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Geographic Concentration of Business Services Firms: A Poisson Sorting Model

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Abstract

This paper estimates a heterogeneous sorting model for firms, employing a semiparametric Poisson approach. We show that there is an equivalence relation between a *locally weighted* Logit and Poisson model. We apply our model to estimate firm-specific preferences of business services firms for location attributes such as diversity of economic activities and specialisation of business services. We correct for endogeneity of our specialisation measure by means of a control function approach, using instruments external as well as internal to the model. We find that business services firms have a relatively strong preference for specialised clusters of business services firms, conditional on density of economic activity. A standard deviation increase in business services specialisation of a location leads to a 40 percent increase in the probability that a business services firm locates there, supporting theories of Marshall, Arrow and Romer. Business services firms also have a preference to locate near a group of firms that belong to the same sector, not necessarily business services firms, so diversity is negatively related to location decisions. Interestingly, firms rely either on within-sector interactions (specialisation) or between-sector interactions (diversity).

Keywords: Sorting; Agglomeration Economies; Specialisation; Diversity; Heterogeneity; Semiparametric Estimation

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1. Introduction

Concentration of firms at certain places is too large to be explained by exogenous differences in natural advantages only (Ellison et al., 2010). It is very likely that firms tend to concentrate because of local interactions with other firms. Proximity to others reduces transport costs of goods, people and ideas (Marshall, 1920; Ellison et al., 2010). Marshall (1920), Arrow (1962) and Romer (1986) (MAR) argue that *specialisation* generates knowledge spillovers between firms. Innovators' ideas will be copied, imitated and improved by their neighbours. It is argued that in particular nearby firms of the same type will be able to copy these technologies (Porter, 1990; Audretsch and Feldman, 1996). Beside these dynamic externalities, static externalities also play a role. For example, a cluster of a specialised industry induces a market for specialised suppliers and generates a thick labour market. In contrast, Jacobs (1969) argues that a *diverse* economy will attract firms because it may lead to a more diverse portfolio of customers and exchange of tacit knowledge, as knowledge and technologies from different sectors may be recombined into new combinations (see Schumpeter, 1942; Fujita et al., 1999).

An extensive literature, started by the seminal work of Glaeser et al. (1992), reviews the effects of specialisation and diversity on growth of cities, regions and even countries (see for a meta-analysis De Groot et al., 2009). However, little attention has been paid to the effect of these forces on location decisions of firms although firms may be considered the backbone of the urban economy. Cities that are able to attract more firms will almost surely face lower unemployment levels and higher productivity growth (Baptista et al., 2008; Van Stel and Suddle, 2008). Current empirical studies that pay specific attention to the impact of diversity and specialisation on location decisions are on an aggregate spatial level and focus mostly on extra-metropolitan agglomeration economies in the *manufacturing sector*, whereas it is suggested that, especially for *business services firms*, local interactions are more relevant (Muller and Zenker, 2001; Duranton and Overman, 2005; Drennan and Kelly, 2010; Ellison et al., 2010). For example, Arzaghi and Henderson (2008) show that interactions between advertising agencies mainly take place within a couple of hundred meters.

Another issue that is typically ignored in the current literature is firm heterogeneity. It may be expected that the contribution of specialisation and diversity to profits may be different between industries and even between firms within the same industry. Possibly because of heterogeneity in firm ‘preferences’, different studies arrive at opposite conclusions about whether specialisation and diversity attract or repel firms.

The main contribution of the paper is that we generalise a heterogeneous sorting framework. We apply this framework to measure business services firms’ preferences for diversity and business services specialisation, conditional on density of economic activities.¹ Specialisation is measured by the local employment share of business services firms. Diversity indicates whether the local composition of industrial sectors mirrors the composition of the broader economy.

The essential assumption of the proposed framework is that in equilibrium, firm preferences are continuous over space, which may lead to a semiparametric conditional Logit model (CLM) that we estimate by means of a locally weighted Poisson regression. This approach reveals firm-specific preferences for specialisation and diversity without making assumptions regarding the distribution of preferences. It has been shown that there is an equivalence relation between a standard CLM and Poisson regression (Guimarães et al., 2003; Schmidheiny and Brülhart, 2011). We show that the equivalence relation also holds in a semiparametric setting, but maybe surprisingly, only when assumptions are made on the values of the weights. It appears that these assumptions imply a ‘ k -nearest neighbour approach’, frequently applied in the semiparametric literature, which has an intuitive economic interpretation.

In our empirical application, we aim to estimate the effect of specialisation and diversity on location choices, so we aim to disentangle the effect of these potentially endogenous measures from (unobserved) natural advantages. We correct for endogenous measures using a control function approach that relies on

¹ Business services are defined as professional services, such as consultancy, financial services, but also include new-technology based services such as telecommunications and Research and Development (Muller and Zenker, 2001).

instruments external to the model.² We also use an internal instruments approach that relies on within region variation (see Bayer and Timmins, 2007).

Our estimation procedure has three attractive features compared to previous methodologies. First, we model heterogeneity of firms' preferences in a general way: rather weak assumptions are made concerning the distributions of preferences. Second, we do not need any data about the characteristics of firms that choose a particular location. Third, our estimation procedure is computationally light and can be carried out using standard statistical software packages.

This paper proceeds as follows. Section 2 outlines our equilibrium sorting model for firms, followed by the estimation procedure in Section 3. In this section we also show when the equivalence relation between locally weighted CLM and Poisson holds. Section 4 discusses our dataset and the instruments used. In Section 5 we discuss the empirical results and provide robustness checks. Standard parametric techniques are compared with the results of our semiparametric approach. Section 6 concludes.

2. A heterogeneous sorting model for firms

In our equilibrium framework, we assume that firm i chooses a location j that maximises profit π_j^i , which is a function of locational attributes \mathbf{X}_j (e.g. employment density) as well as a specialisation measure ρ_j and a diversity index σ_j , where $i = 1, \dots, I$ and $j = 1, \dots, J$. Then:

$$(1) \quad \max \pi_j^i = \alpha_0^i + \mathbf{X}_j' \boldsymbol{\alpha}^i + \beta^i \rho_j + \gamma^i \sigma_j + \epsilon_j^i,$$

where α 's, β 's and γ 's are firm-specific coefficients to be estimated. ϵ_j^i denotes an idiosyncratic preference of firm i for location j . In (1) we assume an additive profit function but it is otherwise very general, as the coefficients are firm-specific.

