

Koster, Hans

## Conference Paper

# Rocketing rents: the magnitude and attenuation of agglomeration economies in the commercial property market

52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia

### Provided in Cooperation with:

European Regional Science Association (ERSA)

*Suggested Citation:* Koster, Hans (2012) : Rocketing rents: the magnitude and attenuation of agglomeration economies in the commercial property market, 52nd Congress of the European Regional Science Association: "Regions in Motion - Breaking the Path", 21-25 August 2012, Bratislava, Slovakia, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/120712>

#### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

#### Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# Rocketing rents

## The magnitude and attenuation of agglomeration economies in the commercial property market

By HANS R.A. KOSTER\*

*This version: 3 August 2012*

**SUMMARY** – Rocketing rents in urban areas are likely explained by agglomeration economies. This paper measures the impact of these external economies on commercial property values using unique micro-data on commercial rents and employment. A measure of agglomeration is employed that is continuous over space, avoiding the modifiable areal unit problem. To distinguish agglomeration economies from unobserved endowments and shocks, I use temporal variation in densities and instrumental variables. The spatial extent of agglomeration economies is determined by estimating a spatial decay parameter within the model. The results show that agglomeration economies have a considerable impact on rents: a standard deviation increase in employment density leads to an increase in rents of about 10 percent. The geographical extent of these benefits is about 15 kilometres. The bias of ignoring and time-invariant unobserved endowments and unobserved shocks seems to be limited.

*JEL-code* – R30, R33

*Keywords* – commercial buildings; hedonic pricing; agglomeration economies; spatial decay; kernel densities

### I. Introduction

The average rent for a unit of office space in New York City is about four times the average rent for a unit of office space in Wichita, Kansas. Also in other high-density cities, such as London, Frankfurt, Milan and Amsterdam, office rents are rocketing. High rents in dense areas are, among other things, caused by agglomeration economies: firms in dense cities

---

\* Department of Spatial Economics, VU University, De Boelelaan 1105 1081 HV Amsterdam, e-mail: h.koster@vu.nl. This paper is written while the author was visiting the Spatial Economics Research Centre, London School of Economics. The author cooperated with The Netherland Environmental Assessment Agency (PBL) on the project '*agglomerations and clusters as determinants of competitiveness of Dutch cities*'. I thank Strabo, NVM, the Basisadministratie Adresgegevens en Gebouwen, and Statistics Netherlands for providing data. This work has benefited from a NICIS-KEI research grant. Giulia Faggio, David Genesove, Wouter Jacobs, Henry Overman, Jos van Ommeren, Piet Rietveld and Anet Weterings are thanked for providing helpful comments, as well as participants of seminars at the VU University Amsterdam and the Hebrew University Jerusalem.

seem to be much more productive than in the sparsely populated countryside and are therefore willing to pay higher rents (Glaeser and Gottlieb, 2009; Puga, 2010). Firms aim to locate in dense urban areas because negative effects of clustering, such as traffic congestion, high wages and increased criminality, are more than offset by these positive external economies (Glaeser et al., 2001). Sources of agglomeration economies are proximity to suppliers, access to a thick and well-educated labour market and knowledge spillovers between workers of different firms (Marshall, 1890; Jacobs, 1969; Glaeser et al., 1992; Duranton and Puga, 2002; Ellison et al., 2010). So, high rents in contemporary business centres are potentially explained by the many opportunities to interact with other firms: deal-making, relationship adjustment and exchange of tacit knowledge are almost impossible without face-to-face contacts (Storper and Venables, 2004; Amiti and Cameron, 2007). For example, headquarters of manufacturing firms may aim to locate in city centres, because it reduces the costs of interacting with consultants, accountants and lawyers (Davis and Henderson, 2008).

Economists and geographers alike are interested in the magnitude of agglomeration economies for several decades but the empirical literature faces a range of challenges in correctly measuring agglomeration economies (see Puga, 2010; Combes et al., 2011).<sup>1</sup> First, identification of agglomeration economies remains a delicate issue, because employment density is likely correlated to unobserved endowments (Ellison and Glaeser, 1997; 1999; Anas et al., 1999; Bayer and Timmins, 2007; Combes et al., 2011; Ahlfeldt et al., 2012).<sup>2</sup> Many studies therefore use long-lagged instruments or use some imperfect proxy of natural advantages, as to control for these unobserved factors (see e.g. Ciccone and Hall, 1996; Melo et al., 2008; Ellison et al., 2011). The validity of the long-lagged instruments, however, may be questioned.<sup>3</sup> Second, the measurement of agglomeration economies is often quite crude. Agglomeration economies are often measured as the density of employment at a city,

---

<sup>1</sup> Many studies confirm the positive relationship of agglomeration economies using data on firm productivity (e.g. Ciccone and Hall, 1996; Ciccone, 2002; Greenstone et al., 2010; Morikawa, 2011), location choices of start-ups (e.g. Woodward, 1992; Figueiredo et al., 2002; Rosenthal and Strange, 2003; Woodward et al., 2006; Arzaghi and Henderson, 2008), wages (e.g. Glaeser and Maré, 2001; Duranton and Monastiriotis, 2002; Amiti and Cameron, 2007; Combes et al., 2008; 2010), and rents (e.g. Eberts and McMillen, 1999; Drennan and Kelly, 2011; Koster et al., 2012).

<sup>2</sup> For example, Ellison and Glaeser (1999) conjecture that at least half of the observed concentration of firms is due to natural advantages.

<sup>3</sup> It has frequently been argued that long-lagged unobserved endowments are uncorrelated to current endowments, whereas the past agglomeration pattern is strongly correlated to the current agglomeration pattern. However, given that one observes extreme persistence of location patterns over time, it may well be that unobserved endowments that were important a century ago are still an important determinant of current rents.

metropolitan or even state level (Rosenthal and Strange, 2004). As geographical units are arbitrary, this may lead to biased estimates (Briant et al., 2010). More importantly, aggregate measures of density make it difficult to determine the geographical extent of agglomeration economies. It is therefore not surprising that the geographical scope of agglomeration economies is to a large extent unknown.<sup>4</sup> Third, Rosenthal and Strange (2004) argue that high rents, as well as high wages, reflect the presence of agglomeration economies, but very few studies use rents to measure the magnitude of agglomeration economies (Puga, 2010). This is particularly unfortunate because agglomeration effects are thought to capitalise mainly into rents rather than into wages (Arzaghi and Henderson, 2008).<sup>5</sup> Using rents to measure agglomeration economies is furthermore insightful, as rents represent a monetary value, in contrast to for example the number of patents or start-ups. Rents are therefore easier to use in appraisals and local cost benefit analyses, allow for a comparison between industries and do not limit the analysis to manufacturing industries (see e.g. Acs et al., 1991; Ellison et al., 2011).

The contribution of this paper is threefold. First, this study uses temporal, rather than geographical, variation in densities to estimate agglomeration economies.<sup>6</sup> To control for unobserved shocks, I use instrumental variables (IV). So, the identification strategy deals with time-invariant unobserved endowments and unobserved shocks.<sup>7</sup> Second, a new method to determine the geographical scope of agglomeration economies is proposed. Third, I use micro-data on employment and rents to measure agglomeration economies in the commercial property market.

To be more specific, Section II discusses the (theoretical) relationship between productivity, rents, agglomeration economies and consumption amenities, and then proposes a three-stage estimation procedure to investigate the magnitude of agglomeration economies on commercial rents. In the first stage, I employ kernel methods to estimate weighted employment densities for each location, avoiding the arbitrary choice of spatial

---

<sup>4</sup> However, some cross-sectional studies find that localisation economies (industry-specific agglomeration economies) tend to be very local and attenuate within 7.5 kilometres, although these studies usually include spatial fixed effects that may capture some agglomeration economies (see Rosenthal and Strange, 2003). Alternatively, they focus on a small study area, so a larger geographical extent is assumed away (see Arzaghi and Henderson, 2008; Ahlfeldt et al., 2012).

<sup>5</sup> A reason may be that wages are often determined in collective bargaining agreements, which limits the spatial heterogeneity of wages (Simón et al., 2006; Rusinek and Tojerov, 2011).

<sup>6</sup> To use temporal variation in densities based on micro-data is rare. Drennan and Kelly (2011) use temporal variation but rely on data that are aggregated at the metropolitan level.

<sup>7</sup> I rely on information on rents rather than sales prices: rents are expected to react more strongly to changes in agglomeration than sales prices, as prices should be forward looking and should capture all expected changes in the environment.

units. Using a spatial decay parameter, employment further away contributes less to the kernel density at a certain location. In the second stage I regress the rent per unit of floor space on kernel employment densities, while controlling for a wide range of control variables. Most important, I include six-digit postcode (PC6) fixed effects. As these areas are about equal to a census block, the unobserved heterogeneity with respect to the economic environment can be completely assumed away (see similarly Van Ommeren and Wentink, 2012). An important identification issue is that the spatial detail of the postcode fixed effects mitigates the role of fixed unobservable components, but exacerbates the problem of random shocks: when specific areas receive positive (negative) demand shocks, this will lead to higher (lower) densities and rents, implying a spurious correlation (Ottaviano and Peri, 2010; Duranton et al., 2011). Together with including fixed effects, I therefore also employ an instrumental variables approach where I use a ‘shift-share’ instrument, following Bartik (1991) and Moretti (2010), among others. So, it is assumed that in absence of local shocks, industries at all locations grew at the national growth rate. In the third stage, I optimise the spatial decay parameter of the employment kernel densities using a cross-validation procedure.<sup>8</sup> So, I estimate for each set of decay parameters a hedonic price function and select the model that minimises the cross-validation score. In contrast to the current paper, Ahlfeldt et al. (2012) use Berlin’s division and reunification as a source of exogenous variation to separate agglomeration economies from unobserved location fundamentals. An attractive feature of their study is they are able to estimate structural parameters, based on information on land prices, residential and workplace employment. The advantage of the current identification strategy refers to the issue of external validity: the current approach may be used in different time periods and locations. It also puts more attention to the estimation of a spatial decay parameter. The current paper also differs from the approach proposed by Greenstone et al. (2010), who compare winning and runner-up locations that competed for attracting large firms. A disadvantage of the current study compared to Greenstone et al. (2010) is that I cannot distinguish between different sources (e.g. labour market pooling) of agglomeration economies, mainly because of data limitations. The advantage of my approach is that I can control for unobserved demand shocks, given the validity of the used instrument.

Section III discusses a unique nation-wide micro-dataset of the Netherlands with employment of *all* establishments and their exact locations from 1996 to 2010. I also

---

<sup>8</sup> This procedure is standard in nonparametric applications and in the determination of the bandwidth in regression-discontinuity designs.

elaborate on another micro-dataset containing 25 thousand rental transactions of offices and industrial buildings in the Netherlands from 1997 to 2011.

In Section IV, I present the main results. It is shown that agglomeration has a strong impact on commercial property values. A standard deviation increase in the (weighted) employment density leads to an increase in rents of about 10 percent. Alternatively, doubling of agglomeration leads to an increase in rents of on average 13.5 percent. The geographical scope of agglomeration economies is found to be about 15 kilometres and is very similar across specifications that use mainly geographical or temporal variation in densities. In line with Combes et al. (2008) and Melo et al. (2008), I find that the bias introduced by ignoring unobserved endowments is limited. Also, unobserved shocks have limited impact on the estimation results, as IV estimates are not statistically significantly different from OLS estimates with fixed effects. I also present three other important findings. First, agglomeration economies are an important determinant of rents in the office market, but there is no effect found on rents of industrial space. Second, although the current paper focuses on the economies of density, so urbanisation economies (see Hoover, 1936; 1937), I do not find that localisation economies, so industry-specific agglomeration advantages, capitalise into rents of commercial properties. Third, I do not find evidence that the effect of agglomeration is significantly different between industries.

The results are shown to be robust in Section V, wherein I use other instruments, test whether the effect of agglomeration also captures the presence of consumer amenities and try a plethora of alternative specifications. Section VI concludes.

## II. Theoretical framework and estimation

### A. Productivity and rents

When agglomeration economies have a positive impact on profits, one expects to observe higher rents in places where densities are higher. To show this, let us assume that  $\pi_{jt}$  is the profit per unit of commercial space of a typical firm in rental property  $j$  at time  $t$ . Let  $\Gamma(n_{jt})$  denote some function of employment of firms in all other properties.  $n_{jt}$  is the spatially weighted employment.  $\Lambda(\ell_{jt}, z_j, v_{jt})$  is a function of some other input  $\ell_{jt}$ , let's say labour, time-invariant locational endowments  $z_j$  and time-varying endowments  $v_{jt}$ . For convenience, I assume that  $\Lambda(\ell_{jt}, z_j, v_{jt}) = (z_j v_{jt})^\eta \ell_{jt}^\alpha$  and  $\Gamma(n_{jt}) = e^{\zeta n_{jt}}$ .<sup>9</sup> The profit per unit of commercial space is then:

---

<sup>9</sup> I pay some attention in the robustness analysis (Section V.D) to functional form assumptions.

$$(1) \quad \pi_{jt} = (z_j v_{jt})^\eta \ell_{jt}^\alpha e^{\zeta n_{jt}} - w_{jt} \ell_{jt} - r_{jt},$$

where  $w_{jt}$  is the wage and  $r_{jt}$  is the rent in rental property  $j$  at time  $t$ .<sup>10</sup> Given zero profits, it may be shown that the rent per square meter paid by firm in rental property  $j$  in time period  $t$  is:

$$(2) \quad r_{jt} = e^{\frac{\zeta}{1-\alpha} n_{jt}} (1-\alpha) \left( \frac{\alpha}{w_{jt}} \right)^{\frac{\alpha}{1-\alpha}} (z_j v_{jt})^{\frac{\eta}{1-\alpha}}.$$

