatedness and, second, we wanted to explicitly analyze how geographical proximity influences both intra- and inter-industry spillovers. It should be noted that models only estimating related or unrelated variety have also been calculated because these variables could affect each other. Since neither the sign nor the levels of significance of covariates were affected by this procedure, the results indicate robustness and can be interpreted with some confidence.

from each plant (Model E1), whereas unrelated variety is more detrimental in combination with increased distance. Except for a non-significant effect when measured within the 0.5 kilometers radii, concentrations of complementary activities have positive effects on plant performance.

Thus, these results are in line with our expectations – neither too much nor too little proximity (geographical or cognitive) is beneficial (Boschma 2005). Similar to what is shown by Bishop and Gripaios (2009) these findings reveal a more complex pattern of spillovers than displayed through regional aggregates. If intra-industry knowledge, typically characterized by cognitive proximity, is combined with other sets of place-specific knowledge, it may produce positive effects on performance. Moreover, the effect of unrelated activities seems to be less harmful in combination with geographical proximity. This can be attributed to the fact that geographical proximity may reduce the communication problems associated with too much cognitive distance. Finally, the results indicate that complementary spillovers overall have the greatest effect on plant performance. However, the results show that increased geographical distance reduces the positive effects of related variety, which implies that the opportunity to benefit from spillovers is not only dependent on sector-specific technologies and skills it is also dependent on geographical distance.

By comparing the original entropy measurements estimated in Models B (on municipalities) and the modified entropy measurements estimated in Models E (which are set to cover most of the Swedish municipalities), it is possible to argue that the modified measurements serve their purpose very well as the estimation scores of the modified measurements in Models E correspond to the estimated score on the original entropy measurements in Models B. These results remain stable when adding covariates on labor flows in the following models.

The effects of skilled labor mobility are presented in Table 2. Since municipalities were included to reveal the effects of relaxing the influence of administrative borders, only flows concerning plant-specific neighborhoods of 0.5 kilometers (Models C3-C5), 5 kilometers (Models D3-D5) and 50 kilometers (Models E3-E5) are presented here. Three different models have been estimated for each neighborhood. First, only the in- and outflows within the defined neighborhoods to reveal the partial effect of local knowledge flows as compared to spillovers. In the next stage, non-local knowledge flows were added, and finally, the combined effect of spillovers and knowledge flows were addressed. Concerning the estimates in Table 2, three characteristics should be highlighted.

– *Table 2 about here* –

First, similar to what is advocated by Boschma *et al.* (2009), the findings presented in Models C3, D3 and E3 show that it is necessary to distinguish the composition of skills for understanding the impact of knowledge flows. However, in contrast to their findings indicating that unrelated inflows within the same region may be beneficial for performance, these estimates more readily consider the sub-regional dimension of labor mobility and show that related inflows are the only types of local knowledge flows with a positive effect on performance, irrespective the distance of the inflow. Neither similar nor unrelated flows show significant effects. Thus, the estimates confirm the propositions made in previous sections by indicating that different but related inter-plant knowledge flows are essential for whether plants can both absorb and utilize new pieces of embodied knowledge. Moreover, by comparing these three models with the models on spillovers in Table 1, it is on the one hand not possible to say that knowledge flows produce stronger effects than spillovers. The two models on knowledge flows produce equal or slightly higher explanatory values within 0.5 and 5 kilometers, respectively, while the spillover model produces higher explanatory value within the largest neighborhood. On the other hand, it is evident that the effects of different types of knowledge flows are less affected by proximity than what spillovers are. Local inflows that are related to what the plant is specialized in are the most important within all distances.