To estimate sorting models based on (1), one needs to impose some restrictions. We assume that in equilibrium, so after sorting, preferences are continuous over space. More formally, we assume that for all

² In many studies there is not a proper distinction made between local interactions and (unobserved) natural advantages, which generally lead to overstated effects of agglomeration. Ellison and Glaeser (1999) conjecture that at least half of the observed concentration is due to natural advantages.

coefficients α and β the absolute difference between coefficients of two firms, so $|\alpha^i - \alpha^{\tilde{i}}|$ and $|\beta^i - \beta^{\tilde{i}}|$, are a positive function of $d_{j\tilde{j}}$, where $d_{j\tilde{j}}$ denotes the distance between the locations of firms i and \tilde{i} . We think this is a natural assumption, as firms with similar preferences will sort themselves across space. It is quite common to make a similar assumption, for example in the econometric literature on spatial discontinuity designs (e.g. Black, 1999; Bayer et al., 2007). Sorting of people and firms with similar preferences is also an outcome of many theoretical urban equilibrium models (e.g. LeRoy and Sonstelie, 1983; Glaeser et al., 2008). In the special case where $d_{j\tilde{j}} = 0$, we assume $\alpha^i = \alpha^{\tilde{i}}$ and $\beta^i = \beta^{\tilde{i}}$. So, firms that locate at exactly the same location (so, for example within the same building) are assumed to have identical preferences regarding the locational attributes. Note that the latter assumption is hardly restrictive when there are few firms per location, so when locations are not too large. This is the case in our application.³ We are not too concerned when the latter assumption does not strictly hold: when firms with different preferences locate at j , the average preference for a location is obtained, and therefore the firm-specific parameters of the profit function are *approximately* identified. When we assume that ε_j^i has an Extreme Value Type I distribution, it can be shown that:

$$(2) \quad \Pi_j^i = \frac{e^{\alpha_0^i + x_j' \alpha^i + \beta^i \rho_j + \gamma^i \sigma_j}}{\sum_{\tilde{j}}^J e^{\alpha_0^i + x_{\tilde{j}}' \alpha^i + \beta^i \rho_{\tilde{j}} + \gamma^i \sigma_{\tilde{j}}}},$$

where Π_j^i denotes the probability that firm i chooses location j , and \tilde{j} are all locations including j . So, (2) implies a firm-specific conditional Logit model.

3. Estimation procedure

3.1 Equivalence relation

Given (2), firm sorting models can in principle be estimated using a CLM. However, in practice there are some serious difficulties when employing this estimation procedure. The main disadvantage is the very

³ To be more specific, in our data, 68 percent of business services firms reside in locations where no other business services firms are located. 16 percent are located in areas where only one other business services firm is located and only 16 percent reside at locations where two or more other business services firms are located.

computational intensive procedures to arrive at results. Firms have many locations to choose from and therefore the choice set grows almost infinitively large when locations are defined more narrowly.⁴ Guimarães et al. (2003; 2004) and Schmidheiny and Brülhart (2011) address this issue by noting that estimation of a CLM and a Poisson model is equivalent given homogeneity assumptions (of firms in our case).⁵ To estimate Poisson models is computationally less intensive and therefore often the preferred method (see for applications, Gabe and Bell, 2004; Holl, 2004; Woodward et al., 2006; Arzaghi and Henderson, 2008). At first sight, it may seem that the homogeneity assumption allow for aggregating of individual firm data but does not allow for a study of heterogeneity in firms' preferences (Defever, 2006). However, we will show that one may still study heterogeneity in firms' preferences using a locally weighted Poisson-approach. In essence, we apply an insight of the hedonic house price literature, where individual household characteristics are not needed in order to derive the household-specific willingness to pay for housing attributes (see Ekeland et al., 2004; Bajari and Benkard, 2005; Bajari and Kahn, 2005).⁶

In the current paper, we estimate a locally weighted Poisson model. 'Local' implies that for each location a weighted Poisson model is estimated. In the empirical literature, several ways to determine the local weights are employed. We employ a k -nearest neighbour approach. This approach estimates for each location j a Poisson regression where the weight equals one when location \tilde{j} is part of the subset of k nearest neighbours and zero otherwise (Fotheringham et al., 2002). The choice of k , also known as the window size, is equal for

⁴ One solution is to focus on large aggregated regions, but then local factors that determine locational choice are not identified. McFadden (1978) argues that the CLM could still be applied given a large number of regions, by randomly selecting a choice subset (e.g. locations) which is obtained from the full choice set. This idea is much applied in locational choice models, including recent studies about sorting of households (see, among others, Bayer et al. 2007, Ioannides and Zabel, 2008). Still, to estimate the conditional Logit model is quite computationally intensive, even if a number of restrictive assumptions concerning the profit/utility function are made.

⁵ Schmidheiny and Brülhart (2011) show that, although coefficients are the same, predictions of the CLM and the Poisson model may differ substantially if the number of locations is limited, as elasticities are then different for both models. In the current study, the number of locations is quite substantial, so this issue does not apply here.

⁶ Firm characteristics are not needed to estimate our sorting model, which is a large advantage of our approach. Nevertheless, when this data is available, firm characteristics may provide some explanation for the estimated differences in preferences. Similar to Bajari and Kahn (2005), characteristics of the firm may be regressed on firm-specific profit parameters in a second stage. In the current application we lack detailed data on firm characteristics.

all locations.⁷ We now show that locally weighted Poisson and the locally weighted CLM are equivalent, but only when weights are either zero or a constant (normalised to one), consistent with the k -nearest neighbour approach. Assume that we have the same profit function as in (1):

$$(3) \quad \max \pi_j^i = \alpha_0^i + \mathbf{V}_j^i + \varepsilon_j^i,$$

where $\mathbf{V}_j^i = \mathbf{X}'_j \boldsymbol{\alpha}^i + \beta^i \rho_j + \gamma^i \sigma_j$. Recall that we assumed that all firms at location j have the same \mathbf{V}_j^i , so the local likelihood for each firm i at j may be defined as (see Fan et al., 1995):

$$(4) \quad \log L^{i, \text{logit}} = \log L_j^{\text{logit}} = \sum_{j=1}^J w_{jj} n_j \log \frac{e^{\alpha_{0j} + \mathbf{V}_j^i}}{\sum_{j=1}^J e^{\alpha_{0j} + \mathbf{V}_j^i}} = \sum_{j=1}^J w_{jj} n_j \log \frac{e^{\mathbf{V}_j^i}}{\sum_{j=1}^J e^{\mathbf{V}_j^i}},$$

where w_{jj} denotes a local weight and n_j denotes the number of firms at a certain location j . In the local regression of j , α_{0j} is a constant. Now assume that $w_{jj} = \{0,1\}$, which encompasses a nearest neighbour approach; $w_{jj} = 1$ for the k nearest locations, where $k < J$ and zero otherwise. Then the likelihood becomes:

$$(5) \quad \log L_j^{\text{logit}} = \sum_{j=1}^k n_j \log \frac{e^{\mathbf{V}_j^i}}{\sum_{j=1}^k e^{\mathbf{V}_j^i}}.$$

Maximisation of (5) with respect to \mathbf{V}_j shows that for $j > k$ the first-order condition $\partial \log L_j^{\text{logit}} / \partial \mathbf{V}_j = 0$ is never fulfilled (as \mathbf{V}_j , $j > k$ appears in the denominator of (5)). So for $j > k$, $\mathbf{V}_j \rightarrow -\infty$, and therefore $e^{\mathbf{V}_j} = 0$. Hence, we may write (5) as:

$$(6) \quad \log L_j^{\text{logit}} = \sum_{j=1}^k n_j \log \frac{e^{\mathbf{V}_j^i}}{\sum_{j=1}^k e^{\mathbf{V}_j^i}}.$$

An alternative approach to arrive at the same result is to assume that the number of firms n_j is independently Poisson distributed, so:

$$(7) \quad E(n_j) = \chi_j = e^{\alpha_{0j} + \mathbf{V}_j^i}.$$

⁷ In principle, one may allow for window sizes that vary between locations (for example, using a fixed distance). However, this will lead to excessive smoothing in areas where there are many observations and to a high variance in areas with sparse data (see Stute, 1984; Cho et al., 2009). McMillen and Redfearn (2010) therefore argue that a k -nearest neighbour approach is preferred. Another issue is that the weighting scheme may seem restrictive, as we have to use discrete weights instead of weights that are continuous over space. However, it is often argued that this will not influence the results that much (e.g. McMillen, 2010). The choice of window size k is much more important. It is also noted that given a large number of locations, our estimation procedure will lead then to approximately continuous preferences over space, in line with Section 2, where we assumed that preferences are continuous over space.

