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Vertical disintegration and spatial co-localization: The case of KIBS in the metropolitan region of Milan

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ABSTRACT

This paper explores the relation between vertical disintegration and the co-localization of knowledge intensive business service (KIBS) firms in the metropolitan region of Milan, using micro-geographic data and nonparametric methods. Our main results are that: (i) compared to other manufacturing and service industries, KIBS firms show a "natural tendency" to cluster; (ii) this tendency increases with the degree of vertical disintegration of KIBS firms.

1. Introduction

Since the seminal contribution by Stigler (1951), the relationship between the co-localization and vertical disintegration of firms has been investigated extensively. The principle behind Stigler's contribution is that spatial proximity to suppliers reduces not only transport, search, and managerial costs (Goldstein and Gronberg, 1984) but also the scope for opportunistic behavior. Using 1987 census data on US manufacturing plants, Holmes (1999) finds that the intensity of input purchases by a plant is positively correlated with the level of employment in the same industry. Ono (2007) for the US and Li and Lu (2009) for China obtain similar results, while positive correlations have also been found for the Turkish textile and engineering industries (Taymaz and Kiliçaslan, 2005) and the Spanish electronics industry (Rama et al., 2003).

For Italy, Antonietti and Cainelli (2008) find that outsourcing knowledge-intensive business services (KIBS) is driven by the interplay between research and development (R&D) and firm localization in an industrial district. In addition, Antonietti et al. (2012) find that the propensity to fully outsource production activities increases with the density of neighboring employment in related industries. Finally, Cainelli and Iacobucci (2012) show that a higher degree of vertically related variety reduces the need for firms to integrate their activities.

However, while most of the above-mentioned studies examine the manufacturing context, the present paper investigates the relation between the vertical disintegration and co-localization of firms in the KIBS industry. By using micro-geographic data and adopting nonparametric methods, it describes the correlation between the geographical concentration and degree of specialization of KIBS firms within a large metropolitan context, namely Milan, Italy.[1]

This paper thus makes two main contributions to the literature. In contrast to previous studies of this topic, we (i) use micro-geographic data in order to investigate the agglomeration–disintegration relationship and (ii) focus on KIBS firms. In developed countries, such firms are not only an engine of growth, but also their outsourcing accounts for the majority of all outsourcing in the whole economic system (Windrum et al., 2009).

The remainder of this paper is organized as follows. Section 2 describes the dataset and the nonparametric methods used for the empirical investigation. Section 3 presents the empirical results. Section 4 concludes.

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[1] For the theoretical modeling of this relationship, see Baumgardner (1988).

2. Data and methods

2.1. Data

The data employed herein were derived from AIDA, a commercial database collected by Bureau Van Dijck, which gathers balance sheet information for a large sample of Italian joint-stock companies. Using information for 2008, and after omitting observations that had negative or zero values for total production costs and/or purchased services, we obtained a dataset of 85,053 manufacturing and service firms located in the metropolitan region of Milan[2]: 12,049 of these firms could be distinguished as KIBS according to the inclusion criteria adopted in this study.[3]

We also considered the geographic coordinates (longitude and latitude) and a disintegration index for each firm. Following the literature on international outsourcing (Feenstra and Hanson, 2008; Bengtsson and Dabhilkar, 2009), the latter is computed as follows:

$$VDIS_i = \frac{CS_i}{TC_i} \tag{1}$$

where CS_i measures the purchase of business services[4] by firm i, which includes the costs incurred for services such as auditing, insurance, legal consultancy, marketing, and advertising, and TC_i is total production costs.

This ratio is an indicator of the "relevance" of the services acquired by a service firm in the market: the higher the index the lower is the degree of vertical integration. This index is particularly appropriate in our case because "many business services are likely to be exactly the kind of locally produced intermediate input that producers in localized areas will have greater access to than producers in isolated areas" (Holmes, 1999, p. 316).

2.2. Methods

From the geographic coordinates observed for each firm, we can compute the bilateral distances on the Earth's surface (geodesic distances) among all firms (Cainelli and Lupi, 2011). The number of bilateral distances for a sample of m firms is $m(m-1)/2$, which means a huge number of distances are considered in the present investigation.

Following Duranton and Overman (2005, 2008), the analysis is conducted in three steps. First, we select firms according to their level of disintegration: since we investigate the relation between vertical disintegration and co-localization patterns, we select three samples of KIBS firms based on their *VDIS* index values. The first sample, which is characterized by low levels of vertical disintegration, is made up of KIBS firms that have a *VDIS* index lower than the first decile. The second sample (median disintegration) is made up of the 10% of KIBS firms positioned around the median. The third sample (high level of vertical disintegration) includes firms that have a *VDIS* index value higher than the ninth decile.