Second, the outcomes of Models C4, D4 and E4, which also include non-local flows, confirm the initial findings that the effect of different types of flows is less influenced by the geographical dimension. Contrary to what was expected, similar inflows do not contribute to increased performance when combined with other types of place-specific skills. Related inflows remain the only type of inflow with a significant effect. Additionally, increased distance seems to worsen the negative effect of unrelated inflows. These two findings are in line with expectations, however. Inflows characterized by both cognitive and geographical distance may cause communication problems and might therefore be difficult to implement within the plant. In sum, these results provide new insights on the geography of knowledge flows by showing that they mainly work within a restricted geographical range. The positive effect of related flows shorter than 500 meters is reduced when also including non-local flows. Similar to the findings presented in Table 1 (Models D2 and E2), the results indicate rather that a certain degree of both geographical distance and cognitive distance is needed for inflows to produce significant effects on productivity growth. Too-short distances may reduce the positive effect while too-long distances (i.e. over 50 kilometers) show no positive effect whatsoever, as indicated by the estimation scores on non-local inflows in Model D4 and Model E4. Thus, knowledge flows via labor mobility are predominantly a local process. This local dimension of knowledge transfer is especially evident in relation to the models including both spillovers and knowledge flows (Models C5, D5 and E5). The agglomeration indicators are highly unaffected by the inclusion of both local and non-local knowledge flows, implying that other types of non-local relations are needed to acquire knowledge from more distant locations (e.g. Rallet and Torre, 1999; Torre, 2008; Ponds *et al.*, 2009). However, the interrelatedness between agglomeration externalities and knowledge flows further reduces the influence of urbanization as such. The positive effect of the quadratic term of population density turns insignificant within 0.5 kilometers and 5 kilometers (Models C5 and D5), and is reduced within 50 kilometers as compared to the effects of diversity (Model E5).

A third observation concerns the effects of skills leaving the plant. Although the economic effect of outflows is likely to be more instantaneous than the effect generated by inflows, the empirical results confirm the notion that skills leaving a plant do not necessarily imply negative outcomes. They also reveal that the geographical dimension is clearly related to this issue. It is less detrimental to the dispatching plant if its former employees remain within the local economy as compared to if they depart for jobs in other parts of the national economy. Hence, knowledge is likely to diffuse both forward and backward via social linkages established between the old and the new workplace (cf. Dahl and Pedersen 2003). However, a certain distance between plants is also needed for efficient backward linkages to occur. The results indicate that outflows of skills into the immediate neighborhood (closer than 0.5 kilometers) have no significant effects on the dispatching firm. It is more beneficial for the firm if the former employee moves a greater distance but remains local.

A final observation concerns the overall explanatory power of the two output tables. Despite the use of micro-data, the R^2 values reach reasonably high levels (58% and higher). What should be noted is the relative change of R^2 between the different models. As compared to the base model, which only included characteristics internal to the plant, the subsequent models show relative moderate increases in explanatory power. Small amounts of explanatory power are gained by increasing the hinterlands in the models, and relatively more explanatory power is gained in the knowledge flow models than in those merely assessing the impact of externalities. Nevertheless, the reported overall moderate effect is in line with previous studies on the effects of agglomeration externalities and labor mobility in Sweden (e.g. Eriksson and Lindgren 2009). Agglomerative effects internal to the workplace tend to affect productivity the most.

5 Summary and conclusions

The analyses carried out in this paper intended to contribute to the perennial discussion on how geographical proximity influences the performance of plants. By creating both plant-specific agglomeration measures and labor markets at 0.5 kilometers, 5 kilometers and 50 kilometers from each of the 8,313 plants in the sample, it was possible to account for (i) what type of industrial composition is most beneficial to productivity growth during a three-year period; (ii) how different types of knowledge flows, into and out from the plant, affect performance; and (iii) how geographical proximity interacts with both spillovers and knowledge flows.