The log likelihood function may then be written as:

$$(8) \quad \log L_j^{poisson} = \sum_{j=1}^J w_{jj} (n_j \log \chi_j - \chi_j - \log n_j!).$$

The first-order condition with respect to α_{0j} can be written as $\sum_{j=1}^J w_{jj} (n_j - \chi_j) = 0$. Solving for α_{0j} , we obtain:

$$(9) \quad \alpha_{0j} = \log \left(\sum_{j=1}^J w_{jj} n_j \right) - \log \left(\sum_{j=1}^J w_{jj} e^{\nu_j} \right).$$

The concentrated likelihood function then yields:

$$(10) \quad \log L_j^{poisson} = \sum_{j=1}^J w_{jj} n_j \log \left(\frac{e^{\nu_j}}{\sum_{j=1}^J w_{jj} e^{\nu_j}} \right) + \sum_{j=1}^J w_{jj} n_j \log \left(\sum_{j=1}^J w_{jj} n_j \right) - \sum_{j=1}^J w_{jj} n_j - \sum_{j=1}^J w_{jj} \log n_j!,$$

We now again make the assumption that $w_{jj} = \{0,1\}$. It can be easily seen that this assumption is not only sufficient but also necessary to establish the equivalence relation between locally weighted CLM and locally weighted Poisson.⁸ So:

$$(11) \quad \log L_j^{poisson} = \sum_{j=1}^k n_j \log \left(\frac{e^{\nu_j}}{\sum_{j=1}^k e^{\nu_j}} \right) + C,$$

where $C = \sum_{j=1}^k n_j \log \left(\sum_{j=1}^k n_j \right) - \sum_{j=1}^k n_j - \sum_{j=1}^k \log n_j!$. The first term of (11) is identical to the likelihood of the conditional Logit model (6). As the log likelihood functions for the locally weighted CLM and the locally weighted Poisson model are identical up to a constant, maximum likelihood yields identical parameter estimates, given the assumption that weights are either zero or one. Our approach implies that firms only take a subset of k nearest locations into account. This assumption seems realistic, as business services firm relocations mostly take place within a couple of kilometres from the original location (about 75 percent) (Van Dijk and Pellenbarg, 2000). The process of firm births is also regarded as a local process, because it implies an evolutionary mechanism of knowledge transfer between 'parental' firms and new firms (Boschma and Lambooy, 1999).

⁸ The weight variable w_{jj} appears in the denominator of the first term of (10) but not in the denominator of (4).

3.2 Control Function Approach

It may be argued that the specialisation measure ρ_j is endogenous with respect to location j , as unobserved natural advantages may cause clustering of business services firms. For example, favourable municipality-specific tax regimes may attract business services to certain locations. To correct for endogeneity, we employ a control function approach (see Blundell and Powell, 2003; Yatchew, 2003; Blundell and Powell, 2004).⁹ This approach treats endogeneity as an omitted variable problem, comparable to Heckman's correction for selectivity bias, through the introduction of an appropriately estimated control function (Heckman, 1979). An important restrictive assumption of the control function approach is that the endogenous variables should be continuously distributed, which is fulfilled in our application. The control function approach is preferred to two main alternative approaches to correct for endogeneity such as IV and plugging in fitted values (Blundell and Powell, 2003).

The procedure to apply the control function is to first regress the endogenous independent variables on all exogenous independent variables and instruments (using the nearest neighbour approach outlined in the previous section). In the second stage one regresses the number of firms per location on all independent variables and the predicted first stage errors (again using the nearest neighbour approach). For a more comprehensive description of the estimation procedure, we refer to Appendix B.

4. Data and instruments

4.1 Dataset and regional context

Our dataset contains information about characteristics of *all* establishments in 2005 in the NUTS3-region Zuid-Holland, located in the west of the Netherlands.¹⁰ This region is 2,860 square kilometres and has the highest population density in the Netherlands (about 1,200 people per square kilometre). It includes Rotterdam, the second largest city of the Netherlands, The Hague, where the national government is located, but also cities such as Leiden and Delft. Zuid-Holland covers about 20 percent of national economic activity.

⁹ For recent applications of the control function approach, see Guevara and Ben-Akiva (2006) and Petrin and Train (2010).

¹⁰ In the remainder of this paper, we label establishments as firms.

The data on firm locations comes from administrative sources and is very reliable, as Dutch firms are obliged by law to provide this information. We have information on the firm's exact location on a 6-digit postcode level (PC6) and the number of employees, as well as detailed information on sector. A PC6 area is small (comparable to the size of a census block in the United States). It includes on average 17 workers of which 3 are employed by a business services firm. About 15 percent of the firms are business services firms and about 17 percent of the total workforce is employed in business services firms (see Table 1).

Table 1: Firms and Employment in Zuid-Holland

	Firms		Employment	
	Number	% of Total	Number	% of Total
Total	62,424	100.00	1,477,354	100.00
Rotterdam	11244	18.01	322,688	21.84
The Hague	7583	12.15	232,630	15.75
Leiden	2110	3.38	53,874	3.65
Dordrecht	1934	3.10	53,990	3.65
Delft	1660	2.66	49,422	3.35
Zoetermeer	1658	2.66	48,094	3.26
Business Services	9,172	14.69	249,722	16.90
Rotterdam	1,994	17.73	64,831	20.09
The Hague	1,456	19.20	54,335	23.36
Leiden	294	13.93	5,440	10.10
Dordrecht	280	14.48	6,452	11.95
Delft	342	20.60	10,587	21.42
Zoetermeer	350	21.11	11,306	23.51

NOTE: Firms refer to establishments with at least 3 employees.

One issue to consider here are the large number of small firms. About 50 percent of the observations are firms with one or two employees. Small firms are likely to make other locational choices than larger firms (Duranton and Overman, 2005).¹¹ Furthermore, in administrative sources, small organisations are frequently fiscal entities that do not require the physical presence of employees. We therefore only select business services firms with three or more employees, in total 9,170 observations.¹² Conditional on this selection, the average firm size is 25 employees.

Following Duranton and Overman (2005), we control for zoning (which restricts the choice set of locations) by allowing firms only to choose from locations where at least one firm is located (which does not

¹¹ For example, a small entrepreneur can work from home. Then, the choice where to live and work is a joint-decision.

¹² We use the Standard Industrial Classification (SIC) to select business services from the complete dataset of firms.

have to be a business services firm). We then have 21,465 locations, so the average number of business services firms per location is 0.427. 76 percent of the locations do not host any business services firm, 16 percent only one business services firm and only 7.7 percent two business services or more. The average distance of a business services firm to all other business services firms is 21.22 kilometres

4.2 Defining the explanatory variables

We aim to measure the importance of specialisation and diversity on location choice. We will use measures which are continuous over space, to overcome biases inherent to the use of indices based on discrete spatial units (Duranton and Overman, 2005; Ellison et al., 2010). Our starting point is to measure the weighted average of the number of jobs in sector G located in the neighbourhood of location j using an exponential distance decay function (see Fujita and Ogawa, 1982; Lucas, 2001; Lucas and Rossi-Hansberg, 2002).