Note, however, that the wage  $w_{jt}$  is endogenous and may be a function of house prices and consumption amenities. To show this, assume a worker that gains utility  $u_{tj}$  in property  $j$  in time  $t$  from house size  $h$  and a composite commodity  $c$ . For convenience, I assume that workers live where they work and therefore do not incur commuting costs.<sup>11</sup> The Cobb-Douglas utility is then  $u_{jt} = \Delta(m_{jt}) c_{jt}^\phi h_{jt}^{1-\phi}$  which is maximised subject to the budget constraint  $w_{jt} = p_{jt} h_{jt} - c_{jt}$ , where  $p_{jt}$  is the price for residential space,  $\phi < 1$ , and  $m_{jt}$  is a spatially weighted density of people and let  $\Delta(m_{jt}) = e^{\kappa m_{jt}}$ . So, when  $\kappa > 0$ , people prefer to live in dense areas because they may offer (population-induced) amenities. Workers may move to another location where they receive reservation utility  $\bar{u}$  and in equilibrium  $u_{jt} = \bar{u}$ . It may then be shown that the price  $p_{jt}$  paid per unit of housing at  $j$  in time period  $t$  is:

$$(3) \quad p_{jt} = \phi^{\frac{\phi}{1-\phi}} e^{\frac{\kappa}{1-\phi} m_{jt}} (1-\phi) \left( \frac{w_{jt}}{\bar{u}} \right)^{\frac{1}{1-\phi}}.$$

The only wage that is consistent with zero commuting costs is the wage that just equates the bid rents of firms and workers for space at a certain location  $j$  (see Lucas and Rossi-Hansberg, 2002). This is given by:

$$(4) \quad w_{jt}^* = K_j e^{\frac{1-\phi}{1-\alpha\phi} \zeta n_{jt}} e^{\frac{\alpha-1}{1-\alpha\phi} \kappa m_{jt}},$$

where  $K_j = \left( \phi^\phi (1-\alpha) \right)^{\frac{(1-\alpha)(\phi-1)}{1-\alpha\phi}} \bar{u}^{\frac{1-\alpha}{1-\alpha\phi}} \left( \alpha^\alpha z_j^\eta v_{jt}^\eta \right)^{\frac{1-\phi}{1-\alpha\phi}}$ . So, given that  $\zeta > 0$  and  $\kappa > 0$ , wages are higher in dense areas because of productivity advantages, whereas wages tend to be lower in areas with consumption amenities. When one inserts  $w_{jt}^*$  into (2) one has:

$$(5) \quad r_{jt} = e^{\frac{\alpha(1-\phi)\zeta n_{jt}}{(1-\alpha\phi)(1-\alpha)}} e^{\frac{\alpha\kappa m_{jt}}{1-\alpha\phi}} (1-\alpha) \left( \frac{\alpha}{K_j} \right)^{\frac{\alpha}{1-\alpha}} (z_j v_{jt})^{\frac{\eta}{1-\alpha}}.$$

<sup>10</sup> To satisfy that second order conditions are negative, it is assumed that  $\eta < 1$  and  $\alpha < 1$ .

<sup>11</sup> The assumption of zero commuting costs seems to be harmless. The same implications will follow when I assume that workers have to commute to work (see similarly Ottaviano and Peri, 2006). I then have to assume that the wage is constant across the city and equates the bid rents of firms and workers for space at the boundary of a central business district.

When the above equation is simplified and written in logs:

(6) 
$$\log r_{jt} = \beta n_{jt} + \gamma m_{jt} + \lambda_j + \xi_{jt},$$
 where  $\beta = \zeta\alpha(\phi - 1)/((\alpha\phi - 1)(1 - \alpha))$ ,  $\gamma = \kappa\alpha/(1 - \alpha\phi)$ ,  $\lambda_j = \eta z_j/(1 - \alpha)$  and  $\xi_{jt} = \eta v_{jt}/(1 - \alpha)$ . This model is only identified given a normalisation assumption on  $\alpha$  and  $\phi$ , so the coefficient  $\beta$  must be interpreted as the effect on productivity, rather than on absolute levels of profits. I assume that  $\beta$  (and  $\gamma$ ) are time-invariant, an assumption which is tested in the robustness analysis, Section V.D.

To distinguish agglomeration economies from time-invariant unobserved endowments  $z_j$  I include location fixed effects. Controlling for time-invariant unobserved endowments is potentially important, because rivers and natural resources may attract firms. Also endowments related to the regulatory framework are highly correlated over time. For example, the city centres of Amsterdam and Utrecht are protected historic districts for many decades. Another concern is that simultaneous changes in density and rents are caused by unobserved shocks, denoted by  $\xi_{jt}$ , leading to a spurious correlation between density and rents. In Section II.C I will therefore pay attention to the construction of an instrument that should be uncorrelated to local shocks.

A second issue is that in equation (5) and (6) it is observed that commercial rents are a function of production effects (related to  $n_{jt}$ ) and amenity effects (related to  $m_{jt}$ ). It has been argued that urban density facilitates consumption amenities and may be an important reason for the recent growth of many cities (Glaeser et al., 2001; Glaeser and Gottlieb, 2006; Rappaport, 2008). The estimates of agglomeration economies using commercial rents therefore may provide an overestimate of productivity effects, when one ignores amenity effects that are correlated with employment density (Roback, 1982).<sup>12</sup> In the presence of productivity advantages, workers have to be compensated for the higher costs of living (Dekle and Eaton, 1999). Note however that, conditional on house prices, locations that offer amenities also offer lower wages (see Rosenthal and Strange, 2002). To separate agglomeration economies from consumption amenities, as in Ahlfeldt et al. (2012), I will first assume that all population-induced amenities are captured by the population density, (time-varying) control variables at a certain location and location fixed effects (locations that are attractive to households will command higher prices and are likely to attract more households). I acknowledge that the latter assumption is somewhat restrictive, for example because certain types of employment may directly be valued by households (as in Koster

---

<sup>12</sup> This issue has been extensively discussed by Roback (1982) and Ottaviano and Peri (2006), among others, but has not received attention yet in the context of the commercial property market.



and Rouwendal, 2012). However, when commercial rents and house prices have the same determinants (e.g. agglomeration), one expects to see a (strong) positive correlation between changes in commercial rents and changes in house prices. In the robustness analysis, Section V.D, I show that changes in rents and house prices are uncorrelated, which lowers the probability that I measure consumption amenities instead of productivity effects.

A third issue is that by including location fixed effects, I may identify a short-term effect of agglomeration rather than a long-term effect in a cross-sectional setting. This may lead to an underestimate of the total effect of agglomeration economies. However, it will be shown that the effect with and without location fixed effects will lead to results that are very similar.

### B. A three-stage estimation procedure

The procedure to estimate equation (6) consists of three stages. First, kernel density functions of employment are estimated, including a spatial decay parameter. In the second stage, these kernel densities are inserted into a hedonic price function. In the third stage the spatial decay parameter is optimised using a cross-validation procedure.

To verify the impact of agglomeration, usually aggregate measures at the county, region, or state level are used. This means that potentially important information is ignored (Duranton and Overman, 2005). It may also lead to an additional bias, especially when the dependent variable is measured in a disaggregate way (as in this paper), while the explanatory variables are not (Briant et al., 2010). In the first stage, I therefore use kernel densities that exploit the continuous nature of the data. The employment density for a rental property  $j$  in period  $t$  is estimated as:

$$(7) \quad n_{jt}(\delta) = \sum_{k=1}^K \ell_{kt} \Omega(d_{jk}, \delta),$$

where  $\ell_{kt}$  is the employment in another rental property  $k$  in time  $t$ , where  $k = 1, \dots, K$ ,  $\Omega(\cdot)$  is some function of  $\delta$ , which denotes a distance decay parameter, and  $d_{jk}$  denoting the distance between  $j$  and  $k$ . I assume that  $\Omega(\cdot)$  is a tricube weighting function, which is often used in spatial applications (McMillen, 2010):

$$(8) \quad \Omega(d_{jk}, \delta) = \left(1 - \left(\frac{d_{jk}}{\delta}\right)^3\right)^3 I(d_{jk} < \delta),$$

where  $I(\cdot)$  is an indicator function that equals one when the condition is true.<sup>13</sup> In contrast to Rosenthal and Strange (2003; 2008) and Arzaghi and Henderson (2008), I estimate smooth density functions instead of using dummies for different distance intervals. The advantage of the current approach is that it is more efficient, because I *impose* that weights decline in distance. I also avoid arbitrariness in the choice of distance intervals and the model estimates only one coefficient related to agglomeration (instead of one per distance band), which facilitates interpretation. A disadvantage of this approach is that the choice of the kernel function  $\Omega(\cdot)$  is arbitrary. I therefore test for alternative kernel functions. Because all kernel functions share the (obvious) feature of declining weights in distance, I show that the estimates are insensitive to the choice of kernel function (see similarly McMillen, 2010; McMillen and Redfearn, 2010). In contrast, the choice of the decay parameter  $\delta$  seems to be more important in the current setting. Moreover, I test the functional form of the decay function using distance interval dummies and I show that the tricube weighting function is not rejected (see Section V.C).

In the second stage I aim to verify the monetary effect of agglomeration economies. A standard hedonic price approach is employed, which implies that the rent that a typical firm is willing to pay for a square meter in rental property  $j$  at time  $t$  is regressed on  $n_{jt}$  and controls, *conditional* on the choice of the spatial decay parameter  $\delta$ . Based on equation (6), I then estimate:

$$(9) \quad \log r_{jt} = \beta n_{jt}(\delta) + \gamma m_{jt} + b'_{jt}\theta + \lambda_j + \tau_t + \epsilon_{jt},$$

where  $\beta$ ,  $\gamma$ ,  $\theta$  are parameters to be estimated,  $b_{jt}$  are building and location attributes that change over time (such as distance to stations, land use),  $\lambda_j$  is a location fixed effect,  $\tau_t$  is a year fixed effect and  $\epsilon_{jt}$  denotes the error term, which is assumed to be independently and identically distributed across firms.<sup>14</sup> As argued by Bayer and Timmins (2007), among others, location decisions alone are insufficient in distinguishing the potential of local spillovers from those of locational advantages. As a result, any positive effect of agglomeration is likely to be overstated (Ellison and Glaeser, 1999; Bayer and Timmins, 2007). Because I include location fixed effects at an extremely low level of aggregation, I effectively control for time-invariant natural advantages and location endowments. So, the

---

<sup>13</sup> As  $d_{jk}$  will be measured in kilometres, the decay parameter  $\delta$  has a clear interpretation. For  $d_{jk} > \delta$  agglomeration effects are assumed to be zero, so  $\delta$  denotes the geographical range of agglomeration economies in kilometres.

<sup>14</sup> In an ideal setting,  $\lambda_j$  should denote a rental property fixed effect. I do not include fixed effects at the rental property level, but at the PC6 level. As a consequence,  $b_{jt}$  therefore also contain time-invariant building attributes and attributes related to the rental contract (so, attributes that vary within a PC6 area). In Section V.D, also building fixed effects are included instead of PC6 fixed effects.

key identifying assumption is that changes in  $\epsilon_{jt}$  are uncorrelated to changes in  $n_{jt}(\delta)$ . This assumption is testable on observable time-varying endowments  $b_{jt}$  (which refer to changes in land use and infrastructure): including  $b_{jt}$  should then lead to a very similar coefficient  $\beta$ . I also will consider the possibility that agglomeration is correlated to unobserved local shocks, by employing an instrumental variables approach (see Section II.C for more details).

In the third stage, the spatial decay parameter  $\delta$  is determined using a cross-validation procedure. Cross-validation is often used in the determination of the smoothing parameter in nonparametric and semiparametric estimation (Cleveland, 1979; Bowman, 1984; Farber and Páez, 2007; McMillen and Redfearn, 2010). Also in regression-discontinuity designs, a cross-validation procedure is frequently employed to determine the bandwidth (Imbens and Lemieux, 2008; Lee and Lemieux, 2010).<sup>15</sup> I define the cross-validation criterion as:

$$(10) \quad CV(\delta) = \frac{1}{J} \sum_{j=1}^J \left( r_{jt} - \hat{r}_{jt}(\delta) \right)^2,$$

where  $j = 1, \dots, J$ . The corresponding decay parameter choice is then given by:

$$(11) \quad \{\delta^*\} = \arg \min CV(\delta).$$

Preferably,  $\delta$  is defined as a continuous decay parameter. However, estimating kernel densities of employment for a large dataset is quite computational intensive. To reduce the computational burden, I therefore assume that  $\delta$  is an integer that is in between 0 and 50 kilometres. I will show that the latter is not a limiting assumption in any respect, as it is found that  $\delta^*$  is always much less than 50 kilometres. The cross-validation scores monotonically increase when  $\delta$  gets larger (see Appendix B for more details), so it does not make sense to increase this distance range. One may argue that there is too little temporal variation in densities to identify the distance decay parameter. Because densities mainly may change at a local level, the estimation procedure may suggest a too low decay parameter. When this argument holds, the estimates that do not include fixed effects should suggest a substantially higher spatial decay parameter (because identification in the latter case mainly relies on geographical variation in densities). However, in the analysis it is shown that the spatial decay parameter is reasonably robust across different specifications, regardless of the inclusion of fixed effects.

---

<sup>15</sup> One may also use other criteria to determine optimal the decay parameter  $\delta$ . For example, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are often used (see e.g. Hurvich et al., 1998). It may be shown that these criteria will lead to exactly the same results.

### C. A shift-share instrument

As emphasised in Section II.A, agglomeration may be correlated to unobserved time-varying variables, implying a spurious correlation between agglomeration and rents. I therefore need an instrument that is correlated to agglomeration but uncorrelated to unobserved local shocks. Following Bartik (1991), Bartik (1994), Ottaviano and Peri (2007), Moretti (2010) and Faggio and Overman (2012), I will therefore use a ‘shift-share’ approach. The instrument uses the initial employment situation and combines that with national employment growth in an industry. It is then assumed that, in absence of local shocks, each location would have received a share of employment that is in proportion to its initial share.<sup>16</sup> Conditional on location fixed effects and when the number of employees in an industry is reasonably large, local shocks should not influence the national employment growth in an industry.

Let then  $N_{st}$  be the total employment in an industry  $s$  in year  $t$ , where  $s = 1, \dots, S$ , and  $t_B$  the base year.<sup>17</sup> The predicted number of workers  $\hat{\ell}_{skt}$  in industry  $s$  in rental property  $k$  in year  $t$  is  $\hat{\ell}_{skt} = (N_{st}/N_{st_B})\ell_{skt_B}$ . As an instrument for agglomeration  $n_{jt}$  I use:

$$(12) \quad \hat{n}_{jt}(\delta) = \sum_{k=1}^K \sum_{s=1}^S \hat{\ell}_{skt} \Omega(d_{jk}, \delta).$$

So, I re-estimate equation (9) with the predicted kernel employment density  $\hat{n}_{jt}(\delta)$  as an instrument for agglomeration  $n_{jt}(\delta)$  in a specific year, using the predicted number of workers  $\hat{\ell}_{skt}$  in a specific industry  $s$ .

