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

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January 2013

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Abstract

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 bandwidth 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 time-invariant unobserved endowments and unobserved shocks seems to be limited.

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 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 crowding effects, such as traffic congestion, high wages and higher crime rates, 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 similar or different firms (Marshall, 1890; Jacobs, 1969; Glaeser et al., 1992; Duranton and Puga, 2002; Ellison et al., 2010).[1] 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. However, the empirical literature faces a range of challenges in correctly measuring agglomeration economies, which are often proxied by employment density (see Puga, 2010; Combes et al., 2011).[2] 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). For example, Ellison and Glaeser (1999) conjecture that at least half of the observed concentration of firms is due to natural advantages. Many studies therefore use long-lagged instruments (e.g. employment density in 1800) 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.[3] Second, the measurement of agglomeration economies is often rather crude. Agglomeration economies are often measured as the density of employment at a city, metropolitan or even state level (Rosenthal and Strange, 2004). As geographical units are arbitrary, this may lead to biased estimates (Briant et al., 2010; Burger 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 too a large extent unknown.[4] Third, Rosenthal and Strange (2004) argue that high rents, as well as

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[1] In this paper I focus on agglomeration economies that arise between firms in all industries. Often, the literature refers to these agglomeration economies as urbanisation economies or economies of density.
[2] 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).
[3] 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 (see e.g. Ciccone and Hall, 1996). 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.
[4] Cross-sectional studies find that localisation economies (industry-specific agglomeration economies) tend to be very local and attenuate within 7.5 kilometres. However, these studies usually include spatial fixed effects that may capture some agglomeration economies (see Rosenthal and Strange,

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, for example because wages are often determined in collective bargaining agreements, which limits the spatial heterogeneity of wages (Arzaghi and Henderson, 2008; Rusinek and Tojerov, 2011; Simón et al., 2006). Additionally, using rents to measure agglomeration economies is 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, allowing for a comparison between industries, so an analysis using commercial rents is not limited 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 in the Netherlands.[5] To control for unobserved shocks, I use instrumental variables (IV). So, the identification strategy deals with time-invariant unobserved endowments and unobserved shocks.[6] 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 two-step estimation procedure to investigate the magnitude of agglomeration economies on commercial rents. In the first step, I employ kernel methods to estimate weighted employment densities for each location, given a spatial bandwidth, avoiding the arbitrary choice of spatial units. Using a distance decay function and a spatial bandwidth, employment further away contributes less to the kernel density at a certain location. In the second step 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 postcode fixed effects. As these areas are about equal to a US census block, the unobserved heterogeneity with respect to the economic environment can be completely assumed away (see similarly Van Ommeren and Wentink, 2012).[7] 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). Therefore, in addition to including fixed

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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).

[5] 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.

[6] I rely on information on rents rather than sales prices: prices likely generate downward biased results, as prices are forward looking and may capture expected changes in the environment.

[7] The average number of employees per postcode six-digit (PC6) location is about 25.

effects, I 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. I optimise the spatial bandwidth using a cross-validation procedure.[8] This implies that one estimates for each bandwidth a hedonic price function and select the model that minimises the cross-validation score.

Greenstone et al. (2010) compare winning and runner-up locations that compete for attracting large firms. A disadvantage of the current study compared to Greenstone et al. (2010) is that I cannot distinguish between different sources of agglomeration economies, due to data limitations. The advantage of this study is that I deal with unobserved demand shocks. 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 that they are able to estimate structural parameters, based on information on land prices, residential and workplace employment. The advantage of the current paper is that it does not has a quasi-experimental set-up, so it seems more general (see also Bajari et al., 2012). The proposed estimation procedure may therefore be used in different time periods and locations. It also puts more emphasis on the estimation of the spatial extent of agglomeration economies.

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. The Netherlands is dominated by the dense polycentric city region of the Randstad, but it also has many rural areas in the upper northern, southern and eastern parts. Many areas have experienced substantial changes in employment density in the last decade. I also use 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. To put it differently, 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. 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 (time-varying) 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 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

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[8] This procedure is standard in nonparametric applications and in the determination of the bandwidth in regression-discontinuity designs, but has not been used in the context of the measurement of agglomeration economies.

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. Fourth, it is found that an increase in agglomeration has a stronger effect in urbanised areas.

The results are shown to be robust in Section V, wherein I use other instruments, investigate the decay of agglomeration in more detail and try a plethora of alternative specifications. I also show that the effect of agglomeration is very similar in the housing market, as suggested by the theoretical framework. Section VI concludes.

II. Theoretical framework and estimation
A. Productivity and rents

When agglomeration economies have a positive impact on productivity, one expects to observe higher rents in places where densities are higher. To show this, let us assume that π_{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 in the neighbourhood or city. $\Lambda(\ell_{jt}, z_j, v_{jt})$ is a function of some other input ℓ_{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 $\Gamma(n_{jt}) = e^{\zeta n_{jt}}$.[9] The profit per square meter of commercial space is then:

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

where w_{jt} is the wage and r_{jt} is the rent in rental property j at time t. 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)
$$r_{jt} = e^{\frac{\zeta}{1-\alpha}n_{jt}}(1-\alpha)\left(\frac{\alpha}{w_{jt}}\right)^{\frac{\alpha}{1-\alpha}}(z_j v_{jt})^{\frac{\eta}{1-\alpha}}.$$

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.[10] 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 $u_{jt} = \bar{u}$.