Formally:

$$(12) \quad \omega_{Gj} = \delta \sum_{\tilde{j}}^J e^{-\delta d_{j\tilde{j}}} \ell_{G\tilde{j}},$$

where ω_{Gj} denotes the weighted employment of location j of sector G , $\ell_{G\tilde{j}}$ is the number of jobs in sector G in location \tilde{j} and δ denotes a fixed decay parameter. We note that $d_{j\tilde{j}}$ is measured in kilometres. Specialisation is a measure of concentration of an industry in a city. Our specialisation measure is defined as:

$$(13) \quad \rho_{Gj} = \frac{\omega_{Gj}}{\sum_{\tilde{G}} \omega_{\tilde{G}j}},$$

which is the share of weighted employment in sector G over the total weighted employment in location j . In our application, we investigate the tendency of business services to cluster. The business services specialisation measure refers to the local share of business services employment (so in our analysis $\rho_j = \rho_{Gj}$, where $G = \text{business services}$).

To measure between-sector diversity σ_j we use a (continuous) measure, based on the diversity index of Duranton and Puga (2000):

$$(14) \quad \sigma_j = 1 / \sum_{\tilde{G}} \left| \rho_{\tilde{G}j} - \rho_{\tilde{G}} \right|,$$

where $\rho_{\tilde{G}} = \sum_j \ell_{\tilde{G}j} / \sum_j \sum_{\tilde{G}} \ell_{\tilde{G}j}$. This index corrects for differences in sectoral employment shares at the regional level. The coefficient related to the diversity index will, conditional on our specialisation measure, represent the preference of a firm to have a diverse portfolio of firms in the neighbourhood. When it is negative, business services will prefer only one type of firm in the neighbourhood (e.g. only manufacturing or only government). To construct the specialisation and diversity indices, we assume that $\delta = 2.5$, so that on average more than 90 percent of the weight is within 1.5 kilometres of location j .¹³ Figures 1 and 2 present the geographical distribution of these two explanatory variables of main interest. Specialisation and diversity are not measures that are orthogonal to each other (see Figure A1).¹⁴

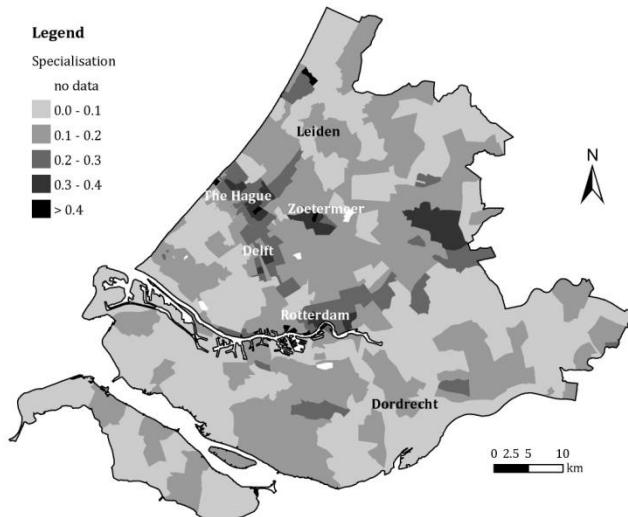


Figure 1: Pattern of specialisation

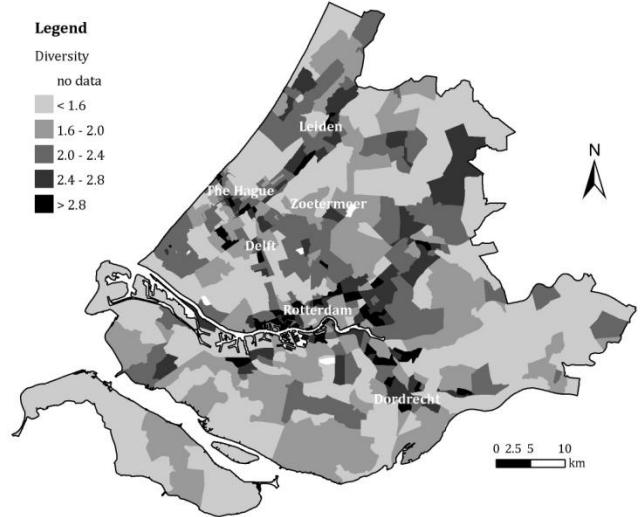


Figure 2: Pattern of diversity

Business services firms are concentrated in the corridor Rotterdam–Delft–The Hague (see Figure 1). In these cities more than 20 percent of the total employment is in the business services sector, which is about 8

¹³ Recent empirical research provides evidence that interactions take place very locally, within 2 kilometres of the location of the firm. See, among others, Rosenthal and Strange (2003; 2008), Arzaghi and Henderson (2008).

¹⁴ In particular, we note that when the specialisation measure ρ_{Gj} approaches one (so $\rho_{\tilde{G}j} = 0$), σ_j approaches $1 / (2 - 2\rho_G)$. So, in this specific case there is a deterministic relation between specialisation and diversity (which is intuitive). However, there are few regions with very high shares of business services, so both variables refer to different concepts and the effect of these variables can be separately identified.

percentage points higher than for regions outside this corridor.¹⁵ Rural areas in the south, the east and the north experience relatively low concentration of business services (see Figure 1). These areas are mostly specialised in rural activities, along with regular retail activities. The pattern of diversity is somewhat similar to the specialisation pattern, although there are some differences (see Figure 2). Generally, urban areas are more diversified than rural areas.¹⁶

In the analysis, we control for other locational attributes. In particular, we control for employment density, so we include the number of employees in the neighbourhood of the firm (which is endogenous), using the distance decay function in (12). This variable may be interpreted as a density variable that captures the combined positive Marshallian externalities and negative effects of higher rents in high density areas, congestion and other crowding effects (Bartik, 1985; Guimarães et al., 2000; Barrios et al., 2006).¹⁷ We also control for the distance to the nearest highway ramp, station, hectare of water and open space. To include the latter is relevant because of zoning regulations, so firms are not allowed to locate everywhere (for example, close to residential areas, or protected agricultural areas). We correct for the size of the postcode area, because larger regions are likely to host more firms.¹⁸ The descriptives of those explanatory variables are presented in Appendix A. To control for unobserved heterogeneity at a local level, we also include a polynomial function of geographic coordinates. This is a flexible way to control for unobserved spatial factors, and in line with the assumptions that, in equilibrium, preferences are continuous.¹⁹

¹⁵ Rotterdam hosts a large cluster of maritime business services which provide services to port-related manufacturing firms, such as the petrochemical industry. The concentration of business services near Delft may be explained by the presence of a technical university, as Research and Development firms may find it attractive to locate near a university (Jaffe, 1989; Woodward et al., 2006).

¹⁶ Rotterdam, the largest city in the region, has a diversified portfolio of employment, maybe because of the mix of port-related industries, urban amenities and business services. The Hague is only partly diversified, because some areas are specialised in public services. Cities such as Dordrecht and Gouda are generally also quite diversified.

¹⁷ Multicollinearity is not to be a problem here: the correlation between specialisation and diversity is only 0.18 and between specialisation and employment density it is 0.56. The correlation between diversity and employment density is also quite low and equal to 0.23.

¹⁸ Area size is potentially endogenous, as areas that attract many firms may be expanded. However, excluding this variable will lead to very similar results. The area size may differ substantially between urban and rural areas. As an illustration: areas that do not host any business services firms are on average 9.34 hectare, whereas areas that host business services firms are on average 4.25 hectare (about 200 by 200 meters).