## III. Data

### A. LISA-data

I use two unique micro-datasets. The first is the *LISA* employment register. These data provide information on the exact location (geocoded at the address level), the number of employees and information on a five-digit SBI level of all establishments with more than

---

<sup>16</sup> When the number of employees in an industry is very small, local shocks may be correlated to the national employment growth of an industry. This is only an issue when the total employment of a sector changes due to local shocks, i.e. when local shocks induce start-ups or exits. Nevertheless, in almost all cases the total number of employees is large (as an illustration, the average size of an industry was 72,235 employees in 1996). Also, in the robustness analysis (Section V) it is shown that the results are insensitive to the detail of sectoral classification. Other instruments are also used.

<sup>17</sup> In the empirical analysis, I use the SBI two-digit classification as an indicator for industry and take 1996 as a base year.

zero employees in the Netherlands between 1996 and 2010.<sup>18</sup> See Van Oort (2004) for a detailed description of these data. The total number of jobs in 1996 was about 6.14 million in 1996 and rose to 7.19 million jobs in 2010 (see Figure 1A). Likely because of the economic crisis, employment growth has slowed down the last decade and total employment even slightly decreases in the last year. In contrast, the number of establishments has increased from 0.66 million in 1996 to 1.11 million in 2010 and is still steadily increasing. As a result, the average firm size is strongly decreasing from 2001 onwards.

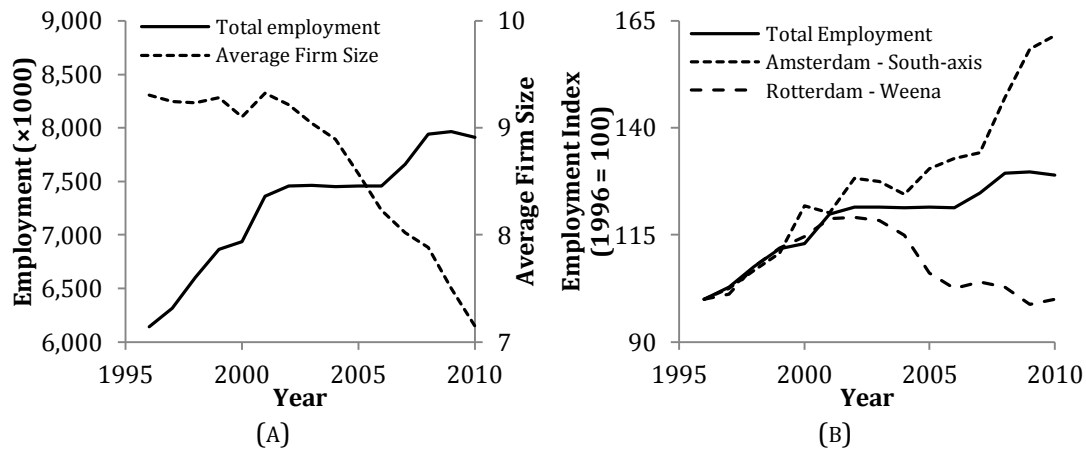


FIGURE 1 — DUTCH EMPLOYMENT FIGURES

Looking at a more disaggregate level, employment growth figures are quite different, which is essential for the identification strategy. For example, the so-called South-Axis in Amsterdam experienced a more than average employment growth. This is the major upcoming business centre in the Netherlands hosting many corporate head offices. On the other hand, another major business centre in the centre of Rotterdam (Weena) showed negative employment growth the last decade. Indeed, some large law firms have recently moved to the South-Axis, likely because of proximity to internationally operating clients and the presence of strong agglomeration economies (see Jacobs et al., 2012).

In Figure 2A I map the spatial distribution of employment. All major employment concentrations are part of the so-called Randstad (which is formed by the cities of Amsterdam, Utrecht, The Hague and Rotterdam). It may be shown that in the absolute number of jobs, the Randstad is also the region where most employment growth takes place. There is however a substantial difference between the northern part of the Randstad, which

<sup>18</sup> This classification is comparable to the SIC (Standard Industrial Classification) and NACE (Nomenclature statistique des Activites dans la Communauté Européenne).

hosts the most important headquarters, business services and ICT firms operating at a supra-regional level, and the southern part of the Randstad, where many logistics and manufacturing activities are located (because of the presence of the port of Rotterdam, which is the largest in Europe). In line with Figure 1B growth rates in the latter part tend to hamper because of the presence of declining industries, whereas Amsterdam and especially some areas nearby Amsterdam tend to experience relatively high growth rates (see Figure 2B).

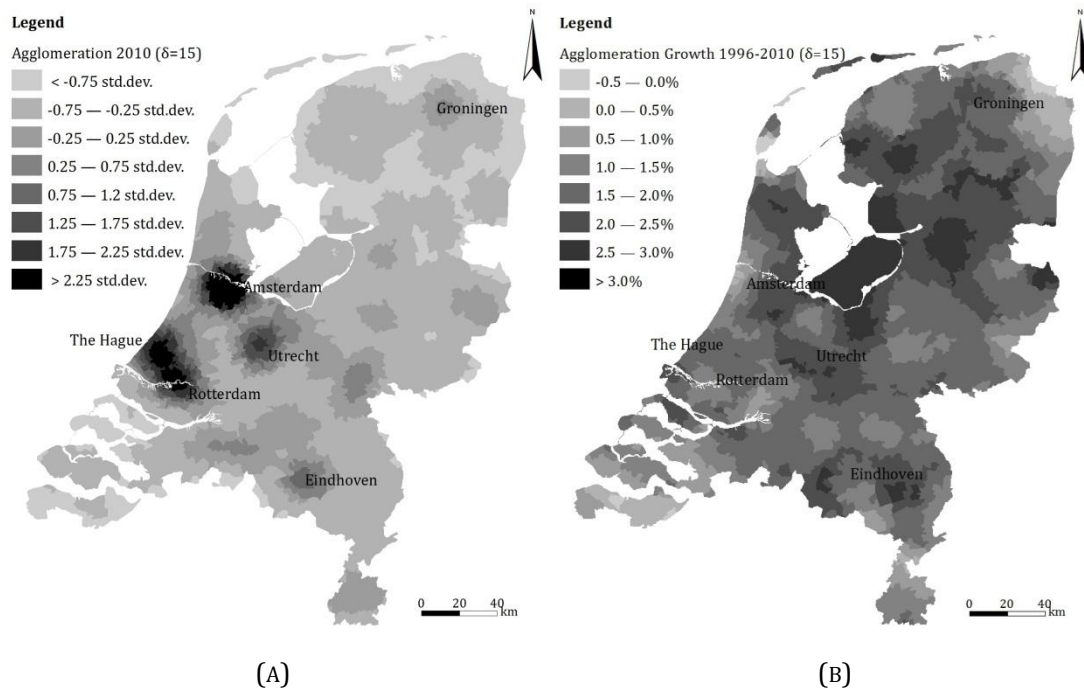


FIGURE 2 — SPATIAL DISTRIBUTION AND GROWTH RATES OF DUTCH EMPLOYMENT  
*Notes:* In Figure 2A, I calculate for 2010 employment densities. For presentational purposes, I estimate equation (7) for centroids of all *four-digit* postcode areas (PC4) instead of PC6 areas (a PC4 area is about equal to a census tract in the United States). I set the decay parameter  $\delta$  to 15 kilometres. It will be shown in Section IV that this is a reasonable value. In Figure 2B, I calculate the compound annual growth rate using the estimated PC4 employment densities in 1996 and 2010.

### B. Commercial property data

The second dataset that is used is a dataset provided by *Strabo*, a consultancy firm that gathers and analyses commercial property data. It consists of transactions of commercial office properties, provided by real estate agents between 1997 and 2011.<sup>19</sup> The property

<sup>19</sup> For the latter year, I only have information for the first two months.

dataset contains information on the transacted or agreed rent, rental property attributes, such as a geocoded address, size (gross floor area in square meters), and whether the building is newly constructed or renovated.<sup>20</sup> Also the share of office and industrial space is included in the dataset, as well as some information on the contract (such as sale-and-lease-back, turnkey properties).<sup>21</sup> The dataset also provides information on the broadly-defined industry of the tenant for about 90 percent of the observations.<sup>22</sup> After selections, I have 24,086 transactions, of which about 70 percent are transactions related to office space.

The rental property dataset is matched to data from the *Administration of Buildings and Addresses*, which provides the exact location, construction year and energy label (if it has one) for *all* buildings in the Netherlands. I also define whether the building is multitenant (when it hosts multiple rental properties) and whether it hosts multiple uses (e.g. office, restaurant, shop). Using the *Listed Building Register*, I include a dummy whether the building is listed. The property dataset is merged with a detailed land use data from *Statistics Netherlands* for 1996, 2000, 2003, 2006 and 2008. I match each transaction year to the nearest year of the land use data. This may lead to some bias, but as the average time difference between transactions in the same postcode is about 2.5 year, I expect that the bias is limited. The latter data enable me to calculate the distance to the nearest hectare of commercial land, open space, water, major roads and railways. I also include the land use of the actual location (industrial, commercial, residential or other) and the distance to the nearest station.

Population density at a postcode four-digit level is also included as a control variable. To calculate the (weighted) population density, I first assume that population is uniformly distributed over all postcode 6-digit locations in a PC4 area. Population density is then measured as  $m_{jt} = \sum_{k=1}^K a_{kt} \Omega(d_{jk}, \omega)$ , where  $a_{kt}$  is the number of people at a certain location  $k$  and  $\omega$  is a fixed decay parameter. So,  $m_{jt}$  is a ‘lumpy’ approximation of the continuous kernel density of population. To save computational time, I will provisionally

---

<sup>20</sup> I also have information on sales prices. The main reason that I do not use this information in the current paper is because of the limited number of observations (about 10 percent of the number of rent transactions). In the office market it is uncommon that users own properties. Further, renting firms are generally more mobile than owning firms, leading to more transactions.

<sup>21</sup> I exclude transactions with missing data on either the price or the size of the rental price, yearly rents per square meter lower than € 20 or higher than € 700 and rental properties that are less than 25 square meters. These selections hardly influence the results.

<sup>22</sup> Firms are divided in 13 industries: manufacturing, construction, logistics, wholesale, retail, consumer services, hospitality industry, education and healthcare, government, ICT, financial services, business services and other firms. In Table A2, Appendix A, it is shown which SBI codes are part of these broadly-defined industries.

assume that  $\omega = 2.5$ ; when population density reflects the presence of amenities, the benefits are expected to be very local. In the sensitivity analysis (Section V.D) I will jointly optimise  $\delta$  and  $\omega$  and show that the results of agglomeration are almost unaffected.

Using the *Listed Building Register* I determine whether the rental property is in an area that is assigned as a historic district, or which is in the process of becoming a historic district. As I include spatial fixed effects at the PC6 location, I identify the coefficients related to land use and population density based on changes. The coefficient of stations is identified using new station openings. It is also important to note that all variables related to the environment (including agglomeration) are referring to the year preceding the transaction to avoid simultaneity bias, but also because location choices likely imply a thorough preliminary study of local markets in a previous period (Greenstone et al., 2010; Hilber and Voicu, 2010).<sup>23</sup>

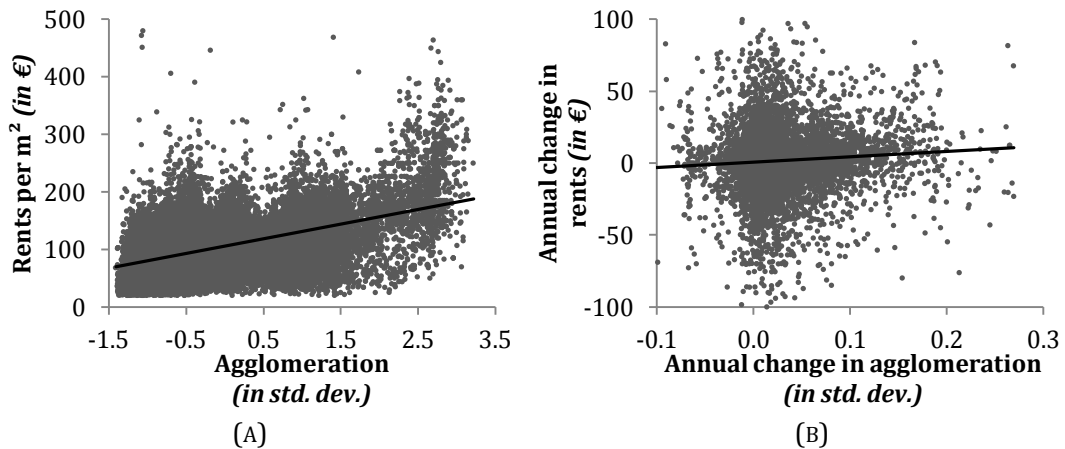


FIGURE 3 — AGGLOMERATION AND RENTS

*Notes:* It is assumed that the decay parameter  $\delta = 15$ . In 3B, I plot the average annual change in rents in a PC6 area  $j$  in year  $t$ ,  $(r_{jt_1} - r_{jt_0}) / (t_1 - t_0)$ , against the average annual change in agglomeration  $n_{jt}$ ,  $(n_{jt_1} - n_{jt_0}) / (t_1 - t_0)$ , in a PC6 area.

In Table A1 in Appendix A descriptive statistics are presented. The average rent is € 105 per square meter and the standard deviation is about € 54 per square meter, which is substantial. The most expensive office space can be found in and close to Amsterdam with

<sup>23</sup> One may argue that kernel densities of employment are biased if the firm's own employment is included in the kernel density. Because the kernel densities are estimated in the year that precedes the transaction and because most observations are movers or start-ups, this bias is likely to be small. Further, I identify agglomeration based on changes in densities. Firms that stay do therefore not contribute to identification of the agglomeration effect. Nevertheless, in the robustness analysis (Section V.D), it is shown that the effect of agglomeration is very similar when I exclude firms that have prolonged their contracts (so, the latter firms are not movers or start-ups).



average rents of about € 180 per square meter, whereas office space in the upper north, east and south of the Netherlands can be as low as € 50 per square meter, so there is substantial spatial variation in the rents for office space. For industrial buildings, the variation is less with average prices ranging from € 30 to € 100 per square meter. Most rental properties are either in a commercial area or at an industrial site, but still about 20 percent of the observations are in a residential area. The average size of the rental property is 1,173 square meters, which is almost twice the median size (630 square meter). Almost 80 percent of the transactions are in postcodes with more than one observation, which seems sufficiently high to use temporal variation in explanatory variables as a source of identification. In Figure 3A, I plot the agglomeration against rents. None of the controls are included, so these results are suggestive, at best. Nevertheless, this univariate regression suggests that a standard deviation in agglomeration increases rents with on average 32 percent. Figure 3B plots the annual changes in rents against annual changes in agglomeration. This suggests that rents increases with 45 percent when agglomeration increases with one standard deviation.