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[9] I pay some attention in the robustness analysis (Section V.E) to functional form assumptions.
[10] The assumption of zero commuting costs is harmless if wage is assumed to be constant across the city. The same implications will follow when I assume that workers have to commute to work (see similarly Ottaviano and Peri, 2006). The wage then equates the bid rents of firms and workers for space at the boundary of a central business district.

It may then be shown that the price p_{jt} paid per square meter of housing at j in time period t is:

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

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)
$$w_{jt}^* = K_j e^{\frac{1-\phi}{1-\alpha\phi} \zeta n_{jt}} e^{\frac{\alpha-1}{1-\alpha\phi} \kappa m_{jt}} \left(z_j v_{jt}\right)^{\frac{\eta(1-\phi)}{1-\alpha\phi}},$$

where $K_j = \left(\phi^\phi (1-\alpha)\right)^{\frac{(1-\alpha)(\phi-1)}{1-\alpha\phi}} \bar{u}^{\frac{1-\alpha}{1-\alpha\phi}} \alpha^{\frac{\alpha(1-\phi)}{1-\alpha\phi}}$. 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) and (3) one has:

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

When the above equation is simplified and written in logs:

(6)
$$\log r_{jt} = \beta n_{jt} + \gamma m_{jt} + \lambda_j + \xi_{jt},$$

Equation (6) is a reduced form equation, so so the coefficient β must be interpreted as the *marginal* effect on productivity, rather than on absolute levels of profits. It holds that $\beta = \zeta/(1-\alpha\phi)$, $\gamma = \kappa\alpha/(1-\alpha\phi)$, $\lambda_j = \eta \log z_j/(1-\alpha\phi)$ and $\xi_{jt} = \eta \log v_{jt}/(1-\alpha\phi)$, so ζ, κ and η are only identified given a normalisation assumption on α and ϕ. Because $\alpha < 1$ and $\phi < 1$, β is larger than the structural parameter ζ. I assume that β is time-invariant, an assumption which is tested in the robustness analysis, Section V.E.

Throughout this study, I refer to employment agglomeration n_{jt} as *agglomeration* and to population agglomeration m_{jt} as *population density*. 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. For example, the port of Rotterdam likely attracts firms, while this is not necessarily because of agglomeration economies (Glaeser, 2008). 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 ξ_{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.

It has been argued that urban density also 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. 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, I will assume that all population-induced amenities are captured by the population density, following Ahlfeldt et al. (2012). This seems reasonable as locations that become attractive to households command higher prices and are likely to attract more households. Consumption amenities are also captured by (time-varying) control variables at a certain location and location fixed 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, which implies that we may have 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.

Another implication of this, probably overly stylised, theoretical framework is that agglomeration should have a similar impact on commercial rents r_{jt} and house prices p_{jt} because in a mixed city $r_{jt} = p_{jt}$. There may be many reasons why this equality does not strictly hold (e.g. wages w_{jt} are not constant across the city, adjustment effects in the housing market; land use planning), but if β is similar for the housing market it provides additional evidence for the importance of agglomeration economies. I test for agglomeration effects in the housing market in Section V.D.

B. A two-step estimation procedure

The procedure to estimate equation (6) consists of two steps. First, kernel density functions of employment are estimated, including a spatial bandwidth. In the second step, these kernel densities are inserted into a hedonic price function. The spatial bandwidth is optimised using by repeating these two steps and minimising 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 step, 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:

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

where ℓ_{kt} is the employment in another rental property k in time t, where $k = 1, \dots, K$, $\Omega(\cdot)$ is some function of δ, which denotes a distance bandwidth, and d_{jk} denoting the Euclidian

distance between j and k.[11] I assume that $\Omega(\cdot)$ is a tricube weighting function, which is often used in spatial applications (McMillen, 2010):

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

where $I(\cdot)$ is an indicator function that equals one when the condition is true. As d_{jk} will be measured in kilometres, the bandwidth δ has a clear interpretation. For $d_{jk} > \delta$ agglomeration effects are assumed to be zero, so δ denotes the geographical range of agglomeration economies in kilometres. 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. Also, an instrumental variables approach is easier to implement because only one instrument is needed, rather than an instrument for each distance interval. 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). 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 contrast, the choice of the bandwidth δ seems to be more important in the current setting.

In the second step I aim to verify the monetary effect of agglomeration economies. A standard hedonic price approach is employed, which implies that the rent 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 bandwidth δ. Based on equation (6), I then estimate:[12]

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

where β, γ, θ are parameters to be estimated, ω is a bandwidth related to population density (the exact definition of $m_{jt}(\omega)$ is given in Section III.B), b_{jt} are building and location attributes that change over time (such as distance to new stations, land use), λ_j is a location fixed effect, τ_t is a year fixed effect and ϵ_{jt} denotes the error term, which is assumed to be independently and identically distributed across firms.[13] As argued by Bayer and Timmins

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[11] I use Euclidian distance rather than network travel time because I do not have detailed data on the network. This does not seem to be a problem in the Netherlands, as the correlation between network travel time and Euclidian distance is 0.95.