Previous studies have highlighted the importance of diversity in explaining the potential of spillovers and knowledge flows, and often associated this with a general urbanization effect (e.g. Glaeser, 1999). The findings in this paper however indicate that the geography of spillovers is more complex than is possible to visualize by only distinguishing between concentrations and relative regional diversification or specialization. It is demonstrated that urbanization is indeed highly important, but mainly within a very short distance from the plant, and therefore cannot be associated only with attributes found in densely populated metropolitan areas. Thus, in line with what is advocated by Malmberg and Maskell (2002), co-location and geographical proximity imply that knowledge can more readily spill over between plants within 'arm's length' without being too influenced by how the external knowledge matches the specialization of the plant. By increasing the geographical range of the agglomeration, and thereby including most of the medium- and large-sized urban areas in Sweden, the absorptive capacity of plants grows in importance for whether or not plants may benefit from spillovers since the composition of economic activities becomes more significant than the absolute number. This is especially the case when also including variables on knowledge flows. However, the more qualitative content of agglomerations is also influenced by proximity. These findings show that diversified economies not only produce different effects for plants in terms of, for instance, productivity or employment effects (e.g. Frenken *et al.*, 2007; Essletzbichler, 2007; Bishop and Gripaios, 2009). The impact of spillovers is also influenced by the geographical dimension. As exemplified in Figure 1, at close range the externalities derived from different but complementary sectors (related variety) are relatively more gainful, whereas intra-industry spillovers are relatively more beneficial at further distances.

	Close proximity	Long distance
Similar knowledge	Ineffective	Useful
Dissimilar knowledge	Useful	Ineffective

Figure 1. Spatial dimensions of the impact of spillovers on plant performance.

This relationship between the cognitive distance of sectors and geographical proximity also seems to be the case when more directly assessing the impacts of inter-plant knowledge flows via labor mobility – only new skills that are complementary to the existing knowledge base of plants and characterized by just the right degree of geographical proximity have a positive effect on performance. While previous studies have clarified the relative importance of local flows of skilled labor (Breschi and Lissoni, 2009; Eriksson and Lindgren, 2009) and of separating the impact of different skills (Boschma *et al.*, 2009), the findings in this paper demonstrate that potential knowledge flows via labor mobility are a much more local phenomenon than is captured by carrying out analyses within local labor market boundaries. By adding a sub-local dimension to knowledge flows, this paper is therefore yet another contribution to the growing body of empirical literature advocating the effects of related variety on economic growth. Since complementary knowledge flows seems to be the main driver of transferring embodied skills between co-located plants, the potential for knowledge flows and spillovers should be higher for plants located in an area characterized by related variety as compared to being located near very similar or very different activities. An interesting feature linked to these findings is the relationship revealed between, on the one hand, knowledge flows and the composition of local industries, and between urbanization and the composition of industries, on the other hand. As compared with the urbanization effect, the effect of related variety grows stronger in combination with knowledge flows. This study is therefore in line with the findings by Breschi and Lissoni (2009). The potential for producing pure externalities may not be the most important localized feature of agglomerations. The local production of appropriate skills may be equally important due to local dimension of labor mobility and the interplay between the local setup of industries and the production of local skills (Storper, 1995). However, as these findings demonstrate, it is the production of local skills characterized by related variety that has a real impact on plant performance. An important question for future studies would therefore be how sufficient degrees of complementarities within local economies can be achieved and what the role played by policies in this process is (e.g. Boschma, 2009).

In the light of these general findings, there are several challenges for future research. In order to learn more about the causality of relationships identified in this study and the impact of different dimensions of proximity, these findings could be supplemented with case studies. Adopting a more dynamic approach to the impact of both externalities and labor mobility by following a certain cluster or a particular industry over time would, for instance, make it possible to investigate the importance in different stages of the product lifecycle (Gordon and McCann 2000; Neffke *et al.*, 2008). A limitation of the current study is the use of static industry codes as a measure of externalities and labor flows. To determine how different combinations of individual skills (e.g. different types of education, occupation and accumulated work experience) within a plant match the surrounding milieu of individual skills and how this changes over time, future studies would benefit from constructing refined measures of relatedness based on the co-occurrences of skills (cf. Neffke and Svensson-Henning, 2008; Breschi et al, 2003). The analysis would also benefit from access to input-output linkages and/or citation tracks to be able to more readily assess inter-plant relations and knowledge flows. Moreover, to address the local/non-local dimension more properly it would also be necessary to account for the degree of social proximity established via labor mobility and how this influences performance (e.g. Breschi and Lissoni, 2003; Agrawal *et al.*, 2006; Timmermans, 2008) and the interplay with more temporal forms of non-local relations (Torre, 2008; Bathelt and Schuldt, 2008; Ponds *et al.*, 2009).