¹⁹ It is noted that one may only include variables that have sufficient *local* variation to avoid local perfect multicollinearity (Wheeler and Tiefelsdorf 2005; Wheeler and Calder 2007; McMillen and Redfearn, 2010). We

4.3 Instruments

Our business services specialisation measure and the control variable employment density are potentially endogenous. We have to seek instruments that are correlated with the pattern of clustering of (business services) firms, but uncorrelated with unobserved attributes that affect directly the location choice (and profits) of business services firms.²⁰ First, we use population density of municipalities *in 1830*.²¹ The instrument's validity rests on the assumption that population density in 1830 is unrelated to current firms' location decisions (and therefore firms' profit), but has a causal effect on the current agglomeration *pattern* (see also Ciccone and Hall, 1996; Rice et al., 2006; Combes et al., 2008). This instrument is strong as population density is strongly autocorrelated and (current) population and employment densities are positively correlated (McMillen and McDonald, 1998).²² We also include an instrument that captures the distance to the nearest station in 1850 (while controlling for the current distance to the nearest station). Railway stations were an important factor enforcing agglomeration of firms and people around that time (Ciccone and Hall, 1996). As a third instrument we include a dummy indicating whether the location was bombed in 1940. In the beginning of the Second World War, the complete city centre of Rotterdam was destroyed. Afterwards, the city centre was completely redeveloped into the most dense city centre in the Netherlands, hosting many business services. As a fourth instrument we measure whether a location was below water in 1830, so whether the land has been reclaimed. For these areas, employment density was

therefore include a second-order polynomial of the geographic coordinates. In principle, it is also possible to use higher-order polynomial, but this leads to severe local multicollinearity.

²⁰ Bayer and Timmins (2007) argue that instruments for agglomeration measures arise naturally out of the sorting model. Therefore, there is no need for external instruments. However, the validity of such internal instruments depends on the variation in preferences for specialisation and diversity. If there is not enough variation, the estimates are not robust to misspecifications of the profit function. We will compare the internal instrument approach with our approach in the sensitivity analysis.

²¹ Municipalities in 1830 were much smaller and do not overlap with the current ones. Zuid-Holland, the region which our data refer to, consisted in 1830 of 267 municipalities, whereas nowadays it consists of only 77 municipalities.

²² One may argue that unobserved natural advantages, which may attract people and firms, may be correlated over time. For example, natural resources may be at certain locations for centuries. Natural resources may be an important input in production for manufacturing firms, but this is certainly not the case for business services. We therefore are not too concerned that unobserved natural advantages of the present time are correlated with natural advantages in 1830.

strictly zero in 1830. So, due to autocorrelation in employment density, we may expect that specialisation and employment density are lower in these areas.

We use four instruments, which exceeds the number of endogenous variables. This is useful although the third and fourth instruments only have local impact. For example, the instrument whether an area was bombed only applies for locations near Rotterdam. Still, as these two instruments locally have a very strong impact, they contribute to the identification of the effects of specialisation and employment density.

5. Results

We present the main results employing parametric and semiparametric approaches to estimate the sorting model in Table 2, where we focus on the latter results. The parametric approach implies that preferences are homogeneous. First, we do not allow for endogeneity, so we estimate an ordinary Poisson model. We also estimate parametric models employing the control function approach. The four instruments have sufficient predictive power: the F-values for both specialisation and employment density exceed 1,300, so our instruments appear to be very strong (and also have the expected signs). For more results of the first stage, we refer to Appendix B.

For the semiparametric approach, we relax the assumption on homogeneity (as explained in Section 3). In line with the literature, we set the window size to 10 percent of the total locations, so $k = 2,147$, to get reliable estimates of the marginal effects.²³ The average effects over all 9,170 firms of a standard deviation increase for specialisation and diversity are presented, as well as the standard deviations of these effects.²⁴ We provide the results of specifications where we do not correct for endogeneity and we provide results of specifications where we use the control function approach to correct for endogeneity.

²³ The average distance of a business services firm to all other business services firms within the window is 5.07 kilometres. The average maximum distance is 9.04 kilometres. Pagan and Ullah (1999) argue that the window size should not be too small when the goal is to estimate marginal effects, although this may lead to an underestimate of the heterogeneity of preferences. In the sensitivity analysis, we will show that lower window sizes lead to unreliable estimates (see also Redfearn, 2009).

²⁴ One may also be interested in the average effects over all 21,465 locations instead of 9,170 firms. It appears that these are very similar to the effects presented here.

Table 2: Results for the presence of business services firms

	Parametric Regression				Semiparametric Regression					
	Poisson		Poisson with Control Function		Weighted Poisson		Weighted Poisson with Control Function			
	Coeff.	Standard Error	Coeff.	Standard Error	Mean Coeff.	Std. Dev.	Mean Coeff.	Std. Dev.		
Specialisation	0.341	(0.010)	***	0.501	(0.115)	***	0.546	0.185	0.394	0.432
Diversity	-0.078	(0.013)	***	-0.101	(0.022)	***	-0.147	0.126	-0.164	0.139
Employment Density (log)	0.522	(0.015)	***	-0.047	(0.133)		0.814	0.288	0.411	0.624
Distance to Highway Ramp	-0.056	(0.008)	***	-0.022	(0.012)	*	0.105	0.342	-0.055	0.327
Distance to Station	0.081	(0.007)	***	-0.012	(0.014)		0.129	0.231	-0.019	0.344
Distance to Water	-0.185	(0.034)	***	-0.437	(0.095)	***	-0.282	0.383	-0.170	0.319
Distance to Open Space	0.108	(0.035)	***	0.522	(0.286)	*	-0.036	0.429	0.617	1.060
Area Size (log)	0.198	(0.007)	***	0.051	(0.024)	**	0.186	0.048	0.146	0.089
Control Function Specialisation				-0.108	(0.117)				0.205	0.465
Control Function Employment Density				0.738	(0.139)	***			0.611	0.826
Geographic Coordinates Included (5)	Yes			Yes			Yes		Yes	
Pseudo R-squared	0.1285									
Number of Locations	21,465			21,465			21,465		21,465	
Number of Firms	9,170			9,170			9,170		9,170	

NOTE: The dependent variable is the number of firms in each postcode 6-digit area. The standard errors are between parentheses for the parametric specifications. In the parametric specification with the control function we present bootstrapped standard errors.

5.1 Preferences for specialisation and diversity

Specialisation is positively related with location decisions of business services firms, in accordance with Head et al. (1995), Guimarães et al. (2000), Figueiredo et al. (2002), Rosenthal and Strange (2003) and Barrios et al. (2006). Between-sector diversity, however, has a much smaller effect and is negatively related to profits of business services. So, business services firms have a preference to locate close to one type of firm (e.g. government). Controlling for endogeneity leads to a *higher* coefficient for specialisation (but to a substantially *lower* effect for the control variable employment density). In the semiparametric approach, we see that specialisation has on average a significantly lower coefficient and a higher standard deviation when we employ a control function approach. Again, the average effect of diversity is hardly influenced by the inclusion of the control function.

Conditional on employment density, one standard deviation in specialisation in business services sector increases the probability that a firm locates there with on average 38 percent. Previous studies that focus on manufacturing firms sometimes find small or no effects of specialisation (see Guimarães et al., 2004; Woodward et al., 2006). It may be expected that *manufacturing* firms do not rely on other manufacturing

firms nearby, but more on specialised business services in vicinity, as they offer access to local market information, technology and skills (Helmsing, 2001). In our study, however, access to specialist services is fully captured by our specialisation measure, which indeed is positively valued by business services firms. Our results suggest that knowledge probably mainly flows between firms within the same sector (MAR-externalities). Other externalities such as labour market pooling and input sharing may also be important reasons why business services have a strong preference to locate near other business services.