[12] Note that when one has exactly two observations per property j, equation (9) would be identical to a standard difference-in-difference equation.

[13] In an ideal setting, λ_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

(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 a very low level of aggregation, I effectively control for time-invariant natural advantages and location endowments. So, the key identifying assumption is that changes in ϵ_{jt} are uncorrelated to changes in $n_{jt}(\delta)$. 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).

Finally, the spatial bandwidth δ 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).[14] I define the cross-validation criterion as:

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

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

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

Preferably, δ is defined as a continuous bandwidth. However, estimating kernel densities of employment for a large dataset is computational intensive. To reduce the computational burden, I therefore assume that δ is an integer between 0 and 50 kilometres. I will show that the latter is not a limiting assumption, as it is found that δ^* is always much less than 50 kilometres. The cross-validation scores monotonically increase when δ 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 parameter. Because densities mainly may change at a local level, the estimation procedure may suggest a too low bandwidth. If this is true, the estimates that do not include fixed effects should suggest a substantially higher spatial bandwidth (because identification in the latter case mainly relies on geographical variation in densities). However, in the analysis it is shown that the spatial bandwidth is reasonably robust across different specifications, regardless of the inclusion of fixed effects.[15]

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building attributes and attributes related to the rental contract (so, attributes that vary within a PC6 area). In Section V.E, also building fixed effects are included instead of PC6 fixed effects.

[14] One may also use other criteria to determine optimal the bandwidth δ. For example, the Akaike Information Criterion (AIC) and the Bayesion 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.

[15] In principle, it is possible to bootstrap this whole procedure to get an estimate for the standard error of δ. However, as in most nonparametric applications, I will not estimate the standard error of δ to keep the estimation procedure computationally tractable. This implies that I may have a small underestimate of the standard error of β. However, I will cluster standard errors at the postcode location and show in Appendix B that the variation of β across different values of δ is limited

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. More specifically, it is assumed that, in absence of local shocks, each location would have received a share of employment growth that is in proportion to its initial share.[16] 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.

More formally, let N_{st} be the total employment in an industry s in year t, where $s = 1, \dots, S$, and t_B the base year. 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:

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

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 positive employment in the Netherlands between 1996 and 2010.[17] 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

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[16] 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 SBI two-digit 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.

[17] This classification is comparable to the SIC (Standard Industrial Classification) and NACE (Nomenclature statistique des Activites dans la Communaute Europeenne).

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.

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., 2013).
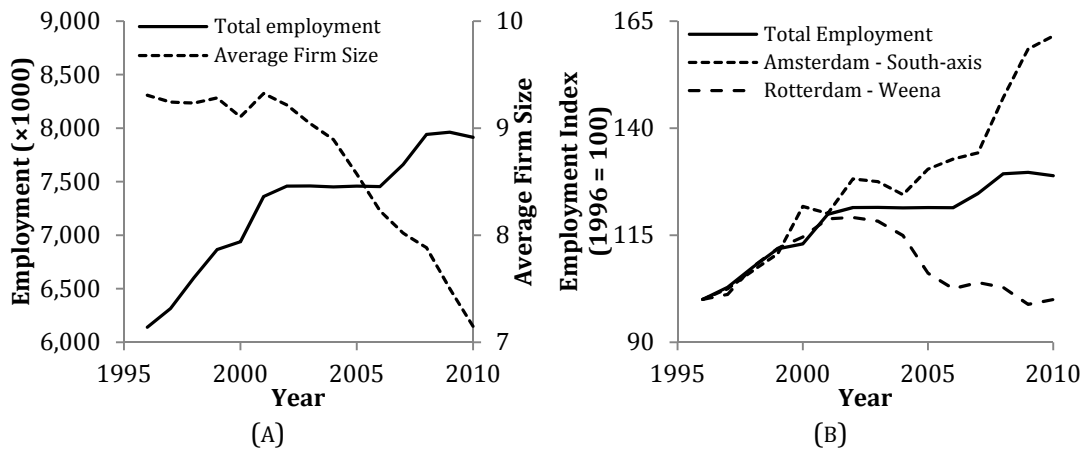

(A)   (B)