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APPENDIX. Table A1: Variable description (N=8,313). Note 1: The statistics for the dependent variable and the plant-specific variables are the same throughout the models and are therefore displayed only once. Note 2: For municipalities the relatedness indicators are measured as presented in Frenken *et al*. (2007), whereas for the three neighborhoods they are modified to capture the plant-specific agglomerations.

Variable	Description	Municipalities				0.5 km				5 km				50 km			
		Mean	S.D	Min	Max	Mean	S.D	Min	Max	Mean	S.D	Min	Max	Mean	S.D	Min	Max
Productivity growth	Change in labor productivity 2001-2003 (log)	-2.88	1.74	-11.61	5.90												
Local Inflow Sima	Local inflows from similar workplaces (log)					0.02	0.21	0.00	4.76	0.07	0.37	0.00	4.99	0.11	0.45	0.00	5.25
Local Inflow RelVar	Local inflows from related workplaces (log)					0.00	0.06	0.00	3.56	0.01	0.12	0.00	3.56	0.02	0.15	0.00	3.58
Local Inflow UnrelVar	Local inflows from unrelated workplaces (log)					0.02	0.23	0.00	5.59	0.12	0.44	0.00	5.62	0.27	0.64	0.00	5.68
Non-local Inflow Sima	Extra-local inflows from similar workplaces (log)					0.16	0.51	0.00	5.29	0.11	0.42	0.00	4.54	0.07	0.32	0.00	4.19
Non-local Inflow RelVar	Extra-local inflows from related workplaces (log)					0.03	0.18	0.00	3.53	0.01	0.14	0.00	3.53	0.01	0.10	0.00	3.53
Non-local Inflow UnrelVar	Extra-local inflows from unrelated workplaces (log)					0.39	0.73	0.00	5.61	0.29	0.63	0.00	5.49	0.13	0.42	0.00	4.67
Total Local Outflow	Total local outflows (log)					0.02	0.21	0.00	5.80	0.12	0.46	0.00	6.21	0.25	0.65	0.00	6.71
Total Non-local Outflow	Total extra-local outflows (log)					0.36	0.76	0.00	6.76	0.28	0.66	0.00	5.92	0.14	0.46	0.00	4.86
Similarity	Degree of similar activities (log)	0.14	0.01	0.13	0.20	0.04	0.05	0.00	0.53	0.03	0.03	0.00	0.13	0.02	0.02	0.00	0.08
RelVar	Degree of related activities (log)	0.01	0.01	0.00	0.07	-0.01	0.03	-0.38	0.09	-0.01	0.02	-0.12	0.02	-0.01	0.01	-0.05	0.01
UnrelVar	Degree of unrelated activities (log)	2.80	0.16	2.50	3.21	2.43	1.38	0.00	9.63	2.97	1.66	1.33	9.28	3.16	1.57	1.66	8.09
PopDensKm^2	Number of employees per km^2 (log)	2.80	2.17	-4.08	5.57	3.12	0.86	-0.73	4.24	3.51	0.75	-4.70	4.25	3.47	0.42	-4.35	3.89
PopDensKm^2^2	Number of employees per km^2 (quadratic term)	12.55	12.46	0.00	30.98	10.47	4.40	0.04	17.97	12.87	4.32	0.01	22.10	12.23	2.65	0.13	18.97
HEducRatio	Share of employees with a Bachelor's degree or higher	0.40	0.32	0.00	1.00												
PlantSize	Number of employees within plant (log)	2.53	1.56	0.00	8.52												
Manufacturing	Dummy =1 if plant is defined as a manufacturing unit	0.35	0.48	0.00	1.00												