In the second step, we estimate the density of the bilateral distances among the firms in each sample. Finally, we draw 1000 random samples from the whole population of firms in the metropolitan region of Milan, irrespective of the firms' sectors. Each of these random samples has the same size as the selected KIBS sample, and on each of the samples we compute the bilateral distances and densities. This final step allows us to compute a 95% local confidence band of the density of the distances of randomly located firms. If, in correspondence to a specified short (long) distance, the observed density exceeds the upper bound of the confidence band, this indicates a tendency for the selected KIBS firms to cluster (be overdispersed) relative to what would be implied were they randomly located. The second and third steps in the analysis are conducted separately for each of the three samples of KIBS firms.[5]

The computation of these densities is technically complex. In particular, given that the distances x are positive quantities, the estimated densities $\hat{f}(x)$ must be zero for $x < 0$. Therefore, consistent with the approach of Duranton and Overman (2005, 2008), we estimate the densities using the reflection method (Silverman, 1986, Chapter 2) with a Gaussian kernel. Bandwidth selection is also a crucial aspect of density estimation. In this paper, we thus use Silverman's (1986 p. 48) "rule of thumb", which sets kernel bandwidth h to $h = 0.9\min(\sigma, IQR/1.34)n^{-1/5}$, with σ and IQR representing the sample standard deviation and interquartile range, respectively, while n is the number of observations.

In our context, Silverman's rule of thumb offers important advantages compared with other bandwidth selection criteria. First, it is theoretically based on the minimization of the mean integrated standard error (MISE) for normal distributions (Silverman, 1986, p. 45). As such, it yields an MISE that is within 10% of the optimum for many unimodal distributions as well as for sufficiently separated normal mixtures. Second, it does not require the visual inspection and ex-post adjustments that cross-validation techniques do (see Sheather (2004) among others). Third, it is easy to compute even for very large n where cross-validation and plug-in methods would not be feasible, especially if applied over thousands of replications (as in our case).

Although it has been shown that Silverman's rule of thumb might oversmooth in the presence of multimodal or highly irregular distributions (see, e.g., Jones et al. (1996)), we still believe that this fact represents only a minor shortcoming in the present analysis. Indeed, the distribution of the observed bilateral distances is extremely regular and unimodal, suggesting that the quasi-optimality properties of Silverman's bandwidth selection rule are likely to be satisfied. In any case, as a robustness check we compare the results that derive from the application of the kernel estimator based on Silverman's rule of thumb with those obtained using the extreme case of a naive (unsmoothed) estimator (see Silverman (1986, Section 2.3)). If the main results are confirmed, we can legitimately conclude that they are not an artifact of the kernel and bandwidth selection procedure.

3. Results and discussion

Fig. 1 illustrates the estimated densities of the bilateral distances in the three KIBS samples (low, median, and high levels of vertical disintegration) together with the 95% local confidence

[2] Milan was chosen on the basis of the available data and because it is considered to be a center of advanced services in Europe as well as a fashion and design center globally (OECD, 2006, p. 87) and the "centre of Italian business management and strategy" (OECD, 2006, p. 93). In particular, the "core of Milan is progressively becoming a technology and service hub" (OECD, 2006, pp. 87–88). The metropolitan region of Milan includes the provinces of Bergamo, Como, Lecco, Lodi, Monza and Brianza, Pavia, Varese, and Novara in Piedmont (which we exclude in order to focus only on the Lombardy region).

[3] We consider KIBS firms to be those that belong to "professional, scientific, and technical activities" industries such as: computer programming, consultancy, and related activities; data processing, hosting, and related activities; legal and accountability activities; head office and management consultancy activities; architectural and engineering activities, technical testing and analysis; scientific R&D; advertising; other professional, scientific, and technical activities.

[4] Since we are interested in the local provision of intermediate inputs, and owing to the nature of the firms under investigation in this study, we explicitly omit the purchase of material inputs, whose provision typically lacks a local dimension.

[5] All computations were carried out using R (R Development Core Team, 2012).