FIGURE 1 — DUTCH EMPLOYMENT FIGURES

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 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).
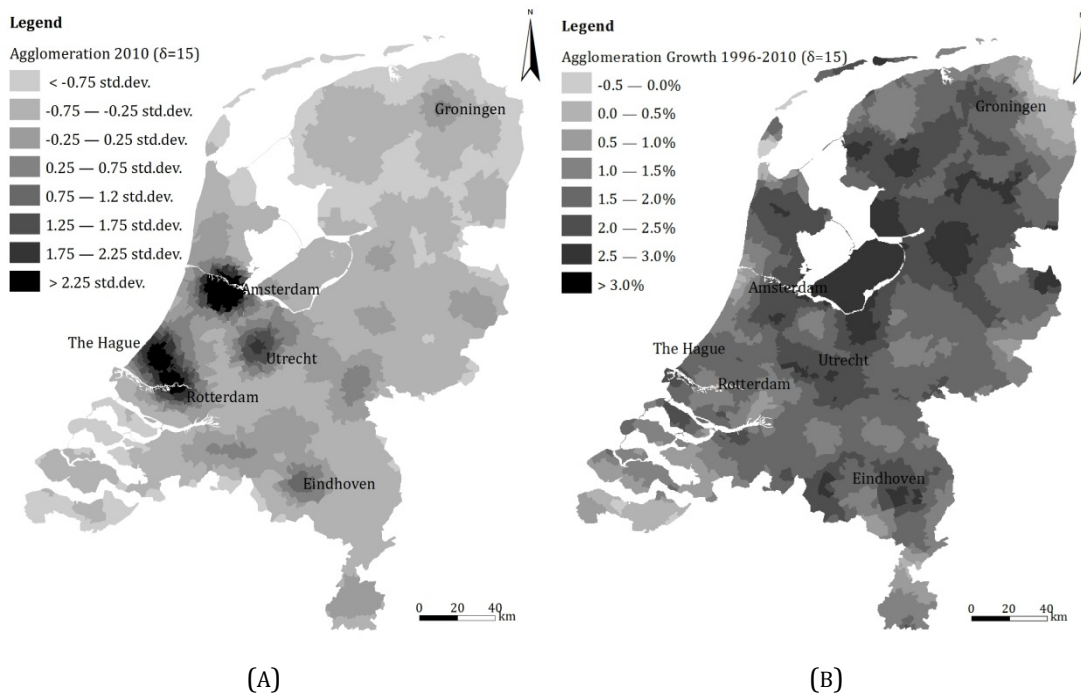
FIGURE 2 — SPATIAL DISTRIBUTION AND GROWTH RATES OF DUTCH EMPLOYMENT
Notes: In Figure 2A, I calculate for 2010 employment densities. For presentational purposes, I estimate equation (7) for centroids of all *four-digit* postcode areas (PC4) instead of postcode six-digit areas (a PC4 area is about equal to a census tract in the United States). I set the bandwidth δ 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.[18] The property 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.[19] 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).[20] The dataset also provides information on the broadly-defined

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[18] For the latter year, I only have information for the first two months.

[19] 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.

[20] 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 do not influence the results.

industry of the tenant for about 90 percent of the observations.[21] 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 preceding year of the land use data. This may lead to some bias, but as the average time difference between transactions in the same postcode six-digit location (PC6) 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 (m_{jt}) 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 PC6 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 ω is a fixed bandwidth. So, m_{jt} is a 'lumpy' approximation of the continuous kernel density of population density. To save computation time, I will provisionally assume that $\omega = 2.5$; when population density reflects the presence of amenities, the benefits are expected to be very local (see Koster and Rouwendal, 2012). In the sensitivity analysis (Section V.E) I will jointly optimise δ and ω 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 designated 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).[22]

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[21] 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.

[22] 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.
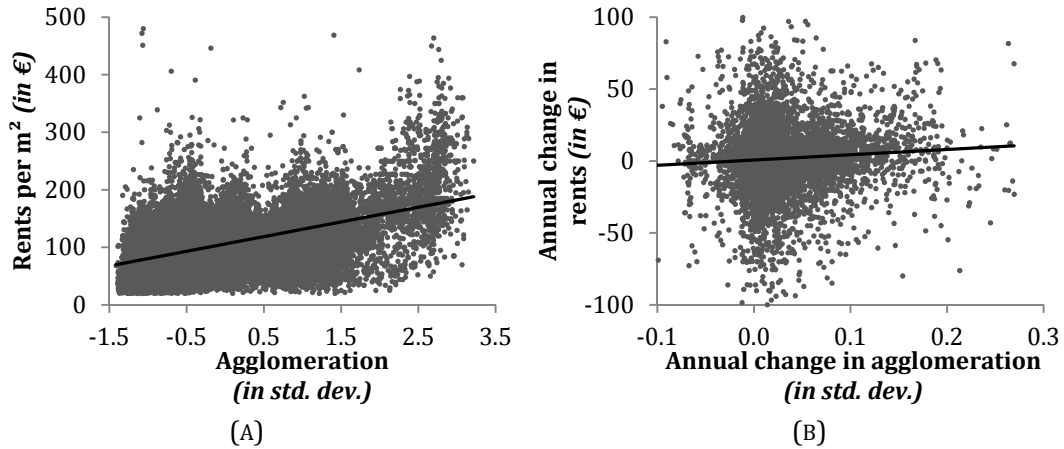
FIGURE 3 — AGGLOMERATION AND RENTS

Notes: It is assumed that the bandwidth $\delta = 15$. 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. The most expensive office space can be found in and close to Amsterdam with 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 agglomeration (using $\delta = 15$) against rents. None of the controls are included, so these results are suggestive, at best. Nevertheless, this univariate regression suggests that a standard deviation increase 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 increase with 45 percent when agglomeration increases with one standard deviation.