Table 1: OLS estimates of the effects of agglomeration externalities on productivity growth (2001-2003) for workplaces with skilled inflows 2001 (N=8,313). Conventional measurements of relatedness as presented by Frenken *et al.* (2007) are estimated at the regional level (B1 and B2), whereas modified measurements are estimated for the plant-specific neighborhoods (C1-E2). Coefficients and t-values (within brackets) are reported. The t-values are White corrected for heteroskedasticity. Significant at the *** 0.01 level, ** 0.05 level and * 0.10 level.

Labor Productivity	Base model (A)	Region (B1)	Region (B2)	0.5 km (C1)	0.5 km (C2)	5 km (D1)	5 km (D2)	50 km (E1)	50 km (E2)
Similarity (log)		10.018***		-0.022***				0.033***	
		(4.680)		(-2.600)		0.007 (1.200)		(4.040)	
RelVar (log)			7.310***		-0.002		0.008**		0.006**
			(6.370)		(-0.240)		(2.080)		(1.960)
UnrelVar (log)			-0.103		-0.006		-0.058***		-0.127***
			(-0.450)		(-0.430)		(-3.590)		(-7.320)
PopDensKm^2 (log)		0.044**	0.005	-0.094***	-0.060**	-0.050	-0.035	-0.043	-0.074
		(2.570)	(0.230)	(-3.310)	(-2.070)	(-1.640)	(-1.200)	(-0.630)	(-1.100)
PopDensKm^2^2 (log)		0.001	0.003	0.010***	0.006*	0.009**	0.007**	0.002**	0.002**
		(0.220)	(0.940)	(2.670)	(1.690)	(2.560)	(2.000)	(2.020)	(1.980)
HEducRatio	0.495***	0.464***	0.416***	0.510***	0.512***	0.476***	0.484***	0.449***	0.467***
	(9.840)	(9.230)	(8.180)	(10.080)	(10.090)	(9.440)	(9.570)	(8.970)	(9.340)
PlantSize (log)	-0.765***	-0.765***	-0.762***	-0.765***	-0.764***	-0.768***	-0.769***	-0.761***	-0.762***
	(-78.200)	(-87.610)	(-78.230)	(-78.330)	(-78.310)	(-78.690)	(-78.640)	(-78.230)	(-78.580)
Manufacturing	-0.310***	-0.283***	-0.204***	-0.338***	-0.328***	-0.271***	-0.098*	-0.139***	0.119**
	(-9.310)	(-8.100)	(-5.780)	(-9.300)	(-7.140)	(-7.200)	(-1.730)	(-3.110)	(2.020)
Intercept	-1.036***	-2.587***	-0.880	-0.925***	-0.928***	-0.991***	-0.912***	-1.040***	-0.816***
	(-24.590)	(-8.210)	(-1.300)	(-15.920)	(-15.850)	(-15.090)	(-13.090)	(-9.450)	(-7.230)
R^2	0.583	0.586	0.587	0.583	0.583	0.584	0.584	0.588	0.590

Table 2: OLS estimates on the effects of different local and non-local labor flows on productivity growth (2001-2003) for workplaces with skilled inflows (N=8,313). Modified indicators for related and unrelated variety are presented for each of the three neighborhoods. Coefficients and t-values (within brackets) are reported. The t-values are White corrected for heteroskedasticity. Significant at the *** 0.01 level, ** 0.05 level and * 0.10 level.