Between-sector diversity is negatively related to location decisions, but its effect is smaller. One standard deviation increase in diversity decreases the probability that a firm chooses that location with on average about 16 percent.²⁵ This implies that, *ceteris paribus*, business services firms have a preference to locate near a group of firms that belong to the same sector, which makes sense. For example, one expects lobbying firms to locate close to governments, maritime service firms close to port-related manufacturing etc.

The control variables have in general plausible signs. Firms prefer to locate in dense employment areas in terms of employment because of proximity to customers and suppliers. Locations near highway ramps are generally favoured, but the effect of railway stations is somewhat unclear. Locations near open water attract business services (consistent with the observation that the Maas river waterfront in Rotterdam is dominated by office locations). The coefficient of open space is positive, indicating that locations near open space are less likely to attract firms, probably due to zoning restrictions. Larger areas are hosting more business services, *ceteris paribus*: 10 percent increase in area size increases the probability with 1.3 percent that a firm locates there.

²⁵ We also regressed the number of establishments on the shares of manufacturing firms, wholesale and retail, public services and other firms, conditional on employment density. It confirms that business services have a much higher preference for within-sector clustering than between-sector clustering, confirmed by the negative coefficient of the diversity index. However, since we are not able to correct for endogeneity (we lack a sufficient number of valid instruments) these results are suggestive, at best.

5.2 Heterogeneity

An important motivation of the current study is to pay attention to heterogeneity in preferences for specialisation and diversity. Figures 3 and 4 present the preference for a standard deviation increase in respectively specialisation and diversity.

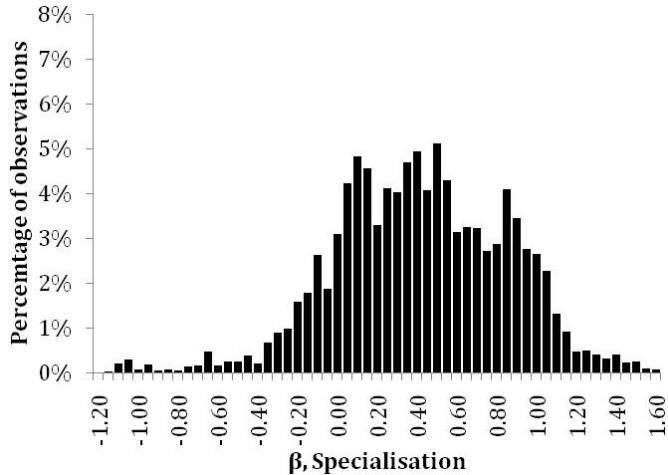


Figure 3: Distribution of preferences for specialisation

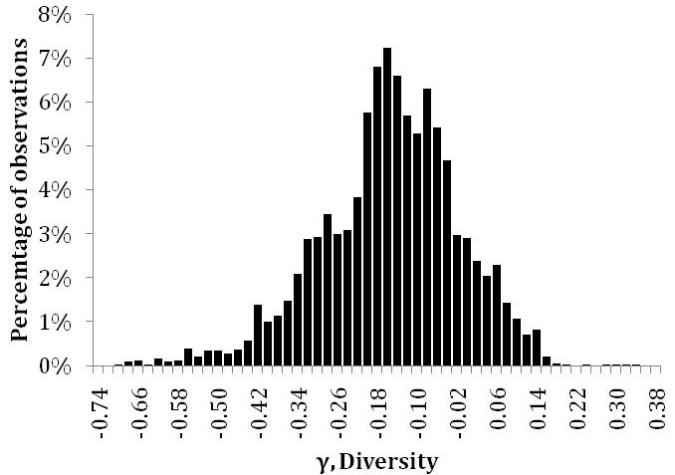


Figure 4: Distribution of preferences for diversity

There is substantial heterogeneity in preference for specialisation, 90 percent of the preference parameters is between -0.40 and 1.00 and about 16 percent of the firms value specialisation negatively.²⁶ So, most business services prefer to locate near other business services.²⁷ We also observe heterogeneity in the preference for diversity, although the spread is somewhat lower than for specialisation. 90 percent of the preferences parameters are between -0.32 and 0.14, 85 percent of the firms value diversity negatively.

It may also be worthwhile to look at the relation between preferences for specialisation and diversity. It appears that there is a negative correlation of -0.49 between the preferences for specialisation and diversity (see Figure 5). Our results imply that business services firms either rely on within-sector interactions or between-sector interactions: relatively few firms have a negative preference for both specialisation and

²⁶ In the literature there is no consensus whether specialisation or diversity are important in firms' location decisions (see Duranton and Puga, 2000). One explanation is that previous studies do not take into account that firms' preferences for specialisation and diversity are rather heterogeneous. As our results suggest that a substantial share of the firms value specialisation negatively, this may be important.

²⁷ We indeed see such local clustering: for example in the city centres of Rotterdam and The Hague, but also specialised clusters of only one type of business services have emerged. For example, maritime business services (lawyers, insurance companies) cluster in the Scheepvaartkwartier near the Maas river in Rotterdam (see Jacobs et al., 2010). These are often small firms that provide complementary knowledge-intensive services to firms located in the port.

diversity (about 11 percent) and even fewer firms have a positive preference for both specialisation and diversity (about 6 percent).

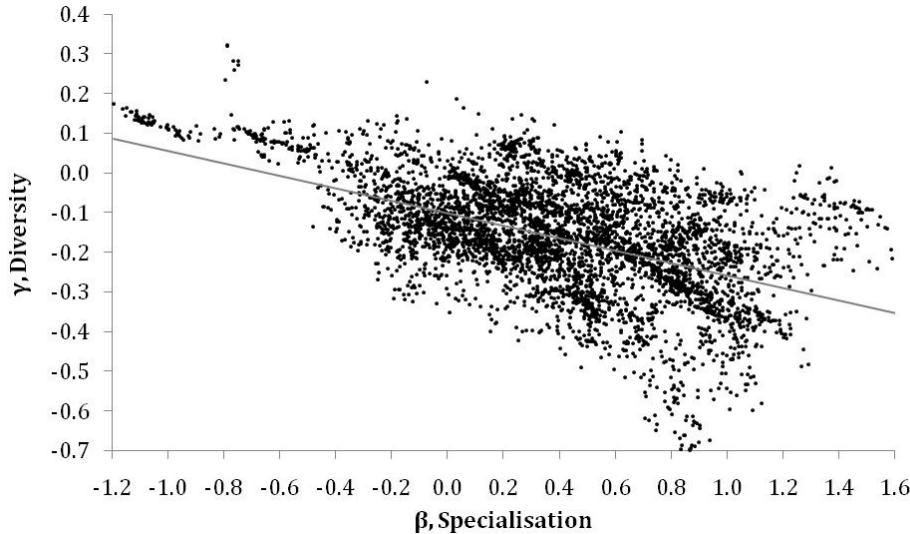


Figure 5: Relationship between preferences for specialisation and diversity

5.3 Internal and external instruments

In the preceding sections we have used instruments that are external to the model. Timmins (2005) and Bayer and Timmins (2007) show that one may also use internal instruments, which naturally arise out of the sorting model. Timmins (2005) and Bayer and Timmins (2007) argue that firm's demand for a certain location j is not only dependent on its own attributes, but also on how it fits in the broader landscape. Therefore, exogenous attributes of other locations may act as proper instrument, as these variables influence the locational equilibrium but do not have a direct impact on profits. Because the number of exogenous attributes of other locations is large, Bayer and Timmins (2007) create a single instrument, which is equal to the predicted employment share of each location when coefficients related to the endogenous variables are set to zero.