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.E), 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).

V. Results

A. Baseline regressions

Table 1 presents the baseline results of the effects of agglomeration n_{jt} on rents. I first run standard OLS and instrumental variables regressions *without* PC6 fixed effects λ_j. 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.[23]

In Specification (2), I estimate an instrumental variables regression. The standard procedure to control for unobserved locational advantages is to use long-lagged instruments. I use the logarithm of municipal population density in 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 I employ is the distance to the nearest station in 1870. Stations were an important factor that caused agglomeration in the second half of the 19th century (Ciccone and Hall, 1996). Specification (2) shows that the impact of agglomeration is only 1.8 percentage points lower.[24] 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).[25] The spatial bandwidth of agglomeration economies is 18 kilometres. The latter specification may produce an inconsistent estimate of agglomeration if current unobserved endowments are correlated with past unobserved endowments.

In Specification (3) I therefore include 8,461 PC6 fixed effects. It is shown that the effect of agglomeration is still substantial and statistically significant.[26] 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

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[23] When I include municipality fixed effects, the estimate of agglomeration is 0.117, which is similar to Specification (1). This suggests that, given the explanatory variables included, municipality fixed effects do not capture unobserved endowments.

[24] First-stage results are presented in Appendix C, as well as descriptives of the instruments.

[25] The Hausman *t*-statistic is calculated as $t_{\hat{\beta}} = (\hat{\beta}_{OLS} - \hat{\beta}_{IV})/\sqrt{\sigma^2_{\hat{\beta}_{IV}} - \sigma^2_{\hat{\beta}_{OLS}}}$ (see Wooldridge, 2002, pp. 120).

[26] In Appendix B it is shown that the cross-validation score is minimised when $\delta = 13$ (Figure B1).

TABLE 1 — REGRESSION RESULTS ON THE IMPACT OF AGGLOMERATION
(Dependent variable: the logarithm of commercial 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 density, 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 m² *(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 m² *(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 bandwidth δ^* *(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

area with a median level of agglomeration, this is 9.9 percent. It is important to note that the bandwidth 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).[27]

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 slightly higher than the estimate in Specification (3). However, 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. Because Specification (3) is then more efficient, this is the preferred specification. So, conditional on covariates, time-invariant unobserved endowments and unobserved shocks seem to play a limited role in the market for commercial properties, 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). One 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. Another reason may be that commuting trips, which capitalise in wages, are only made once a day, while intra-firm trips are made multiple times a day.

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

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[27] 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.

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.[28] 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. Therefore, I 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 bandwidth 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, when firms in offices likely rely much more on costly face-to-face contacts.[29] The negative point estimate suggests the possibility of a negative effect of employment density. However, the point

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[28] 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 V.E for more details.

[29] As an illustration, the average (standardised) value of agglomeration for industrial buildings is -0.349, while it is 0.188 for offices for $\delta = 13$.

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

Specification (7) adds a variable that measures the number of employees in the own-industry (or localisation) (see Table A2, Appendix A for the industrial classification).[30] 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. Note that the spatial bandwidth of localisation is much lower (2 kilometre) because it is hard to properly estimate a spatial bandwidth 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)). It is shown in Figure 4 that the effect of agglomeration is not statistically significantly different across different industries (the *F*-test is 1.33).[31]

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	-0.079	0.098		
	(0.033) ***	(0.088)	(0.031) ***		
Localisation, n_{jt}^{loc}			0.003		
			(0.002)		
Agglomeration, n_{jt}, industry-specific effects (14)	No	No	No	Yes	No
Agglomeration, n_{jt}, 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 bandwidth δ^* *(km)*	11	6	13	14	14
Spatial bandwidth localisation δ_{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 (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

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[30] I estimate localisation densities as $n_{sjt}^{loc}(\delta^{loc}) = \sum_{k=1}^{K} \ell_{skt}\Omega(d_{jk}, \delta^{loc})$. For 10 percent of the transactions I do not have data on the industry s, so I cannot estimate localisation densities. I then include a dummy in the specification when localisation is missing. Excluding these observation will lead to almost identical results.

[31] Koster et al. (2013) 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 more for agglomeration. However, in that paper, also shops are taken into account, which explains the strong preference of retailers for dense areas.

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 seems 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.
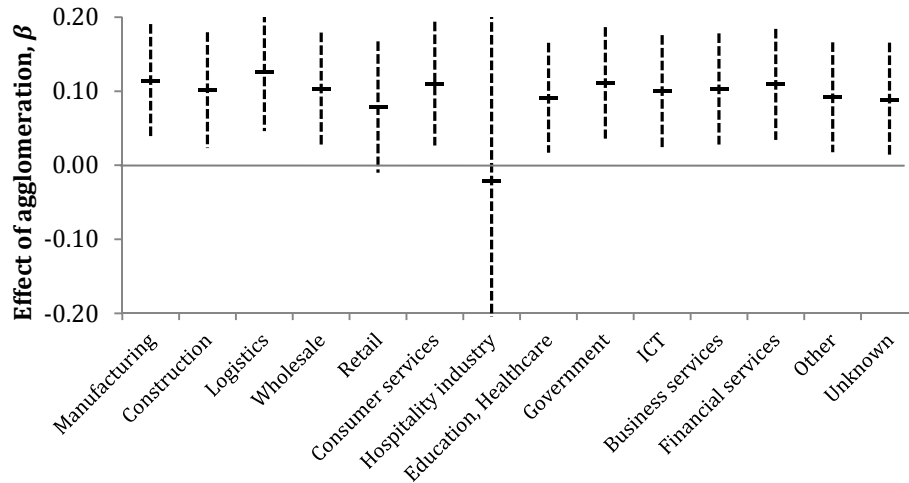