#### IV. Results

##### A. Baseline regressions: OLS, IV and OLS with fixed effects

Table 1 presents the baseline results of the effects of agglomeration  $n_{jt}$ . I first run standard OLS and instrumental variables regressions *without* PC6 fixed effects. Specification (1) suggests that there is a considerable effect of agglomeration: one standard deviation increase in (weighted) employment density  $n_{jt}$  may lead to an increase in rents of 13.1 percent. Using the cross-validation procedure, it appears that the geographical range of agglomeration economies is 17 kilometres.<sup>24</sup>

In Specification (2), I estimate an instrumental variables regression. The standard procedure to control for unobserved locational advantages is to use long-lagged instruments. As in Koster et al. (2012) I use the logarithm of municipal population density in

---

<sup>24</sup> Note that when I include municipality fixed effects, the estimate of agglomeration is 0.117, which is very similar to Specification (1). This suggests that municipality fixed effects do not capture unobserved endowments.

TABLE 1 — REGRESSION RESULTS ON THE IMPACT OF AGGLOMERATION  
(Dependent variable: the logarithm of rent per square meter)

|   | (1)               | (2)               | (3)               | (4)               |
|---|-------------------|-------------------|-------------------|-------------------|
|   | OLS               | IV                | FE                | IV – FE           |
| Agglomeration, $n_{jt}$                       | 0.133 (0.004)***  | 0.115 (0.021)***  | 0.099 (0.031)***  | 0.120 (0.035)***  |
| Population, $m_{jt}$                          | 0.022 (0.005)***  | 0.036 (0.013)***  | 0.012 (0.039)     | 0.014 (0.038)     |
| Land use – residential                        | -0.019 (0.011)*   | -0.019 (0.011)*   | 0.048 (0.016)***  | 0.048 (0.016)***  |
| Land use – industrial site                    | -0.121 (0.011)*** | -0.116 (0.012)*** | -0.010 (0.014)    | -0.011 (0.014)    |
| Land use – other                              | -0.034 (0.014)**  | -0.030 (0.015)**  | 0.034 (0.018)*    | 0.033 (0.018)*    |
| Distance to industrial land (km)              | -0.048 (0.024)**  | -0.044 (0.026)*   | -0.109 (0.031)*** | -0.110 (0.031)*** |
| Distance to major road (km)                   | -0.100 (0.030)*** | -0.082 (0.034)**  | -0.048 (0.061)    | -0.044 (0.061)    |
| Distance to railway (km)                      | 0.006 (0.002)***  | 0.005 (0.002)**   | -0.007 (0.007)    | -0.007 (0.007)    |
| Distance to station (km)                      | -0.016 (0.002)*** | -0.015 (0.002)*** | 0.006 (0.012)     | 0.006 (0.012)     |
| Distance to open space (km)                   | -0.086 (0.018)*** | -0.088 (0.018)*** | -0.086 (0.033)*** | -0.086 (0.033)*** |
| Distance to water (km)                        | -0.027 (0.006)*** | -0.030 (0.008)*** | -0.034 (0.021)    | -0.034 (0.021)    |
| Historic district – in process                | 0.054 (0.033)*    | 0.053 (0.033)     | 0.043 (0.033)     | 0.045 (0.033)     |
| Historic district – assigned                  | 0.048 (0.014)***  | 0.048 (0.014)***  | 0.122 (0.045)***  | 0.121 (0.049)***  |
| Green heart                                   | 0.060 (0.012)***  | 0.046 (0.013)***  | 0.023 (0.015)     | 0.024 (0.015)     |
| Size in m <sup>2</sup> (log)                  | -0.036 (0.004)*** | -0.035 (0.004)*** | -0.041 (0.004)*** | -0.041 (0.004)*** |
| Share industrial space                        | -0.759 (0.009)*** | -0.763 (0.010)*** | -0.550 (0.013)*** | -0.550 (0.013)*** |
| Newly Constructed                             | 0.097 (0.011)***  | 0.098 (0.011)***  | 0.065 (0.009)***  | 0.065 (0.009)***  |
| Renovated                                     | 0.094 (0.024)***  | 0.097 (0.026)***  | 0.052 (0.014)***  | 0.052 (0.014)***  |
| Parking spaces (log)                          | 0.050 (0.005)***  | 0.049 (0.005)***  | 0.033 (0.004)***  | 0.033 (0.004)***  |
| Listed building                               | 0.061 (0.019)***  | 0.060 (0.019)***  | 0.019 (0.027)     | 0.018 (0.027)     |
| Energy label A                                | 0.027 (0.030)     | 0.025 (0.030)     | 0.052 (0.029)*    | 0.052 (0.029)*    |
| Building surface area in m <sup>2</sup> (log) | -0.005 (0.003)*   | -0.005 (0.004)    | -0.015 (0.004)*** | -0.015 (0.004)*** |
| Building – multitenant                        | 0.034 (0.007)***  | 0.033 (0.007)***  | 0.002 (0.008)     | 0.002 (0.008)     |
| Building – multiple uses                      | -0.045 (0.008)*** | -0.045 (0.008)*** | -0.016 (0.010)    | -0.016 (0.010)    |
| Rent – turnkey                                | 0.151 (0.035)***  | 0.158 (0.035)***  | 0.133 (0.029)***  | 0.133 (0.029)***  |
| Rent – sub rent                               | 0.022 (0.015)     | 0.027 (0.015)*    | -0.015 (0.012)    | -0.015 (0.012)    |
| Rent – sale and lease back                    | 0.064 (0.024)***  | 0.060 (0.025)**   | 0.036 (0.029)     | 0.036 (0.030)     |
| Rent – contract prolongation                  | 0.019 (0.012)     | 0.022 (0.012)*    | -0.013 (0.009)    | -0.013 (0.009)    |
| Rent – length contract (in years)             | 0.018 (0.003)***  | 0.018 (0.003)***  | 0.005 (0.003)     | 0.005 (0.003)     |
| Other control variables (9)                   | Yes               | Yes               | Yes               | Yes               |
| Year fixed effects (15)                       | Yes               | Yes               | Yes               | Yes               |
| PC6 fixed effects (8,461)                     | No                | No                | Yes               | Yes               |
| Spatial decay $\delta^*$ (km)                 | 16                | 18                | 13                | 17                |
| Cross validation score $CV(\delta^*)$         | 0.07941           | 0.07940           | 0.03706           | 0.03707           |
| $R^2$   | 0.7329            |                   | 0.9192            |                   |
| $F$ -Test weak instruments                    |                   | 103.218           |                   | 3,187.732         |

Notes: The number of observations is 24,086. Other control variables are parking spaces missing, contract length missing and seven construction decade dummies. In Specification (2), the instruments of agglomeration are the logarithm of municipal population density in 1830 and distance to station in 1870. In Specification (4), the shift-share instrument is used (see equation (12)). First-stage results are presented in Table C2, Appendix C. Standard errors are clustered at the postcode six-digit location.

\*\*\* Significant at the 0.01 level

\*\* Significant at the 0.05 level

\* Significant at the 0.10 level

1830. Note that municipalities in 1830 were much smaller and do not overlap with current ones. The Netherlands in 1830 consisted of 1,228 municipalities, whereas nowadays it consists of only 431 municipalities. The instrument's validity rests on the (debatable) assumption that population density in 1830 is unrelated to current unobserved locational advantages (and therefore productivity of firms), 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 geographical concentration of firms and people are strongly autocorrelated (McMillen and McDonald, 1998). The second instrument we employ is the distance to the nearest station in 1870. Stations were an important factor that caused agglomeration in the second half of the 19<sup>th</sup> century (Ciccone and Hall, 1996). Specification (2) shows that the impact of agglomeration is only 1.6 percentage points lower.<sup>25</sup> Using the Hausman *t*-statistic, it appears that the coefficient of agglomeration is not statistically significantly different from the estimate in Specification (1) at the five percent level (the *t*-statistic is 0.89).<sup>26</sup> The spatial decay parameter of agglomeration economies is 18 kilometres.

In Specification (3), which is the preferred specification, I include 8,461 PC6 fixed effects. It is shown that the effect of agglomeration is still substantial and statistically significant.<sup>27</sup> One standard deviation increase in agglomeration leads to an increase in rents of 9.9 percent. Alternatively, doubling of agglomeration leads to an increase in rents of on average 13.6 percent. For an area with a median level of agglomeration, this is 9.9 percent. It is important to note that the decay parameter is very similar to the specifications that (mainly) rely on geographical variation in densities as a source of identification. Compared to Specifications (1) and (2), the results of Specification (3) suggest that estimates employing ordinary least squares and instrumental variables are *not* upward biased. The Hausman *t*-statistic for the difference with the OLS without fixed effects is 1.11. The difference with the IV estimates without fixed effects is also statistically insignificant (the Hausman *t*-statistic is 0.69).<sup>28</sup>

---

<sup>25</sup> First-stage results are presented in Appendix C, as well as descriptives of the instruments.

<sup>26</sup> The Hausman *t*-statistic is calculated as  $\tau_{\hat{\beta}} = (\hat{\beta}_{OLS} - \hat{\beta}_{IV}) / \sqrt{\sigma_{\hat{\beta}_{IV}}^2 - \sigma_{\hat{\beta}_{OLS}}^2}$  (see Wooldridge, 2002, pp. 120).

<sup>27</sup> In Appendix B it is shown that the coefficients of agglomeration are different for different decay parameters  $\delta$  (Figure B2). I also show that the cross-validation score is minimised for  $\delta = 13$  (Figure B1).

<sup>28</sup> This result only holds because of the large number of relevant control variables. When I exclude all variables except year fixed effects and re-estimate Specifications (2) and (3) the coefficients are respectively 0.241 and 0.103. The Hausman *t*-statistic is then 5.53.

In Specification (4) agglomeration is instrumented with the predicted agglomeration pattern based on the shift-share methodology. The instrument is very strong, so most of the changes in employment can be explained by the initial sectoral employment share and national trends. The coefficient of agglomeration suggests that a standard deviation increase in agglomeration leads to an increase in rents of 12 percent, which is surprisingly somewhat higher than the estimate in Specification (3). Nonetheless, this coefficient is not significantly different from the coefficient in Specification (3) (the Hausman  $t$ -statistic is -1.40). One may conclude that unobserved shocks are not strongly correlated to measures of employment density. More generally time-invariant unobserved endowments and unobserved shocks seem to play a limited role in the market for commercial properties which is in line with Combes et al. (2008) and Melo et al. (2008), among others. In accordance with Arzaghi and Henderson (2008), it seems that agglomeration economies mainly capitalise into rents, rather than into wages, as the effect of agglomeration economies on wages is found to be an order of magnitude smaller (typically between two and five percent, see Combes et al. 2008; 2010; and for the Netherlands: Groot et al., 2011). An explanation may be that wage bargaining agreements limit geographical variation in wages and therefore also the possibility of agglomeration economies to capitalise into wages. In contrast, there are no rent-controls in the commercial property market in the Netherlands.

It appears that the geographical range of agglomeration economies is about 15 kilometres. That is not to say that there are no interactions over longer distances. For example, input-output relationships between firms are likely to decay slower and are even occurring between firms in different continents. However, these long-distance input-output relationships are unlikely to be a main driver of *local* rents. Storper and Venables (2004) Amiti and Cameron (2007) and Arzaghi and Henderson (2008) argue that especially an abundant supply of possibilities to engage in face-to-face contacts capitalises into rents, which seems to be in line with the results of the current study. For example, these findings are in accordance with the observation that businesses that offer specialised services to maritime industries are mostly located in Rotterdam, which hosts Europe's largest port (see Jacobs et al., 2011). Similarly, many large law and accountants firms that offer face-to-face services to corporate headquarters are concentrated in Amsterdam, which hosts the largest concentration of headquarters in the Netherlands (see Jacobs et al., 2012).

Control variables have in general plausible effects on rents. Population density has a positive impact on commercial rents in Specifications (1) and (2). However, when I include

PC6 fixed effects, the effect of population density becomes statistically insignificant.<sup>29</sup> It is shown that locations further away from commercial land are much cheaper, ranging from 6 to 11 percent per kilometre. Locations near open spaces are also considered as attractive, likely because they offer amenities to workers. I also find a statistically significant positive effect of historic district designation, implying a rent increase ranging from 6 to 12 percent. Further, industrial buildings tend to be cheaper, which is not surprising as office space refers to a much higher quality building, in particular internally, whereas industrial buildings are usually bare. Also newly constructed and renovated buildings tend to be more expensive. The number of available parking spaces is positively related to rents (see similarly Van Ommeren and Wentink, 2010). In line with Eichholtz et al. (2010), energy-efficient buildings tend to be more expensive, although this effect is only marginally significant.

### *B. Other results*

In this subsection I discuss other relevant results. In particular, one may wonder whether the results differ for offices and industrial buildings, whether there is an effect of localisation (or industry-specific agglomeration economies), whether the importance of agglomeration economies differs between industries and whether the effect of agglomeration is nonlinear. The results are presented in Table 2 and Figures 4 and 5.

It may be expected that agglomeration economies are not equally important for firms occupying offices and industrial buildings. I therefore estimate separate specifications for these submarkets. Specification (5) only includes rental transactions for which at least half of the rented size refers to office space. It appears that the effect of agglomeration is very similar to the effect found in Specification (3): one standard deviation increase in agglomeration leads to an increase in rents of 10 percent. It is also shown that the spatial decay parameter is now slightly lower and 11 kilometres. In Specification (6), I concentrate on industrial buildings. It is shown that the coefficient of agglomeration is statistically insignificant. This is not too surprising as industrial buildings are often located in low-density low-rent areas where agglomeration economies seem to be less important, likely because firms in offices rely much more on costly face-to-face contacts.<sup>30</sup> The negative point estimate suggests a negative effect of employment density. However, the point estimate is

---

<sup>29</sup> One may argue that population density may pick up some effect of agglomeration economies (e.g. external economies related to a thick labour market). Nevertheless, when I exclude population density, the coefficient of agglomeration is almost identical. See Section VI.D for more details.