Labor Productivity	**0.5 km (C3)**	**0.5 km (C4)**	**0.5 km (C5)**	**5 km (D3)**	**5 km (D4)**	**5 km (D5)**	**50 km (E3)**	**50 km (E4)**	**50 km (E5)**
Local Inflow Sima (log)	0.041	0.055	0.054	0.001	0.035	0.030	0.006	0.030	0.025
	(0.520)	(0.710)	(0.710)	(0.040)	(0.930)	(0.790)	(0.200)	(0.950)	(0.780)
Local Inflow RelVar (log)	0.373**	0.346*	0.347*	0.270**	0.267**	0.276**	0.182**	0.191**	0.193**
	(2.550)	(1.920)	(1.950)	(2.530)	(2.470)	(2.560)	(2.360)	(2.410)	(2.430)
Local Inflow UnrelVar (log)	0.015	0.033	0.034	-0.015	0.018	0.020	-0.027	0.001	0.003
	(0.190)	(0.410)	(0.420)	(-0.380)	(0.440)	(0.480)	(-0.960)	(0.010)	(0.120)
Non-local Inflow Sima (log)		-0.062**	-0.062**		-0.115***	-0.116***		-0.156***	-0.151***
		(-2.310)	(-2.310)		(-3.250)	(-3.280)		(-3.630)	(-3.530)
Non-local Inflow RelVar (log)		0.162**	0.163**		0.111	0.114		0.051	0.072
		(2.410)	(2.400)		(1.310)	(1.350)		(0.450)	(0.680)
Non-local Inflow UnrelVar (log)		-0.040	-0.040		-0.085***	-0.083***		-0.136***	-0.127***
		(-1.590)	(-1.580)		(-2.930)	(-2.860)		(-3.360)	(-3.150)
Total Local Outflow (log)	0.113	0.095	0.095	0.100***	0.111***	0.114***	0.045*	0.051*	0.054***
	(1.390)	(1.160)	(1.150)	(3.010)	(3.000)	(3.080)	(1.780)	(1.910)	(2.020)
Total Non-local Outflow (log)		0.056**	0.056**		0.034	0.036		0.048	0.055
		(2.460)	(2.480)		(1.250)	(1.310)		(1.380)	(1.570)
RelVar (log)			-0.001			0.009**			0.006**
			(-0.020)			(2.370)			(2.030)
UnrelVar (log)			-0.007			-0.057***			-0.124***
			(-0.530)			(-3.480)			(-7.160)
PopDensKm^2 (log)	-0.007**	-0.007**	-0.058**	-0.007**	-0.006**	-0.027	-0.009	-0.007	-0.052
	(-2.580)	(-2.510)	(-1.980)	(-2.430)	(-2.110)	(-0.940)	(-1.330)	(-1.060)	(-0.780)
PopDensKm^2^2 (log)	0.001**	0.001**	0.006	0.001***	0.001***	0.006	0.001***	0.001**	0.018*
	(2.100)	(2.040)	(1.620)	(3.190)	(2.820)	(1.640)	(2.720)	(2.360)	(1.830)
HEducRatio	0.506***	0.512***	0.512***	0.456***	0.485***	0.491***	0.446***	0.473***	0.480***
	(10.010)	(9.700)	(9.680)	(8.960)	(9.270)	(9.380)	(8.730)	(9.150)	(9.310)
PlantSize (log)	-0.769***	-0.771***	-0.772***	-0.781***	-0.769***	-0.771***	-0.771***	-0.763***	-0.767***
	(-77.390)	(-58.900)	(-58.160)	(-70.680)	(-60.500)	(-60.660)	(-62.780)	(-60.430)	(-60.920)
Manufacturing	-0.339***	-0.338***	-0.321***	-0.281***	-0.282***	-0.094*	-0.251***	-0.251***	0.120**
	(-9.360)	(-9.260)	(-6.930)	(-7.820)	(-7.890)	(-1.850)	(-7.340)	(-7.350)	(2.020)
Intercept	-0.918***	-0.916***	0.914***	-0.944***	-0.980***	-0.908***	-1.088***	-1.124***	-0.833***
	(-15.810)	(-14.730)	(-14.570)	(-14.030)	(-14.030)	(-12.250)	(-9.820)	(-10.120)	(-7.190)
R^2	0.583	0.584	0.584	0.585	0.586	0.587	0.587	0.589	0.592