FIGURE 4 — HETEROGENEITY IN THE EFFECT OF AGGLOMERATION
Notes: The dashed vertical bars denote 95 percent confidence intervals and the horizontal bars denote point estimates for each industry.
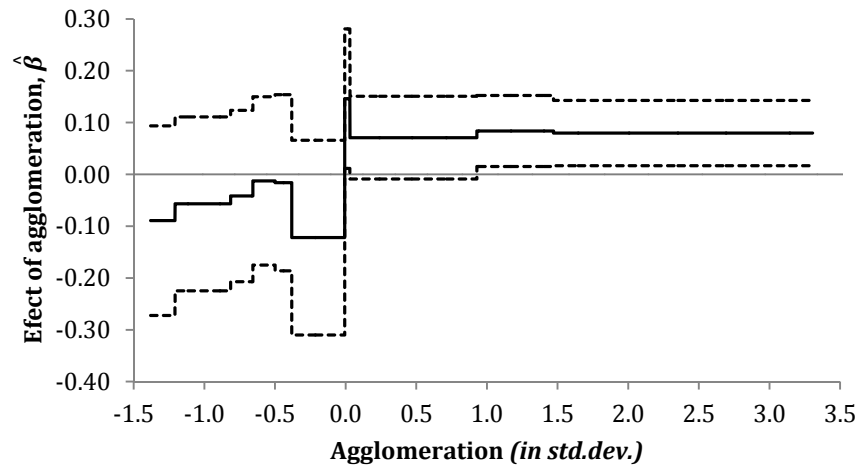
FIGURE 5 — NONLINEAR EFFECT OF AGGLOMERATION

VI.   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 shocks. Second, is the assumption of a Tricube weighting function for the spatial decay of agglomeration appropriate? Third, does

agglomeration impact house prices in a similar way, as is suggested by the theoretical framework? Fourth, is the measure of agglomeration robust to excluding time-varying locational endowments and 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.

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
	SBI five-digit instrument	Municipality trends	NUTS2-year, coordinates	Political instruments	Political instruments
Agglomeration, n_{jt}	0.121	0.163	0.162	0.132	0.208
	(0.034)***	(0.066)**	(0.040)***	(0.097)	(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 bandwidth δ^* *(in km)*	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 (13) and (14) 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.

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 biased and 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.

One may criticise the use of a shift-share instrument, for example because trends in employment growth may be correlated with initial industrial shares at certain locations. To deal with this criticism, I assume that shocks 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 h in each year.[32] 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 $\log r_{hjt} = \beta n_{jht}(\delta) + \gamma m_{jht} + b'_{jht}\theta + \Theta_h(x, y, t) + \mu_{ht} + \lambda_j + \tau_t + \epsilon_{jht}$, where $\Theta_h(\cdot)$ is a flexible NUTS2-specific function of the x-coordinate, the y-coordinate and year t, and μ_{ht} denotes a NUTS2-year fixed effect. It is shown that the coefficient of agglomeration is statistically significantly higher than the preferred estimate, so the 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 guarantee high levels of education. As government assistance to individual firms is considered as undesirable, vote shares arguably only impact rents via aggregate changes in agglomeration levels, conditional on control variables (see Duranton et al., 2011 for a similar argument). 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.[33] 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 Specification (3), but now I include region-year fixed μ_{ht} effects and a flexible function of location and time $\Theta_h(\cdot)$. Specification (14) shows that the coefficient of agglomeration is now higher (0.208) but is not statistically significantly different from Specification (3) (the Hausman t-value is -0.76)

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[32] 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, usually labelled provinces. The time period of the sample is 15 years, which implies 180 fixed effects.

[33] 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.

Specification (15) shows that an increase of 113,429 employees within 5 kilometres increases rents with 10.5 percent.[34] 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 6, together with the spatial attenuation implied by Tricube weighting function, based on Specification (3). It is shown that the Tricube weighting function is 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.

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
	Stepwise decay	*Triangular kernel*	*Epanechnikov kernel*	*Exponential kernel*
Agglomeration, n_{jt}		0.101	0.099	0.103
		(0.031) ***	(0.031) ***	(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 bandwidth δ^* *(in km)*		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 $\Omega(d_{jk}, \delta) = \left(1 - (d_{jk}/\delta)\right) I(d_{jk} < \delta)$, the Epanechnikov kernel as $\Omega(d_{jk}, \delta) = \left(1 - (d_{jk}/\delta)^2\right) I(d_{jk} < \delta)$ and the Exponential kernel as $\Omega(d_{jk}, \delta) = \left(1 - \sqrt{d_{jk}/\delta}\right) I(d_{jk} < \delta)$.