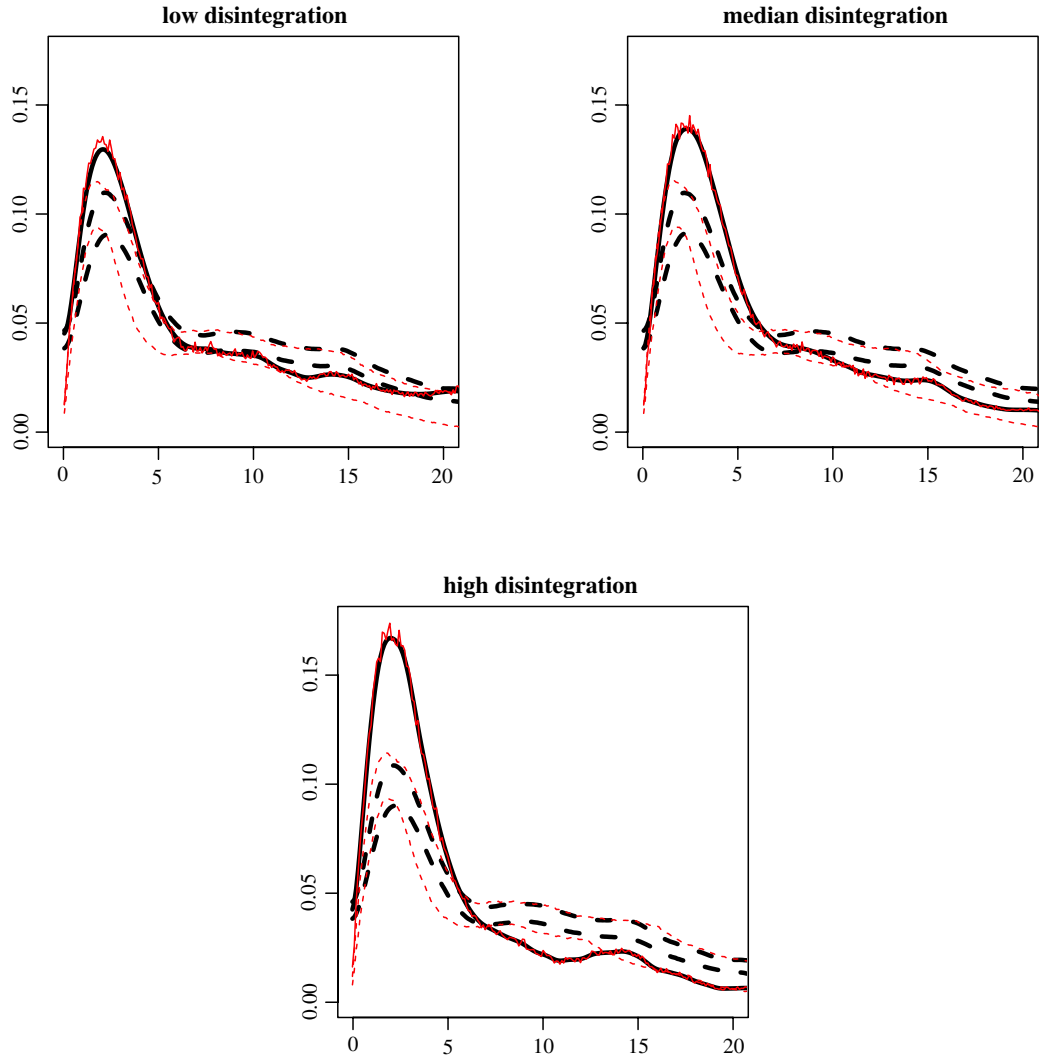

Fig. 1. Estimated densities of the bilateral distances (solid lines) and 95% local confidence bands (dashed lines). The thick lines are derived using the Gaussian kernel estimator with Silverman's "rule of thumb" bandwidth selection. The thin lines are derived using the naive estimator. Distances in kilometers on the *x*-axis.

bands computed under the null hypothesis of random firm localization. The results are robust with respect to the kernel choice and bandwidth selection criterion. Further, even though the confidence intervals are somewhat wider in the case of the naive estimator, the main conclusions are supported by both estimators.[6]

The main message from Fig. 1 is that KIBS firms show a strong tendency to cluster, especially with respect to manufacturing and other service firms. Moreover, this tendency increases with the degree of vertical disintegration and is much stronger when firms are highly vertically disintegrated.

Since KIBS firms buy and demand other services, being co-localized in large metropolitan areas has at least three advantages: the local availability of specialized suppliers and customers, the higher probability of face-to-face interactions, and reduced transport and transaction costs because of increased mutual visibility and reciprocal trust (Helsley and Strange, 2007). Therefore, by nature, they follow a business-to-business co-location pattern (Arbia et al., 2012).

[6] Of course, given the better properties of the kernel estimator (see, e.g., Silverman (1986) and Sheather (2004)), we take the results that derive from the kernel estimator as the reference and those that come from the naive estimator simply as a robustness check.

4. Conclusion

Most studies show that spatial concentration induces firms to vertically disintegrate. However, this evidence is based on the manufacturing context, while very little attention has been paid to the service sector. In this paper, we used micro-geographic data and nonparametric techniques in order to investigate the vertical disintegration–co-localization relation for KIBS firms located in the metropolitan region of Milan. Our analysis showed that (i) KIBS firms have a natural tendency to cluster, particularly compared with those in manufacturing and other service industries and (ii) this tendency seems to increase with the degree of vertical disintegration and is much stronger if KIBS firms are highly vertically disintegrated.

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