Following this idea, we regress employment and business services employment (for locations where employment is located) on the average values of exogenous attributes between 2.5 and 3.5 kilometres of

location j , using a Poisson model.²⁸ Using the estimated coefficients, we estimate the predicted number of employees and employees in the business services sector for each location j and estimate the business services specialisation measure $\hat{\rho}_j$ and the employment density $\sum_G \hat{\omega}_{Gj}$, which are used as instruments. This approach relies on cross-sectoral variation in preferences for locational attributes to ensure variation in the instruments, as emphasised by Bayer and Timmins (2007). Without any effective variation in geographic preferences, the parameter estimates are not robust to misspecification of the profit function or the distributional assumptions of the error term. In our application, distributions of the coefficients to be estimated are nonparametric, so variation in preferences is explicitly allowed for (and ensured as seen in Section 5.2).

Using the internal instruments, we find that the average effect of specialisation is 0.470 with a standard deviation of 0.474 and the average effect of diversity is -0.196 with a standard deviation of 0.192. Although the effect of specialisation is slightly higher (closer to the estimates without instruments), both the internal and external instruments approaches lead to the same conclusion. Figures 6 and 7 present correlations between the preferences for both approaches. We observe reasonably high correlations between preferences for specialisation (0.65) and between preferences for diversity (0.64).

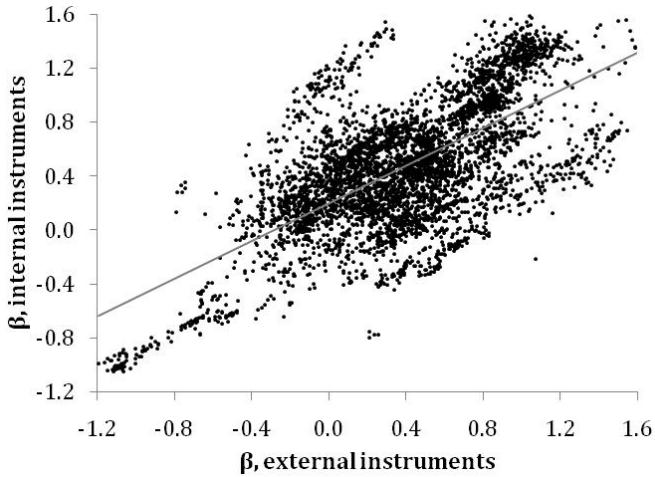


Figure 6: Correlation preferences for specialisation with internal vs. external instruments

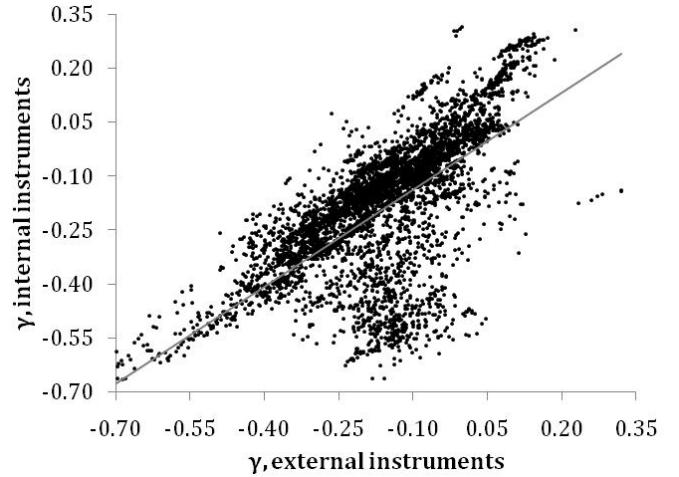


Figure 7: Correlation preferences for diversity with internal vs. external instruments

²⁸ So, the direct effect of employment that is located farther than 2.5 kilometres of the location is assumed to have a negligible effect on location choices. This is a reasonable assumption. For example, for $\delta = 2.5$, on average about 99 percent of the weight is within 2.5 kilometres of location j .

5.4 Other robustness checks

We also will demonstrate that our results are robust to changes in specifications and estimation procedures.

Table 3 summarises the results.

Table 3: Robustness checks for impact of specialisation and diversity on presence of business services firms

	GLM-IV		Distance Decay, $\delta=1$		Distance Decay, $\delta=5$		No Area Size		No Diversity		
	Coeff.	Standard Error	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
			Coeff.	Dev.	Coeff.	Dev.	Coeff.	Dev.	Coeff.	Dev.	
Specialisation	0.460	(0.103)	***	0.479	0.746	0.478	0.477	0.396	0.443	0.355	0.463
Diversity	-0.222	(0.023)	***	-0.392	0.467	-0.027	0.132	-0.240	0.164		
Number of Firms		9,170		9,170		9,170		9,170		9,170	

NOTE: See Table 2.

First, we compare our parametric control function approach with a two-step instrumental variables Poisson model using the generalised linear model approach as proposed by Hardin et al. (2003) and Carroll et al. (1995). We see that the estimated coefficients are very comparable to those presented in Table 2, although the effect of diversity is somewhat more negative. Second, in this study we assumed that the distance decay parameter δ is equal to 2.5, so that most of the weight of the employment density measure is within 1.5 kilometres. We check whether the choice of δ influences our results. It appears that specialisation has a somewhat larger impact for both higher and lower values of δ , so our estimate may be somewhat conservative. For $\delta = 1$, the effect of diversity becomes almost twice as large, suggesting that the negative effect of diversity is stronger over longer distances. When we set $\delta = 5$, so that most of the weight of the employment is within a few hundred meters, the negative effect of diversity almost disappears. This suggests that potential benefits of diversity are primarily local.

Third, we check whether the results are influenced by excluding the potentially endogenous variable area size. We see that the effects are very similar. Excluding the diversity measure leads to almost the same result for specialisation. We also verify whether our results are robust to the number of locations considered in the choice set of firms, so to the choice of window size. Figures 8 and 9 display the results.