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[34] 113,429 employees is a standard deviation increase in (weighted) employment for a Tricube kernel function given $\delta = 13$.
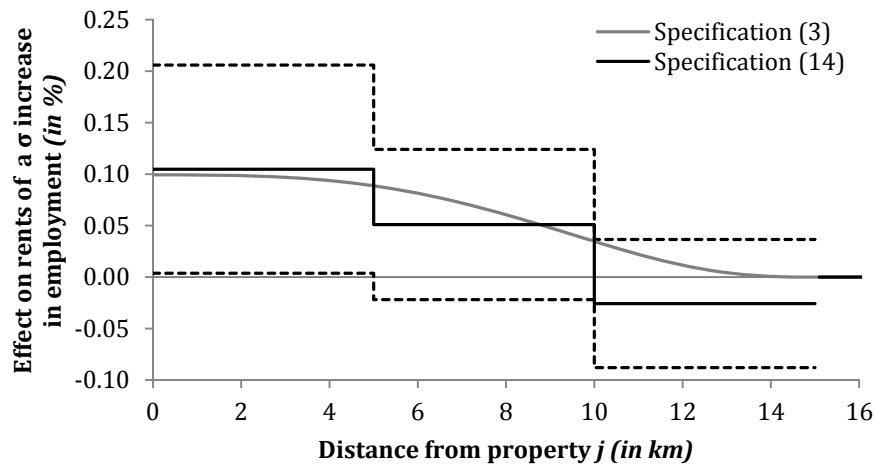
FIGURE 6 — SPATIAL ATTENUATION OF AGGLOMERATION ECONOMIES
Notes: The dashed lines indicate the 95 confidence interval of Specification (15)

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 bandwidths are very similar to the spatial bandwidth 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 bandwidth are very small (see Figure D2 in Appendix D).

D.   Agglomeration economies and house prices

In the theoretical framework (Section II.A) it is shown that commercial rents and house prices at a certain location should be equal in a mixed city. Given the stylised nature of the framework, it is unlikely that this holds in practice, for example because of land use restrictions and externalities that impact commercial rents and house prices differently. Nevertheless, a less restrictive implication of the framework is that agglomeration should have a similar impact on house prices and on commercial rents, given that wages equalise rents and prices in the city. I test this implication in the current subsection using a very large dataset on house prices in the Netherlands.[35] The data on house prices is obtained from NVM (Dutch Association of Real Estate Agents). It contains information on a large majority (about 75 percent) of (owner-occupied) house transactions between 1997 and 2009. I know the transaction price, the exact address, and a wide range of structural attributes such as inside floor space size (in square meters), number of rooms, parking, garden, the construction year and whether the house is a listed building.[36] I also include the state of maintenance, whether

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

[36] I exclude transactions with prices that are above € 1 million or below € 25,000 and have a price per square meter which is above € 5,000 or below € 500. I furthermore leave out transactions that refer to

a house is insulated and has central heating. In the analysis, I control for the same locational attributes as in the commercial rent regressions. After selections, the data consists of 1,517,970 observations. I then estimate $\log p_{jt} = \beta n_{jt}(\delta) + \gamma m_{jt}(\omega) + b'_{jt}\theta + \lambda_j + \tau_t + \epsilon_{jt}$, and assume that $\omega = 2.5$ to save computation time. Table 5 presents the results.

TABLE 5 — REGRESSION RESULTS, AGGLOMERATION ECONOMIES AND HOUSE PRICES
(Dependent variable: the logarithm of house price per square meter)

	(19)	(20)	(21)	(22)
	FE	FE	FE	FE
	NUTS2 FE	*PC6 FE*	*No population*	*No controls*
Agglomeration, n_{jt}	0.115	0.074	0.067	0.077
	(0.002)***	(0.003)***	(0.003)***	(0.004)***
Population density, m_{jt}	-0.071	-0.077		
	(0.002)***	(0.005)***		
Control variables included (40/13)	Yes	Yes	Yes	Yes
NUTS2 fixed effects (12)	Yes	Yes	Yes	Yes
PC6 fixed effects (149,764)	No	Yes	Yes	Yes
Spatial bandwidth δ^* *(in km)*	5	5	6	7
Cross validation score $CV(\delta)$	0.05447	0.02085	0.02084	0.03071
R^2	0.6254	0.8709	0.8708	0.8306

Notes: See Table 1. The number of observations is 1,517,970.