<sup>30</sup> As an illustration, the average (standardised) value of agglomeration for industrial buildings is -0.349, while it is 0.188 for offices for  $\delta = 13$ .

very sensitive to the choice of decay parameter, e.g. when  $\delta = 4$ , the point estimate is -0.003.

TABLE 2 — REGRESSION RESULTS, ALTERNATIVE SPECIFICATIONS  
(Dependent variable: the logarithm of rent per square meter)

|   | (5)                 | (6)                  | (7)                 | (8)                      | (9)              |
|---|---------------------|----------------------|---------------------|--------------------------|------------------|
|   | FE                  | FE                   | FE                  | FE                       | FE               |
|   | Offices             | Industrial Buildings | Localisation        | Industry-specific effect | Nonlinear effect |
| Agglomeration, $n_{jt}$                                     | 0.100<br>(0.033)*** | -0.079<br>(0.088)    | 0.098<br>(0.031)*** |                          |                  |
| Localisation, $n_{jt}^{loc}$                                |                     |                      | 0.003<br>(0.002)    |                          |                  |
| Agglomeration, $n_{jt}$ ,<br>industry-specific effects (14) | No                  | No                   | No                  | Yes                      | No               |
| Agglomeration, $n_{jt}$ ,<br>centile-specific effects (10)  | No                  | No                   | No                  | No                       | Yes              |
| Control variables included (51)                             | Yes                 | Yes                  | Yes                 | Yes                      | Yes              |
| PC6 fixed effects (8,461)                                   | Yes                 | Yes                  | Yes                 | Yes                      | Yes              |
| Spatial decay agglomeration $\delta^*$ (km)                 | 11                  | 6                    | 13                  | 14                       | 14               |
| Spatial decay localisation $\delta_{loc}^*$ (km)            |                     |                      | 2                   |                          |                  |
| Cross-validation score                                      | 0.02441             | 0.04523              | 0.03706             | 0.03699                  | 0.03701          |
| $R^2$   | 0.8612              | 0.8400               | 0.9193              | 0.9195                   | 0.9194           |

Notes: The number of observations in Specifications (5) and (6) is respectively 15,823 and 8,263. See Table 1.

Specification (7) also adds a variable that measures the number of employees in the own-industry (or localisation). For 10 percent of the transactions I do not have data on the industry, so I cannot estimate localisation densities. I then include a dummy in the specification when localisation is missing.<sup>31</sup> It is shown that the coefficient of agglomeration is about the same as in Specification (3) and localisation does not have an effect on rents. It is therefore that the spatial decay parameter of localisation is much lower because it is hard to properly estimate a spatial decay when an effect is (almost) absent.

It may be that the effect of agglomeration is heterogeneous between firms in different industries. So, agglomeration is interacted with industry dummies (see Specification (8) and Table A2, Appendix A for the classification). It is shown in Figure (4) that the effect of agglomeration is very similar across different industries. Only the effect of the hospitality industry is statistically significantly different from some other industries, but that is likely due to the relatively low number of observations (only 131).<sup>32</sup>

<sup>31</sup> Excluding these observations will lead to almost identical results.

<sup>32</sup> Koster et al. (2012) also found that there is only modest heterogeneity of the agglomeration effect between industries. They show that only retailers and the government are willing to pay substantially

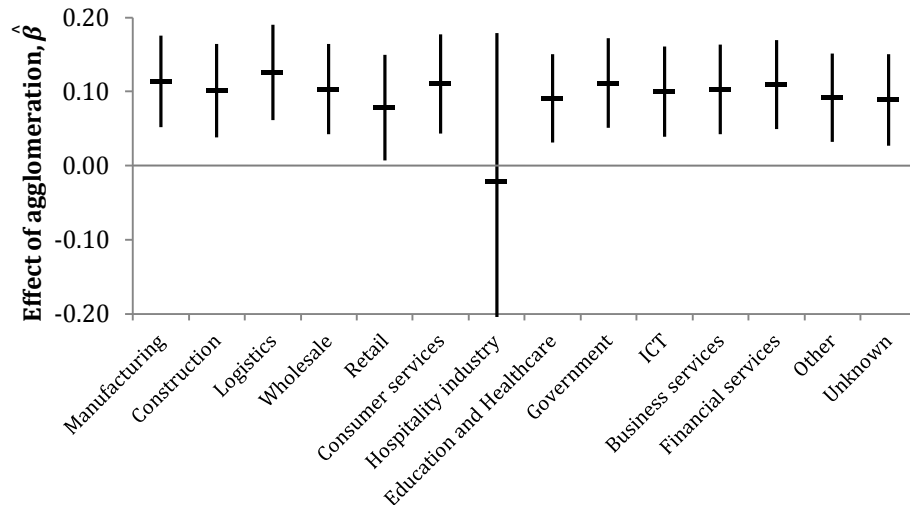


FIGURE 4 — HETEROGENEITY IN THE EFFECT OF AGGLOMERATION

*Notes:* The vertical bars denote 95 percent confidence intervals and the horizontal bars denote point estimates for each industry.

Specification (9) considers the possibility of a nonlinear effect of agglomeration. Agglomeration  $n_{jt}$  is therefore interacted with centile dummies. Figure 5 shows the marginal effect of agglomeration for different values of agglomeration. The results suggest that agglomeration benefits are more pronounced in dense areas. For example, in a strongly urbanised area (e.g. Amsterdam or Rotterdam) a standard deviation increase in agglomeration leads to an increase in rents of about 10 percent, whereas on the countryside a standard deviation increase in agglomeration seem to have no impact on rents. For low values of agglomeration, the confidence intervals are relatively wide, so I cannot reject a linear relationship of agglomeration, as the coefficient of Specification (3) almost always falls in the 95 confidence interval.

---

more for agglomeration. However, in that paper, also shops are taken into account, which explains the strong preference of retailers for dense areas. I also investigate

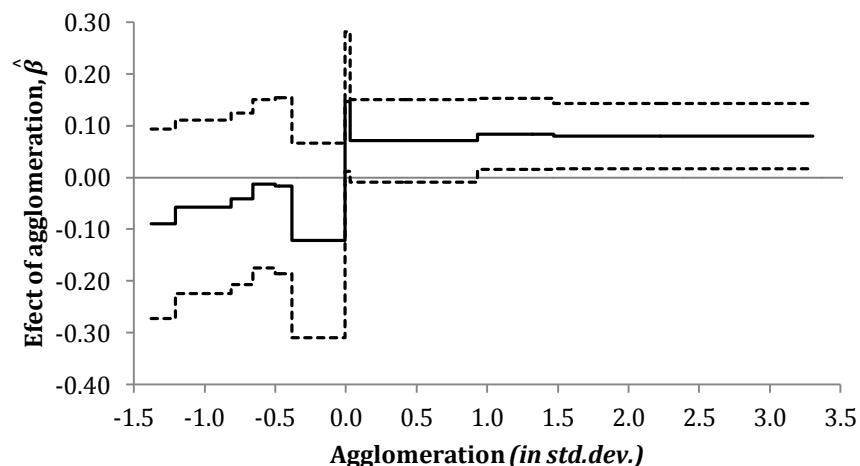


FIGURE 5 — NONLINEAR EFFECT OF AGGLOMERATION

## V. Robustness analysis

### A. Introduction

The robustness analysis focuses on four sets of issues. First, is the regression using a shift-share instrument robust? I will use other instruments and use other approaches to test the correlation of agglomeration to unobserved negative shocks. Second, is the assumption of a Tricube weighting function for the spatial decay of agglomeration appropriate? Third, is it possible that a large portion of the effect of agglomeration is explained by the presence of consumption amenities? If this is the case, changes in house prices and changes in commercial rents should move in the same direction. Fourth, is the measure of agglomeration robust to excluding time-varying locational endowments, geographical size of the fixed effects?

### B. Endogeneity of agglomeration

To identify the causal impact of agglomeration on commercial rents, changes in unobserved endowments should be uncorrelated to changes in agglomeration. In this subsection I will investigate whether the results of Specification (4) are robust to other assumptions on how shocks impact the local environment. The results are presented in Table 3.

First, in Specification (10), I construct the shift-share instrument on the SBI five-digit level. It may be argued that when industries are reasonably small, the shift-share instrument may be correlated to local shocks. Again, this argument only applies when local shocks impact the total number of employees in an industry, so when local shocks induce start-ups or exits. When I use the most detailed SBI five-digit sectoral classification (the



average size of an industry was only 7,782 employees in 1996), one may conjecture that the results are different from the estimates in Specification (4), which relies on a much less detailed sectoral classification. However, it is shown that the results are almost identical to the results of Specification (4), suggesting that my instrument is valid.

TABLE 3 — REGRESSION RESULTS, AGGLOMERATION AND SHOCKS  
(Dependent variable: the logarithm of rent per square meter)

|   | (10)                | (11)               | (12)                | (13)               | (14)               |
|---|---------------------|--------------------|---------------------|--------------------|--------------------|
|   | IV – FE             | FE                 | FE                  | IV – FE            | IV – FE            |
|   | <i>SBI 5-digit</i>  | <i>Municipa-</i>   | <i>NUTS2-year,</i>  | <i>Political</i>   | <i>Political</i>   |
|   | <i>instrument</i>   | <i>lity trends</i> | <i>coordinates</i>  | <i>instruments</i> | <i>instruments</i> |
| Agglomeration, $n_{jt}$                       | 0.121<br>(0.034)*** | 0.163<br>(0.066)** | 0.162<br>(0.040)*** | 0.132<br>(0.097)   | 0.208<br>(0.147)   |
| Control variables included (51)               | Yes                 | Yes                | Yes                 | Yes                | Yes                |
| PC6 fixed effects (8,461)                     | Yes                 | Yes                | Yes                 | Yes                | Yes                |
| Municipality-specific trends (714)            | No                  | Yes                | No                  | No                 | No                 |
| NUTS2-year fixed effects (180)                | No                  | No                 | Yes                 | No                 | Yes                |
| Function of location and year $\theta(\cdot)$ | No                  | No                 | Yes                 | No                 | Yes                |
| Spatial decay $\delta$                        | 17                  | 11                 | 14                  | 10                 | 13                 |
| Cross validation score $CV(\delta)$           | 0.03707             | 0.03589            | 0.03649             | 0.03707            | 0.03610            |
| $R^2$   |                     | 0.9241             | 0.9214              |                    |                    |
| $F$ -Test first-stage                         | 2,816.425           |                    |                     | 194.023            | 135.929            |

Notes: See Table 1. The instrument in Specification (8) is the shift-share instrument (see equation (12)) based on a five-digit SBI level. Instruments in Specification (11) and (12) are the municipal share of voters for socialist parties, the share of voters for liberal parties and the share of voters for Christian parties and the share if these parties have the maximum share. Reference category is the share of voters for local parties. First-stage results are presented in Table B1, Appendix B.

I also may avoid the use of a shift-share instrument, for example because pre-trends may be correlated with the initial industrial shares. Alternatively, I assume that shocks only operate at a municipal scale. For example, some municipality-specific subsidies may attract firms, which lead to higher rents. In Specification (11), I include linear-quadratic time trends for each municipality to control for changes in unobservables. It is shown that the effect of agglomeration is somewhat higher: one standard deviation increase in agglomeration leads to an increase in rents of 16.2 percent, which suggests that the preferred estimate is a lower bound estimate of the effect of agglomeration. However, the Hausman  $t$ -statistic does not suggest that the coefficient of agglomeration economies is statistically different from Specification (3) (the  $t$ -value is -1.09).

Another way to proceed is to include fixed effects for each NUTS2 area  $A$  in each year.<sup>33</sup> However, it is likely that there are local unobserved time-varying endowments. It is then assumed that these time-varying unobserved endowments are continuous and smooth over space and not (perfectly) collinear with agglomeration, so that these are captured by a flexible nonparametric function of geographic coordinates and time. I estimate  $\log r_{jt} = \beta n_{jt}(\delta) + \gamma m_{jt} + z'_{jt}\theta + \Theta_A(x, y, t) + \mu_{Ajt} + \lambda_j + \tau_t + \epsilon_{jt}$ , where  $\Theta(\cdot)$  is a flexible NUTS2-specific function of the  $x$ -coordinate, the  $y$ -coordinate and year  $t$ , and  $\mu_{Ajt}$  denotes a NUTS2-year fixed effect. It is shown that the coefficient of agglomeration is statistically significantly higher than the preferred estimate, so my initial estimate may be somewhat conservative (the Hausman  $t$ -statistic is -2.40).

Specification (13) uses alternative instruments to control for unobserved shocks. Following Duranton et al. (2011), I use political instruments. Using data from the *Election Council*, I calculate the municipal shares of votes for local parties, liberal (right-wing) parties, socialist (left-wing) parties and Christian parties. Especially socialist parties tend to focus on low unemployment rates and therefore aim to create new jobs. Right-wing liberal parties tend to be more focused on attracting high income households and high levels of education. As it is forbidden by law to provide government assistance to individual firms, vote shares arguably only impact rents via changes in agglomeration levels, conditional on control variables. Municipal elections took place in 1994, 1998, 2002, 2006 and 2010, so there is spatial and temporal variation in vote shares. Specification (13) shows that agglomeration has a positive impact on rents similar to Specification (3), but the effect is not statistically significant.<sup>34</sup> Duranton et al. (2011) argue that the validity of the political instruments may be questioned without spatial differencing, because the share of voters for a political party may be correlated with unobserved shocks. I therefore re-estimate equation (11), but now I include region-year fixed  $\mu_{Ajt}$  effects and a flexible function of location and time  $\Theta_A(\cdot)$ . Specification (14) shows that the coefficient of agglomeration is now somewhat higher (0.208) but still is not statistically significantly different from Specification (3) (the Hausman  $t$ -value is -0.76)

---

<sup>33</sup> A NUTS2 (Nomenclature of Territorial Units for Statistics) area is comparable in size to Metropolitan Statistical Areas (MSAs) in the United States. In the Netherlands, there are 12 NUTS2 regions. The time period of the sample is 15 years, which implies 180 fixed effects.