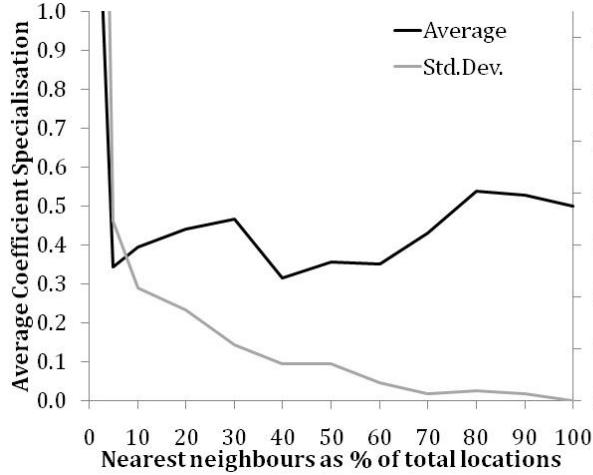


Figure 8: Average effect of specialisation the window size

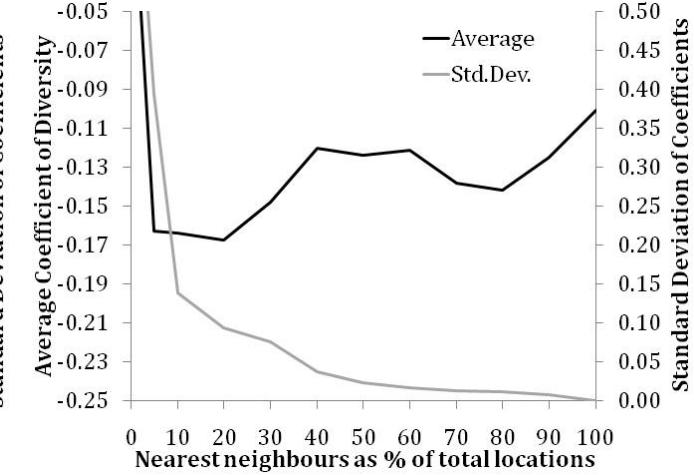


Figure 9: Average effect of diversity given the window size

Except when the number of locations in the choice set is very small, the average effects of specialisation and diversity are respectively between 32 and 54 percent and -10 percent and -17 percent. For a larger window size k , the effect of diversity is closer to zero. When the number of nearest neighbours k becomes too small, we cannot provide a reliable estimate of the effects of specialisation and diversity on firms' location decisions, because the standard deviations of the specialisation and diversity coefficients are too large. More specifically, Figures 8 and 9 reveal that for window sizes smaller than 2,147 observations (or 10 percent of the total number of locations), the standard deviation becomes unrealistically large.²⁹

6. Conclusions

In this paper we propose a new way to estimate a heterogeneous sorting model for firms. Allowing for heterogeneity implies that one has to estimate a semiparametric conditional Logit model, which is cumbersome to estimate. We introduce a tractable estimation procedure. More specifically, we show that there is an equivalence relation between a locally weighted CLM and a locally weighted Poisson model, given a k -nearest neighbour approach. We estimate such a geographically weighted Poisson model to investigate

²⁹ When k is equal to the total number of locations, the estimated average effect is equal to the estimates of the parametric specification with the control function. The standard deviation is then, obviously, equal to zero.

the impact of specialisation and diversity on location decisions of business services firms in Zuid-Holland, a region in the west of the Netherlands. We correct for endogeneity by means of a control function, so we are able to make a distinction between local interactions and unobserved natural advantages.

The results show that firms have a relatively strong preference for specialised clusters of business services. A standard deviation increase in specialisation will, on average, lead to a 39 percent increase in the probability that a firm chooses that location. Between-sector diversity is generally negatively related to firm location decisions, so business services firms prefer to locate close to one type of sector (e.g. government), but the effect is smaller. Different specifications and estimation procedures show that these findings are robust. We also show that there is considerable heterogeneity in preferences for specialisation and diversity: 84 percent of firms prefer locations with high levels of specialisation, whereas only 11 percent prefer diversified areas. It appears that there is a significant negative correlation between preferences for specialisation and diversity, so business services firms rely either on within-sector interactions or on between-sector interactions. Our results provide strong support for theories of Marshall, Arrow and Romer: local interactions mainly take place between firms of the same sector. Interactions between firms belonging to different sectors – Jacobs type externalities – are important for only a limited number of firms in the business services sector.

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Appendix A. Descriptive Statistics

Table A1: Descriptives

	Mean	Std.Dev.	Min	Max
<i>Dependent variables</i>				
Number of Firms	0.427	1.239	0.000	40
Number of Employees	11.204	81.766	0.000	4,194
<i>Independent variables</i>				
Specialisation (of business services)	0.153	0.091	0.000	0.785
Diversity	1.972	0.706	0.522	7.266
Employment Density	6,373.672	8,226.440	9.264	64,382.340
Distance to Ramp (in km)	2.951	2.240	0.027	15.686
Distance to Station (in km)	3.225	3.562	0.009	29.065
Distance to Water (in km)	0.352	0.276	0.000	2.409
Distance to Open Space (in km)	0.197	0.188	0.000	1.792
Area Size in ha	8.131	61.666	0.001	2175.337
<i>Instruments</i>				
Population Density per km ² 1830	965.680	2,567.992	7.337	19,934.830
Location Bombed in 1940	0.030	0.169	0.000	1.000
Distance to Station 1850 (in km)	8.737	7.770	0.015	42.274
Location Below Water 1830	0.016	0.126	0.000	1.000
Number of Locations	21,466			

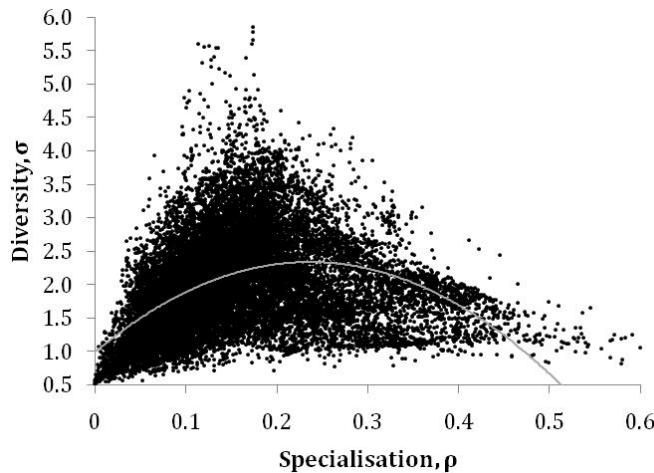


Figure A1: Relation between the specialisation measure and the diversity index

Appendix B. Estimation Procedure

In this appendix we outline our estimation procedure in more detail. We also present some first-stage results. The estimation procedure consists of the following steps. First, select appropriate instruments, external to the model, or internal to the model as proposed by Bayer and Timmins (2007). We use as external instruments the log population density 1830, area bombed in 1940, distance to stations in 1850 and whether locations were below water in 1830. Then, we regress (standardised) specialisation and log employment densities on exogenous attributes of location and instruments, using the k -nearest neighbour approach. We set the window size to 10 percent. In Table B1 we present the first stage results for the parametric and semiparametric specification. We see that we have very strong instruments: the F-values exceed 1,300. The instruments also have the expected signs. The effect of bombing is substantially larger in the parametric model, because in the semiparametric regression, many locations are not close to Rotterdam, and therefore the coefficient is equal to zero. The average coefficient is therefore also lower.

Table B1: First-Stage Results

	Parametric Regression				Semiparametric Regression					
	Specialisation		Employment Density (log)		Specialisation		Employment Density (log)			
	Coeff.	Standard Error	Coeff.	Standard Error	Mean Coeff.	Std. Dev.	Mean Coeff.	Std. Dev.		
Population Density 1830 (log)	0.176	(0.004)	***	0.213	(0.004)	***	0.073	0.092	0.074	0.06
Distance to Station 1850	0.000	(0.002)		-0.025	(0.001)	***	-0.105	0.447	-0.184	0.297
Location Bombed in 1940	1.555	(0.039)	***	0.572	(0.034)	***	0.217	0.374	0.098	0.176
Location Below Water 1830	-0.110	(0.046)	**	-0.123	(0.041)	***	-0.081	0.235	-0.117	0.268
Other variables included (11)	Yes			Yes			Yes		Yes	
R-squared	0.358			0.645						
F-Test for instruments	1,347			1,387						
Number of Locations	21,465			21,465			21,465		21,465	
Number of Firms	9,170			9,170			9,170		9,170	

NOTE: See Table 2.

Third, using the first stage estimates, we calculate for each location the residual of the regression of specialisation and employment density. We then include the residuals as control functions in the geographically weighted Poisson regression of number of business services firms per location on locational attributes, specialisation, diversity and employment density (see Petrin and Train, 2010). Using this approach, we correct for the endogeneity of specialisation and employment density.