<sup>34</sup> I include vote shares and the vote shares if it is the maximum share. As, in the Netherlands, parties almost always have to form coalitions, it makes sense to include also the maximum vote shares.

All in all, the results suggest that agglomeration is not strongly correlated to shocks. The specifications in this subsection suggest a slightly higher coefficient of agglomeration, so the preferred estimate (Specification (3)) seems to be somewhat conservative.

### C. Spatial attenuation of agglomeration economies

As acknowledged earlier, the choice of the kernel function is arbitrary. I will first employ a nonparametric weighting function by including the total employment in 5 kilometres rings around the employment location, following Rosenthal and Stange (2002). Then, I compare the estimates using the Tricube weighting function with a Triangular, an Exponential and an Epanechnikov kernel. Table 4 presents the results.

TABLE 4 – REGRESSION RESULTS, ATTENUATION OF AGGLOMERATION ECONOMIES  
(Dependent variable: the logarithm of rent per square meter)

|                                      | (15)            | (16)                     | (17)                       | (18)                      |
|--------------------------------------|-----------------|--------------------------|----------------------------|---------------------------|
|                                      | FE              | FE                       | FE                         | FE                        |
|                                      |                 | <i>Triangular kernel</i> | <i>Epanechnikov kernel</i> | <i>Exponential kernel</i> |
| Agglomeration, $n_{jt}$              |                 | 0.101 (0.031)***         | 0.099 (0.031)***           | 0.103 (0.031)***          |
| Agglomeration 0-5 km                 | 0.105 (0.052)** |                          |                            |                           |
| Agglomeration 5-10 km                | 0.051 (0.037)   |                          |                            |                           |
| Agglomeration 10-15 km               | -0.026 (0.032)  |                          |                            |                           |
| Control variables included (51)      | Yes             | Yes                      | Yes                        | Yes                       |
| PC6 fixed effects (8,461)            | Yes             | Yes                      | Yes                        | Yes                       |
| Spatial decay agglomeration $\delta$ |                 | 12                       | 11                         | 12                        |
| Cross validation score $CV(\delta)$  | 0.03706         | 0.03706                  | 0.03706                    | 0.03705                   |
| $R^2$                                | 0.9192          | 0.9192                   | 0.9192                     | 0.9193                    |

Notes: See Table 1. The Triangular kernel is calculated as  $\Omega(d_{jk}, \delta) = (1 - (d_{jk}/\delta))I(d_{jk} < \delta)$ , the Epanechnikov kernel as  $\Omega(d_{jk}, \delta) = (1 - (d_{jk}/\delta)^2)I(d_{jk} < \delta)$  and the Exponential kernel as  $\Omega(d_{jk}, \delta) = (1 - \sqrt{d_{jk}/\delta})I(d_{jk} < \delta)$ .

Specification (15) shows that an increase of 113,429 employees within 5 kilometres increases rents with 10.5 percent.<sup>35</sup> This effect is almost half when this increase is between 5 and 10 kilometres of the firm location. For distances larger than 10 kilometres, the effect becomes effectively zero. I plot this relationship in Figure 4, together with the spatial attenuation implied by Tricube weighting function, based on Specification (3). It is shown that the Tricube weighting function is almost always within the 95 confidence interval of the ‘nonparametric’ attenuation function. This is mainly because of relatively wide confidence intervals, which stresses the importance of the more efficient estimation approach proposed in this paper. Nevertheless, also the point estimates of Specification (15) more or less follow the attenuation function implied by the Tricube kernel.

<sup>35</sup> 113,429 employees is a standard deviation increase in (weighted) employment for a Tricube kernel function given  $\delta = 13$ .

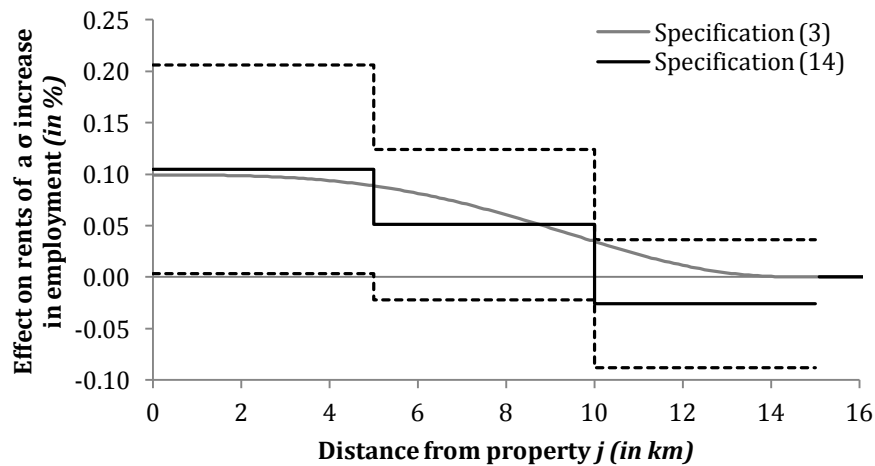


FIGURE 4 – SPATIAL ATTENUATION OF AGGLOMERATION ECONOMIES

Notes: The dotted lines indicate the 95 confidence interval of Specification (15)

When I test for different kernel functions, the effects of agglomeration are almost identical to the coefficients of Specification (3) (see Specifications (16), (17) and (18)). Also the spatial decay parameters are very similar to the spatial decay of a Tricube weighting function. It may be shown that the Exponential kernel fits the data slightly better than the other kernel functions, but the differences in cross-validation scores for the optimal spatial decay parameter are very small (see Figure D2 in Appendix D).

#### D. Production effects and consumption amenities

The theoretical framework Section III.A suggests a very strong relationship between house prices and commercial rents, as changes in density influence both equilibrium rents of commercial and residential properties via wages.<sup>36</sup> This may be worrisome when one is interested in the pure productivity effects of agglomeration instead of consumption amenities that are correlated with density. More specifically, when employment density is also an important determinant of residential rents, the previous specifications overestimate the productivity benefits of agglomeration.

Although in the current paper I cannot fully exclude the possibility that some consumption amenities capitalise into commercial rents, I will investigate the (temporal) correlation between commercial rents and residential property values. When there is a

<sup>36</sup> One may argue that it is preferable to use data on residential rents instead of prices. However, in the Netherlands, the large majority of rents are controlled and owners of rent-controlled apartments are not allowed to sell these apartments by terminating rent controls. So, rents are almost certainly not reflecting the true market price (see Van Ommeren and Koopman, 2009)

strong correlation, commercial rents and house prices likely have the same determinants (e.g. employment density). Absence of a correlation suggests that rents and prices have different determinants. I then estimate the following (non-causal) regression:

$$(13) \quad \log r_{jt} = \nu \log \bar{p}_{jt} + \lambda_j + \tau_t + \epsilon_{jt},$$

where  $\bar{p}_{jt}$  is the average house price per square meter in year  $t$  in a PC6 area and  $\nu$  is a parameter to be estimated.  $\lambda_j$  and  $\tau_t$  are respectively a location and year fixed effect and  $\epsilon_{jt}$  represents an identically and independently distributed error term.

I use a dataset that contains about 2 million residential property transactions from the NVM (Dutch Association of Real Estate Agents). It consists of a large majority (about 75 percent) of (owner-occupied) housing transactions between 1995 and 2009. I calculate the logarithm of the average price per square meter in a PC6 area. I only select commercial transactions for which I have observations of prices in a certain year in the same postcode. Unfortunately, the number of observations is limited and 1,173, which most likely leads to higher standard errors.

TABLE 5 — COMMERCIAL RENTS AND HOUSE PRICES  
(Dependent variable: the logarithm of rent per square meter)

|                                     | (19)  | (20)       | (21)   |
|-------------------------------------|-------|------------|--------|
|                                     | OLS   | FE         | FE     |
| House prices, $\log \bar{p}_{jt}$   | 0.537 | *** -0.140 |        |
| House prices, $\log \bar{p}_{jt-1}$ |       |            | -0.006 |
| Year fixed effects (15)             | Yes   | Yes        | Yes    |
| PC6 fixed effects (663)             | No    | Yes        | Yes    |
| $R^2$                               | 0.154 | 0.932      | 0.920  |

Notes: See Table 1. The number of observations is 1,173 in Specifications (B11) and (B12) and 1,261 in Specification (B13). The standard errors are clustered at the postcode six-digit level.

Table 5 presents the results. To investigate *spatial* correlation between house prices and commercial rents, Specification (14) only includes year fixed effects and finds that house prices and commercial rents are positively correlated. However, when I include PC6 fixed effects to investigate whether changes in house prices and changes in commercial rents are correlated, I find a negative but statistically insignificant effect (see Specification (15)). Specification (16) includes the house prices of the previous year  $\bar{p}_{jt-1}$  as a determinant of commercial rents. Again, there is no statistically significant correlation between commercial rents and house prices. These results suggest that changes in commercial rents and house prices are uncorrelated, which suggests that commercial rents and house prices have different determinants. So, this reduces the probability that a large part of the productivity

effect found in Specification (3) is just representing the presence of consumption amenities in dense areas.

#### E. Robustness analysis – other specifications

In this subsection, I investigate robustness of the results with respect to control variables and the choice of kernel function. Results are presented in Table 6. Specification (22) does not include any of the 13 location control variables to test the assumption that agglomeration is correlated to other changes in the environment. It is shown that the coefficient of agglomeration is very similar and 0.106, suggesting that changes in control variables are not strongly correlated to changes in agglomeration.

TABLE 6 – REGRESSION RESULTS, ALTERNATIVE SPECIFICATIONS  
(Dependent variable: the logarithm of rent per square meter)

|   | (22)                 | (23)                | (24)                   | (25)                      | (26)                |
|---|----------------------|---------------------|------------------------|---------------------------|---------------------|
|   | FE                   | FE                  | FE                     | FE                        | FE                  |
|   | No location controls | Population flexible | Building fixed effects | Time-varying coefficients | Only moving firms   |
| Agglomeration, $n_{jt}$                       | 0.106<br>(0.032)***  | 0.121<br>(0.032)*** | 0.076<br>(0.032)**     |                           | 0.092<br>(0.031)*** |
| Agglomeration, $n_{jt}$ , 1997-2001           |                      |                     |                        | 0.160<br>(0.047)***       |                     |
| Agglomeration, $n_{jt}$ , 2002-2006           |                      |                     |                        | 0.153<br>(0.042)***       |                     |
| Agglomeration, $n_{jt}$ , 2007-2011           |                      |                     |                        | 0.141<br>(0.041)***       |                     |
| Population, $m_{jt}$                          |                      | -0.111<br>(0.097)   | -0.001<br>(0.051)      | 0.010<br>(0.038)          | 0.010<br>(0.039)    |
| Control variables included (38/51)            | Yes                  | Yes                 | Yes                    | Yes                       | Yes                 |
| PC6 fixed effects (8,461)                     | Yes                  | Yes                 | No                     | Yes                       | Yes                 |
| Building fixed effects (12,988)               | No                   | No                  | Yes                    | No                        | No                  |
| Spatial decay $\delta^*$ (in km)              | 12                   | 10                  | 13                     | 16                        | 13                  |
| Spatial decay population $\omega$ (in km)     |                      | 9                   | 2.5                    | 2.5                       | 2.5                 |
| Cross validation score $CV(\delta^*, \omega)$ | 0.03719              | 0.03705             | 0.02596                | 0.03704                   | 0.03727             |
| $R^2$   | 0.9189               | 0.9193              | 0.9598                 | 0.9193                    | 0.9194              |

Notes: See Table 1. The number of observations in Specification (26) is 23,644. The standard errors are clustered at the PC6 level in Specification (22), (23), (25) and (26) and at the building level in Specification (24).

In Specification (23) I do not fix the decay parameter related to population  $\omega$  to 2.5, but jointly optimise  $\delta$  and  $\omega$ . It is shown that the effect of agglomeration is similar, but the coefficient of population is negative and statistically insignificant. This is again evidence that amenities are unlikely to be strongly correlated with productivity effects, as locations with strong population growth are less attractive to firms. One may also argue that population

reflect effect of labour market pooling. Absence of a positive effect of population would then be surprising. However, in my opinion, population does not reflect labour market pooling, as it does capture any measure of skill relatedness (see e.g. Amiti and Cameron, 2007; Andersson et al., 2007; Ellison et al., 2010).

One may still argue that I do not control for all spatial variation in unobserved endowments by including six-digit postcode effects. In Specification (24) I therefore include 12,988 building fixed effects instead of PC6 fixed effects. The results show that agglomeration is still positively related to rents and statistically significant at the five percent level: a standard deviation increase in agglomeration leads to an increase in rents of 7.6 percent. Note that the spatial decay of agglomeration effects is found to be exactly the same as in Specification (3).

In the estimated equation (9) it is assumed that the coefficient of agglomeration  $\beta$  is time-invariant (and so are the underlying structural parameters  $\alpha$ ,  $\zeta$  and  $\phi$ ). I test this assumption by interacting agglomeration with a dummy for each five-year period from 1997 onwards. Specification (25) shows that the coefficients are slightly higher (because  $\delta$  is different) than the estimates in Specification (3) but, more importantly, the effect is very persistent over time.

In equation (7) the kernel employment densities are estimated based on employment of firms in the preceding year. It is well known that including the own-firm employment may lead to biases. This is not an issue here, as in most cases the tenant is a start-up or mover. Furthermore, I identify agglomeration based on changes in densities. Firms that stay do therefore not contribute to identification of the agglomeration effect. Nonetheless, to avoid the possibility of any bias, I exclude firms that have prolonged their contract. It appears that the coefficient of agglomeration is slightly lower but very similar to Specification (3) (see Specification (26)).

## VI. Conclusions

In this study I use unique micro-data to estimate the impact of agglomeration economies. The contribution of this paper is threefold. First, rather than using long-lagged instruments, agglomeration economies are identified based on temporal variation in densities. The key identifying assumption is that unobserved natural advantages and locational endowments are time-invariant. I relax this assumption by using a 'shift-share' instrumental variables approach. Second, the space-continuous data enable me to introduce a new method to determine the geographical scope of agglomeration economies by minimising a cross-validation score. Third, this is one of the first papers that uses commercial rents to measure

agglomeration economies. Rents represent a monetary value and are easy to compare across industries and time.

The results indicate that a standard deviation increase in agglomeration leads to an increase in rents of about 10 percent. Agglomeration economies are found to be important in the office market, but not in the market for industrial buildings. Localisation economies do not seem to capitalise into commercial rents. The geographical scope of agglomeration economies is about 15 kilometres, confirming results of other studies that find that agglomeration economies are rather localised and are therefore more likely to capitalise into rents, rather than in wages. The results also suggest that unobserved time-invariant as well as unobserved shocks are not strongly correlated with agglomeration.

Further research should pay attention to the relative importance of different sources of agglomeration economies and how they capitalise into commercial rents (see Ellison et al., 2010; Greenstone et al., 2010). For example, localised knowledge spillovers are likely to capitalise into rents, whereas long-distance input-output relationships that extend over the region are more likely to capitalise into wages.

### References

- Acs, Z.J., Audretsch, D., Feldman, M. (1991). Real Effects of Academic Research: a Comment. *American Economic Review* 82(1): 363-367.
- Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N. (2012). The Economics of Density: Evidence from the Berlin Wall. *Mimeo, London School of Economics*.
- Amiti, M., Cameron, L. (2007). Economic Geography and Wages. *Review of Economics and Statistics* 89(1): 15-29.
- Anas, A., Arnott, R., Small, K.A. (1998). Urban Spatial Structure. *Journal of Economic Literature* 36(3): 1426-1464.
- Andersson, F., Burgess, S., Lane, J.I. (2007). Cities, Matching and the Productivity Gains of Agglomeration. *Journal of Urban Economics* 61: 112-118.
- Arzaghi, M., Henderson, J.V. (2008). Networking off Madison Avenue. *Review of Economic Studies* 75: 1011-1038.
- Bartik, T.J. (1991). Who Benefits from State and Local Economic Development Policies? *Kalamazoo: Upjohn Institute Press*.
- Bartik, T.J. (1994). The Effects of Metropolitan Job Growth on the Size Distribution of Family Income. *Journal of Regional Science* 34(4): 483-501.
- Bayer, P., Timmins, C. (2007). Estimating Equilibrium Models of Sorting Across Locations. *Economic Journal* 117: 353-374.
- Bowman, A.W. (1984). An Alternative Method of Cross-Validation for the Smoothing Density Estimates. *Biometrika* 71(2): 353-360.



- Briant, A., Combes, P.P., Lafourcade, M. (2010). Dots to Boxes: Do the Size and Shape Jeopardise Economic Geography Estimations. *Journal of Urban Economics* 67(3): 287-302.
- Combes, P.P., Duranton, G., Gobillon, L. (2008). Spatial Wage Disparities: Sorting Matters! *Journal of Urban Economics* 63: 723-742.
- Combes, P.P., Duranton, G., Gobillon, L., Roux, S. (2011). Estimating Agglomeration Economies with History, Geology, and Worker Fixed Effects. In: *Glaeser, E.L. (ed.). Agglomeration Economics*, pp. 15-35. Chicago, IL: The University of Chicago Press.
- Combes, P.P., Duranton, G., Gobillon, L. (2011). The Identification of Agglomeration Economies. *Journal of Economic Geography* 11(2): 253-266.
- Ciccone, A., Hall, R.E. (1996). Productivity and the Density of Economic Activity. *American Economic Review* 86(1): 54-70.
- Ciccone, A. (2002). Agglomeration Effects in Europe. *European Economic Review* 46: 213-227.
- Cleveland, W.S. (1979). Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association* 74(368): 829-836.
- Davis, J.C., Henderson, J.V. (2008). The Agglomeration of Headquarters. *Regional Science and Urban Economics* 38: 445-460.
- Dekle, R., Eaton, J. (1999). Agglomeration and Land Rents: Evidence from the Prefectures. *Journal of Urban Economics* 46: 200-214.
- Drennan, M.P., Kelly, H.F. (2011). Measuring Urban Agglomeration Economies with Office Rents. *Journal of Economic Geography* 11(3): 481-507.
- Duranton, G., Gobillon, L., Overman, H.G. (2011). Assessing the Effects of Local Taxation Using Microgeographic Data. *The Economic Journal* 121: 1017-1046.
- Duranton, G., Monastiriotis, V. (2002). Mind the Gaps: the Evolution of Regional Earnings Inequalities in the UK, 1982-1997. *Journal of Regional Science* 42(2): 219-256.
- Duranton, G., Overman, H.G. (2005). Testing for Localization Using Micro-Geographic Data. *Review of Economic Studies* 72, 1077-1106.
- Eberts, R., McMillen, D. (1999). Agglomeration Economies and Urban Public Infrastructure. In: *Cheshire, P., Mills, E. (eds). Handbook of Regional and Urban Economics 3, Applied Urban Economics*, pp. 1455-1495. Amsterdam: North-Holland.
- Eichholtz, P., Kok, N., Quigley, J.M. (2010). Doing Well by Doing Good? Green Office Buildings. *American Economic Review* 100: 2492-2509.
- Ellison, G., Glaeser, E.L. (1997). Geographic Concentration in US Manufacturing Industries: a Dartboard Approach. *Journal of Political Economy* 105(5): 889-927
- Ellison, G., Glaeser, E.L. (1999). The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? *American Economic Review* 89(2): 311-316.
- Ellison, G., Glaeser, E.L., Kerr, W.R. (2010). What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns. *American Economic Review* 100: 1195-1213.
- Faggio, G., Overman, H.G., (2012). The Effect of Public Sector Employment on Local Labour Markets. *Mimeo, London School of Economics*.

- Farber, S., Páez, A. (2007). A Systematic Investigation of Cross-Validation in GWR Model Estimation: Empirical Analysis and Monte Carlo Simulations. *Journal of Geographic Systems* 9(4): 371-396.
- Figueiredo, O., Guimarães, P., Woodward, D. (2002). Home-Field Advantage.: Location Decisions of Portuguese Entrepreneurs. *Journal of Urban Economics* 52(2): 341-361.
- Fotheringham, A.S., Brunsdon, C., Charlton, M. (2002). Geographically Weighted Regression. The Analysis of Spatially Varying Relationships. *Chichester: Wiley*.
- Glaeser, E.L., Gottlieb, J.D. (2009). The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature* 47(4): 983-1028.
- Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Shleifer, A. (1992). Growth in Cities. *Journal of Political Economy* 100(6): 1126-1152
- Glaeser, E.L., Kolko, J., Saiz, A. (2001). Consumer City. *Journal of Economic Geography* 1: 27-50.
- Glaeser, E.L., Maré, D. (2001). Cities and Skills. *Journal of Labour Economics* 19: 316-342.
- Greenstone, M., Hornbeck, R., Moretti, E. (2010). Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings. *Journal of Political Economy* 118(3): 536-598.
- Groot, S.P.T., De Groot, H.L.F., Smit, M.J. (2011). Regional Wage Differences in the Netherlands: Micro-Evidence on Agglomeration Externalities. *Tinbergen Discussion Paper TI 2011-050/3*
- Hilber, C.A.L., Voicu, I. (2010). Agglomeration Economies and the Location of Foreign Direct Investment: Empirical Evidence from Romania. *Regional Studies* 44(3): 355-371.
- Hoover, E.M. (1936). The Measurement of Industrial Localisation. *Review of Economics and Statistics* 18(4): 161-171.
- Hoover, E.M. (1937). Location Theories and the Shoe and Leather Industries. *Cambridge MA: Harvard University Press*.
- Hurvich, C.M., Simonoff, J.S., Tsai, C.L. (1998). Smoothing Parameter Selection in Nonparametric Regression Using an Improved Akaike Information Criterion. *Journal of the Royal Statistical Society B* 60(2): 271-293.
- Imbens, G.W., Lemieux, T. (2008). Regression Discontinuity Design: A Guide to Practice. *Journal of Econometrics* 142: 615-635.
- Jacobs, J. (1969). The Economy of Cities. *New York: Vintage*.
- Jacobs, W., Koster, H.R.A., Hall, P.V. (2011). The Location and Global Network Structure of Maritime Advanced Producer Services. *Urban Studies* 48(13): 2749-2769.
- Jacobs, W., Koster, H.R.A., Van Oort, F. (2012). Start-ups of Knowledge Intensive Business Services and Proximity to MNEs: Testing for Co-agglomeration in the Netherlands. *Under review in Journal of Economic Geography*.
- Koster, H.R.A., Rouwendal, J. (2012). The Impact of Mixed Land Use on Residential Property Values. *Forthcoming in Journal of Regional Science*.
- Koster, H.R.A., Van Ommeren, J.N., Rietveld, P. (2012). Agglomeration Economies and Productivity: A Structural Estimation Approach using Commercial Rents. *Forthcoming in Economica*.
- Lee, D.S., Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature* 48: 281-355.

- Lucas, R.E., Jr., Rossi-Hansberg, E. (2002). On the Internal Structure of Cities. *Econometrica* 70(4): 1445-1476.
- Marshall, A. (1890). Principles of Economics. *London: MacMillan*.
- McMillen, D.P. (2010). Issues in Spatial Data Analysis. *Journal of Regional Science* 50(1): 119-141.
- McMillen, D.P., McDonald, J.F. (1998). Suburban Employment and Employment Density in Metropolitan Chicago. *Journal of Urban Economics* 43: 157-180.
- McMillen, D.P., Redfearn, C.L. (2010). Estimation and Hypothesis Testing for Nonparametric Hedonic House Price Functions. *Journal of Regional Science* 50(3): 712-733.
- Melo, P.C., Graham, D.J., Noland, R.B. (2009). A Meta-Analysis of Estimates of Urban Agglomeration Economies. *Regional Science and Urban Economics* 39: 332-342.
- Moretti, E. (2010). Local Multipliers. *American Economic Review: Papers and Proceedings* 100: 1-7.
- Morikawa, M. (2011). Economies of Density and Productivity in Service Industries: An Analysis of Personal Service Industries Based on Establishment-Level Data. *Review of Economics and Statistics* 93(1): 179-192.
- Ottaviano, G.I.P., Peri, G. (2006). The Economic Value of Cultural Diversity: Evidence from US Cities. *Journal of Economic Geography* 6(1): 9-44.
- Puga, D. (2010). The Magnitude and Causes of Agglomeration Economies. *Journal of Regional Science* 50(1): 203-219.
- Rappaport, J. (2008). Consumption Amenities and City Population Density. *Regional Science and Urban Economics* 38(6): 533-552.
- Rice, P., Venables, A.J., Patacchini, E. (2006). Spatial Determinants of Productivity: Analysis for Regions of Great Britain. *Regional Science and Urban Economics* 36: 727-752.
- Roback, J. (1982). Wages, Rents and the Quality of Life. *Journal of Political Economy* 90(6): 1257-1278.
- Rosenthal, S.S., Strange, W.C. (2003). Geography, Industrial Organisation, and Agglomeration. *Review of Economics and Statistics* 85(2): 377-393.
- Rosenthal, S.S., Strange, W.C. (2004). Evidence on the Nature and Sources of Agglomeration Economies. In: *Henderson, J.V., Thisse, J. (eds.). Handbook of Urban and Regional Economics, 4*.
- Rosenthal, S.S., Strange, W.C. (2008). Attenuation of Human Capital Spillovers. *Journal of Urban Economics* 64(2): 373-389.
- Rusinek, M., Tojerow, I. (2011). The Regional Dimension of Collective Wage Bargaining: the Case of Belgium. *Regional Studies* 12(13): 1-17.
- Simón, H., Ramos, R., Sanróma, R. (2006). Collective Bargaining and Regional Wage Differences in Spain: An Empirical Analysis. *Applied Economics* 38: 1749-1760.
- Storper, M., Venables, A.J. (2004). Buzz: Face-to-Face Contact and the Urban Economy. *Journal of Economic Geography* 4(4): 351-370.
- Van Ommeren, J.N., Koopman, M. (2009). Public Housing and the Value of Apartment Quality to Households. *Regional Science and Urban Economics* 41: 207-213.
- Van Ommeren, J.N., Wentink, D. (2011). The (Hidden) Cost of Employer Parking Policies. *International Economic Review, forthcoming*.

- Van Oort, F.G. (2004). Urban Growth and Innovation. Spatially Bounded Externalities in the Netherlands. *Aldershot: Ashgate.*
- Woodward, D. (1992). Locational Determinants of Japanese Manufacturing Start-Ups in the United States. *Southern Economic Journal* 58: 690-708.
- Woodward, D., Figueiredo, O., Guimarães, P. (2006). Beyond the Silicon Valley: University R&D and High-Technology Location. *Journal of Urban Economics* 60(1): 15-32.
- Wooldridge, J. (2002). Econometric Analysis of Cross-section and Panel Data. *Cambridge MA: MIT Press.*

## Appendix A - Descriptives

TABLE A1 – DESCRIPTIVE STATISTICS

|   | Mean    | Median  | Std.dev. | Min   | Max     |
|---|---------|---------|----------|-------|---------|
| Price per m <sup>2</sup> (in €)           | 105.782 | 105     | 53.716   | 20    | 668     |
| Agglomeration, $n_{it}$ ( $\delta = 15$ ) | 182,716 | 133,970 | 127,068  | 3,231 | 591,360 |
| Population, $m_{it}$ ( $\omega = 2.5$ )   | 22,873  | 17,913  | 19,112   | 25    | 109,869 |
| Land use - commercial                     | 0.127   |         |          |       |         |
| Land use - residential                    | 0.203   |         |          |       |         |
| Land use - industrial site                | 0.597   |         |          |       |         |
| Land use - other                          | 0.073   |         |          |       |         |
| Distance to industrial land (km)          | 0.046   | 0.000   | 0.130    | 0.000 | 4.560   |
| Distance to major road (km)               | 0.103   | 0.068   | 0.107    | 0.000 | 0.956   |
| Distance to railway (km)                  | 1.317   | 0.706   | 1.904    | 0.000 | 21.398  |
| Distance to station (km)                  | 2.256   | 1.619   | 2.337    | 0.033 | 22.532  |
| Distance to open space                    | 0.210   | 0.163   | 0.174    | 0.000 | 1.377   |
| Distance to water                         | 0.462   | 0.301   | 0.509    | 0.000 | 5.629   |
| Historic district - not assigned          | 0.926   |         |          |       |         |
| Historic district - in process            | 0.010   |         |          |       |         |
| Historic district - assigned              | 0.064   |         |          |       |         |
| Green heart                               | 0.034   |         |          |       |         |
| Size (m <sup>2</sup> )                    | 1,173   | 630     | 2,125    | 25    | 64,414  |
| Share office space                        | 0.681   | 1.000   | 0.432    | 0.000 | 1.000   |
| Share industrial space                    | 0.319   | 0.000   | 0.432    | 0.000 | 1.000   |
| Newly Constructed                         | 0.046   |         |          |       |         |
| Renovated                                 | 0.013   |         |          |       |         |
| Parking spaces                            | 18.178  | 10.000  | 28.072   | 2.000 | 450.000 |
| Parking spaces - missing                  | 0.861   |         |          |       |         |
| Listed building                           | 0.041   |         |          |       |         |
| Energy label A                            | 0.008   |         |          |       |         |
| Construction year                         | 1 971   | 1 989   | 65.177   | 1 190 | 2 011   |
| Building surface area (m <sup>2</sup> )   | 2,163   | 960     | 4,775    | 10    | 257,172 |
| Building - multitenant                    | 0.590   |         |          |       |         |
| Building - multiple uses                  | 0.348   |         |          |       |         |
| Rent - turnkey                            | 0.003   |         |          |       |         |
| Rent - sub rent                           | 0.023   |         |          |       |         |
| Rent - sale and lease back                | 0.006   |         |          |       |         |
| Rent - contract prolongation              | 0.018   |         |          |       |         |
| Rent - length contract (in years)         | 6.612   | 7.000   | 4.018    | 0.250 | 20.667  |
| Rent - length contract missing            | 0.975   |         |          |       |         |
| Industry missing                          | 0.091   |         |          |       |         |
| Transaction year                          | 2 004   | 2 004   | 3.990    | 1 997 | 2 011   |

*Note:* The number of observations is 24,086. The values referring to agglomeration and population density are unstandardised.

TABLE A2— INDUSTRIAL COMPOSITION

| Industry                 | SBI two-digit industry  |
|--------------------------|---|
| Manufacturing            | 6, 8, 9, 10, 18, 19, 20, 23, 25, 26, 27, 28, 29, 30, 35, 36, 37, 38, 39 |
| Construction             | 41, 42, 43  |
| Logistics                | 49, 50, 51, 52, 53  |
| Wholesale                | 45, 46  |
| Retail                   | 47  |
| Consumer services        | 33, 79, 80, 95, 96  |
| Hospitality industry     | 55, 56  |
| Education and healthcare | 85, 86, 87, 88  |
| Government               | 84  |
| ICT                      | 58, 59, 60, 63  |
| Financial services       | 64, 65, 66, 68, 69, 70, 71, 72, 73, 74, 75, 77, 78                      |
| Business services        | 82  |
| Other                    | 1, 2, 3, 90, 92, 93, 94, 97, 98,  |

### Appendix B –Estimating the distance decay parameter

In this Appendix I will pay attention to the determination of the distance decay parameter. For Specification (3), Figure B1 shows that the Cross-Validation score is minimised when  $\delta = 13$ . As in regression-discontinuity designs, there may be local minima (e.g. when  $\delta = 2$ ). I therefore do not use the Golden Section Search technique (see Fotheringham et al., 2002), but I search along a wide range of values of  $\delta$ . For values of  $\delta > \delta^*$  the Cross-Validation score is monotonically increasing. The range of  $\delta < 50$  seems therefore appropriate. In Figure B2 I show the estimated coefficients for agglomeration for different values of  $\delta$ . In this particular case,  $\beta$  is maximised when the cross-validation score is minimised. For large values of  $\delta$ , the coefficient of agglomeration becomes statistically insignificant.

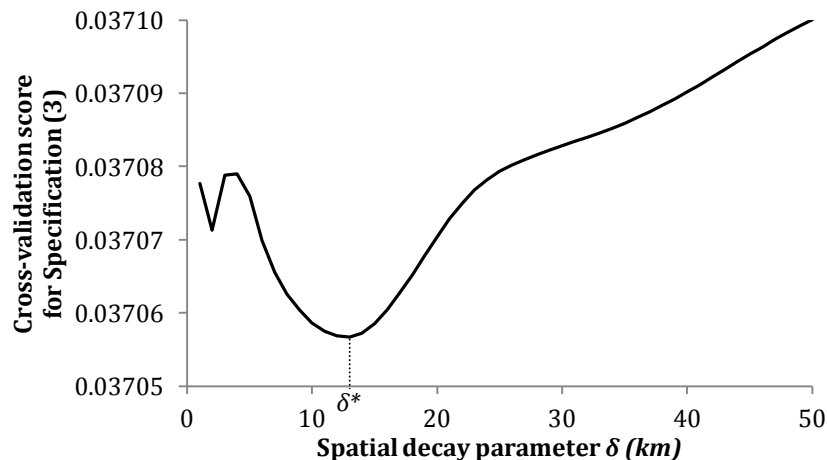


FIGURE B1 — CROSS-VALIDATION SCORES FOR SPECIFICATION (3)

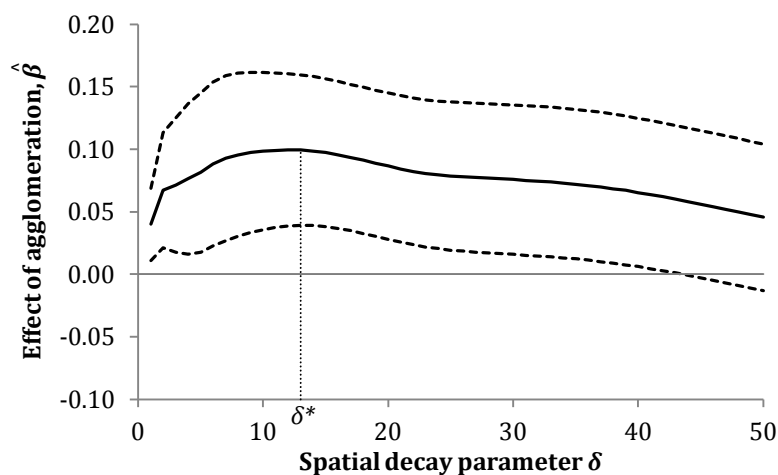


FIGURE B2 — MARGINAL INCREASE IN RENTS OF STANDARD DEVIATION INCREASE IN AGGLOMERATION FOR DIFFERENT DECAY PARAMETERS

### Appendix C - First-stage results

TABLE C1 — DESCRIPTIVE STATISTICS OF INSTRUMENTS

|  | Mean    | Median  | Std.dev.  | Min   | Max        |
|--|---------|---------|-----------|-------|------------|
| Population density 1830  | 899.339 | 82.997  | 2,564.873 | 6.219 | 19,934.827 |
| Distance to station 1870   | 4.278   | 2.682   | 4.572     | 0.007 | 35.958     |
| Agglomeration shift-share, $\hat{\pi}_{it}$ ( $\delta = 15$ ) SBI2 | 182,760 | 135,400 | 128,006   | 3,314 | 573,250    |
| Agglomeration shift-share, $\hat{\pi}_{it}$ ( $\delta = 15$ ) SBI5 | 180,291 | 131,465 | 126,411   | 3,207 | 560,300    |
| Share voters local party   | 0.221   | 0.203   | 0.129     | 0.000 | 1.000      |
| Share voters liberal party   | 0.230   | 0.226   | 0.083     | 0.000 | 0.547      |
| Share voters socialist party                                       | 0.339   | 0.342   | 0.136     | 0.000 | 0.724      |
| Share voters Christian party                                       | 0.208   | 0.193   | 0.102     | 0.000 | 0.780      |
| Share voters local party, maximum                                  | 0.087   | 0.000   | 0.173     | 0.000 | 1.000      |
| Share voters liberal party, maximum                                | 0.048   | 0.000   | 0.126     | 0.000 | 0.547      |
| Share voters socialist party, maximum                              | 0.237   | 0.325   | 0.223     | 0.000 | 0.724      |
| Share voters Christian party, maximum                              | 0.043   | 0.000   | 0.132     | 0.000 | 0.780      |

Note: The number of observations is 24,086. The values are unstandardised.

TABLE C2 – FIRST STAGE REGRESSION RESULTS  
*(Dependent variable: the logarithm of rent per square meter)*

|   | (2)                                      | (4)  | (9)  | (12)  | (13)  |
|---|--|--|--|---|---|
|   | IV – FE<br><i>Population<br/>density</i> | IV – FE<br><i>SBI 2-digit<br/>instrument</i> | IV – FE<br><i>SBI 5-digit<br/>instrument</i> | IV – FE<br><i>Political<br/>instruments</i> | IV – FE<br><i>Political<br/>instruments</i> |
| Population density 1830 ( <i>log</i> )        | -0.077<br>(0.008)***                     |  |  |   |   |
| Distance to station 1870                      | -0.032<br>(0.003)***                     |  |  |   |   |
| Agglomeration shift-share, $\hat{n}_{jt}$     |  | 0.761<br>(0.013)***                          | 0.766<br>(0.014)***                          |   |   |
| Share voters liberal party                    |  |  |  | -0.026<br>(0.004)***                        | -0.022<br>(0.004)***                        |
| Share voters socialist party                  |  |  |  | 0.090<br>(0.008)***                         | 0.053<br>(0.006)***                         |
| Share voters Christian party                  |  |  |  | -0.003<br>(0.005)                           | -0.012<br>(0.005)**                         |
| Share voters liberal party,<br>maximum        |  |  |  | -0.004<br>(0.003)                           | 0.009<br>(0.003)***                         |
| Share voters socialist party,<br>maximum      |  |  |  | -0.025<br>(0.003)***                        | -0.009<br>(0.004)**                         |
| Share voters Christian party,<br>maximum      |  |  |  | -0.004<br>(0.003)                           | 0.010<br>(0.003)***                         |
| Control variables included (51)               | Yes                                      | Yes  | Yes  | Yes   | Yes   |
| PC6 fixed effects (8,461)                     | Yes                                      | Yes  | Yes  | Yes   | Yes   |
| NUTS2-year fixed effects (180)                | No                                       | No   | No   | No  | Yes   |
| Function of location and year $\theta(\cdot)$ | No                                       | No   | No   | No  | Yes   |
| Spatial decay $\delta$                        | 18                                       | 17   | 17   | 10  | 13  |
| $R^2$ First-stage                             | 0.4074                                   | 0.9991                                       | 0.9991                                       | 0.9969                                      | 0.9983                                      |
| $F$ -Test weak instruments                    | 103.218                                  | 3,187.732                                    | 2,816.425                                    | 194.023                                     | 135.929                                     |

Notes: See Table 1. All instruments are transformed to have zero mean and unit standard deviation.

### Appendix D – Kernel functions

Throughout the paper, I employ a Tricube kernel to estimate employment densities. The average weight for a Tricube function is relatively high, in contrast to the Exponential distance decay function, which decays much more quickly. For example, for  $\delta = 13$ , 95 percent for the weight of a Tricube weighting function is within 9 kilometres of the location, given a uniform distribution of employment over space. For a Triangular, Epanechnikov and Exponential distance decay function, this is respectively 10.09, 10.56 and 5.8 kilometres. Figure D1 illustrates the shapes of the different kernel functions. Table D1 contains the regression results for different kernel functions (see also Section V.D). Figure D2 presents the cross-validation scores for three specifications with different kernel functions and highlights that the decay parameter is very similar for different kernel functions.



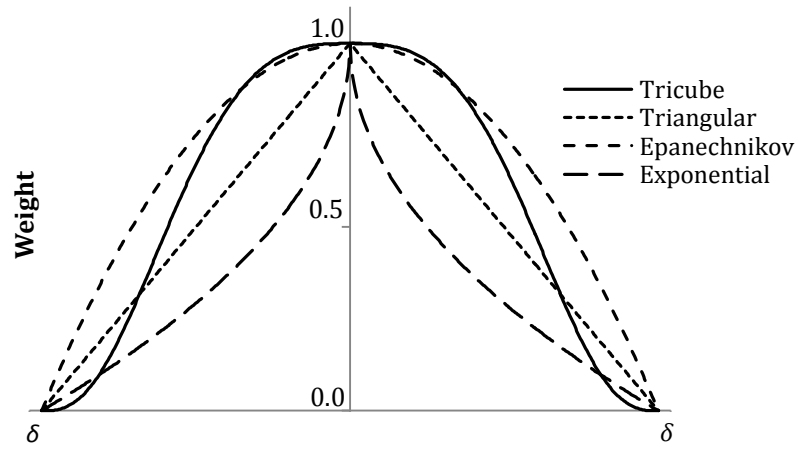


FIGURE D1 – KERNEL FUNCTIONS

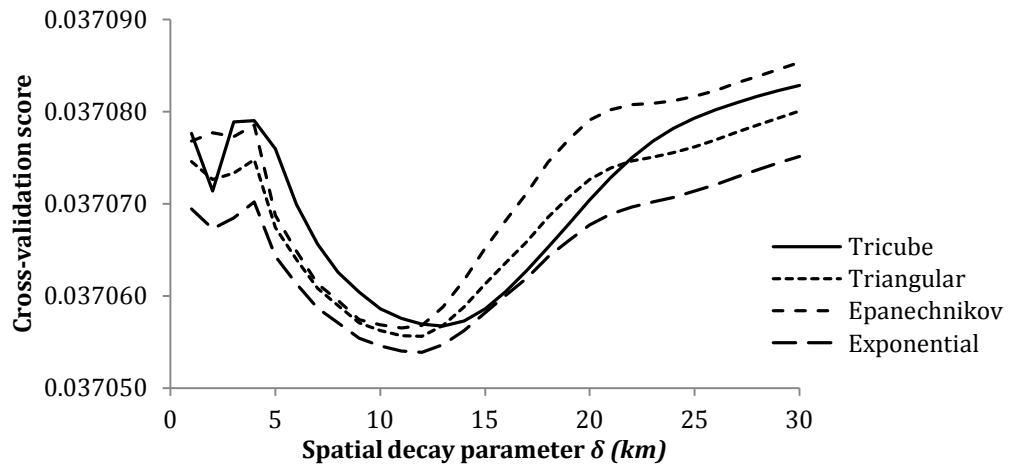


FIGURE D2 – CROSS-VALIDATION SCORES FOR SPECIFICATIONS (3), (16), (17) AND (18)