Specification (19) includes all control variables and NUTS2 fixed effects. The effect is similar to Specification (1), which also identifies agglomeration effects based on geographical variation in employment density. The effect of agglomeration is very similar in magnitude to Specification (1): one standard deviation increase in agglomeration increases house prices with 11.5 percent. It is also observed that population density is strongly negatively influencing house prices. For no obvious reason, the spatial decay parameter is much lower than in the commercial property market. Specification (20) includes 149,764 PC6 fixed effects and confirms that agglomeration has a strong impact on house prices. It shows that one standard deviation increase in agglomeration leads to an increase in house prices of 7.4 percent. This effect is similar but slightly lower than in market for commercial properties, likely because house owners are, in contrast to commercial tenants, increasingly forward looking, so prices are expected to anticipate to some extent changes in employment. One may argue that multicollinearity is a problem in Specification (20), due to correlation between agglomeration and population density. In Specification (21) I therefore exclude population density, but the effect of agglomeration is still substantial and statistically significant. In Specification (22) I exclude all control variables, except year and location fixed effects. The effect of agglomeration is then very similar to Specification (20), suggesting that the correlation of agglomeration with endowments is limited.

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properties that are larger than 250 square meters or smaller than 25 square meters. These selections comprise less than one percent of the data.

E. Robustness analysis – other specifications

In this subsection, I investigate robustness of the results with respect to control variables and fixed effects. Results are presented in Table 6. Specification (23) 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)

	(23)	(24)	(25)	(26)	(27)
	FE	FE	FE	FE	FE
	No location controls	*Population flexible*	*Building fixed effects*	*Time-varying coefficients*	*Only moving firms*
Agglomeration, n_{jt}	0.106	0.121	0.076		0.092
	(0.032) ***	(0.032) ***	(0.032) **		(0.031) ***
Agglomeration, n_{jt}, 1997-2001				0.160	
				(0.047) ***	
Agglomeration, n_{jt}, 2002-2006				0.153	
				(0.042) ***	
Agglomeration, n_{jt}, 2007-2011				0.141	
				(0.041) ***	
Population density, m_{jt}		-0.111	-0.001	0.010	0.010
		(0.097)	(0.051)	(0.038)	(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 bandwidth δ^* *(in km)*	12	10	13	16	13
Spatial bandwidth population density ω *(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 (24) I do not fix the bandwidth related to population density ω to 2.5, but jointly optimise δ and ω. It is shown that the effect of agglomeration is similar, but the coefficient of population density 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 density reflects effects of labour market pooling. Absence of a positive effect of population density would then be surprising. However, in my opinion, population density is unlikely to 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 (25) 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 bandwidth is found to be exactly the same as in Specification (3).

In the estimated equation (9) it is assumed that the coefficient of agglomeration β is time-invariant (and so are the underlying structural parameters α, ζ and ϕ). I test this assumption by interacting agglomeration with a dummy for each five-year period from 1997 onwards. Specification (26) shows that the coefficients are slightly higher (because δ 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 (27)).

VII.   Conclusions

In this study I use unique micro-data to estimate the impact of agglomeration economies on commercial property values. The contribution of this paper is threefold. First, rather than identifying agglomeration using spatial variation in density and using (historic) long-lagged instruments, which is common, 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, based on space-continuous data, I 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 studies 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 into 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 are more likely to capitalise into wages.

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Appendix A.　Descriptives

TABLE A1 — DESCRIPTIVE STATISTICS

	Mean	Median	Std.dev.	Min	Max
Price per m² *(in €)*	105.782	105	53.716	20	668
Agglomeration, n_{jt} $(\delta = 15)$	182,716	133,970	127,068	3,231	591,360
Population density, m_{jt} $(\omega = 2.5)$	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 *(m²)*	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 *(m²)*	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 spatial bandwidth

In this Appendix I will pay attention to the determination of the spatial bandwidth. 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 δ. For values of $\delta > \delta^*$ the Cross-Validation score is monotonically increasing. The range of $\delta < 50$ therefore seems appropriate. In Figure B2 I show the estimated coefficients for agglomeration for different values of δ. In this particular case, β is maximised when the cross-validation score is minimised. For large values of δ, the coefficient of agglomeration becomes statistically insignificant.
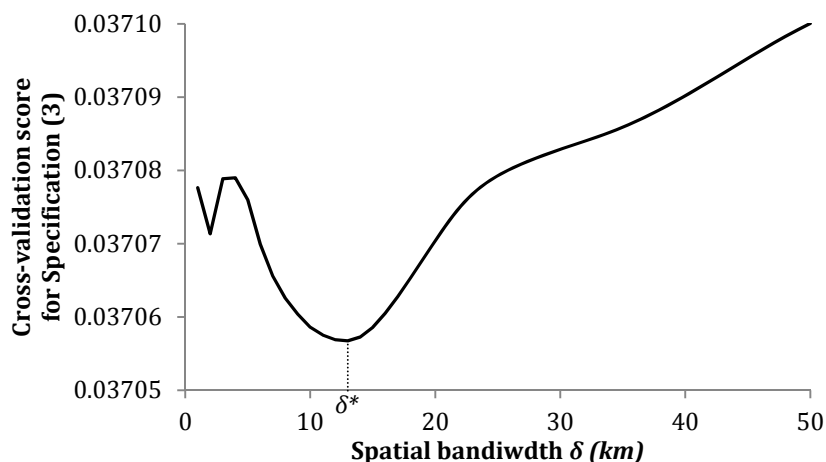

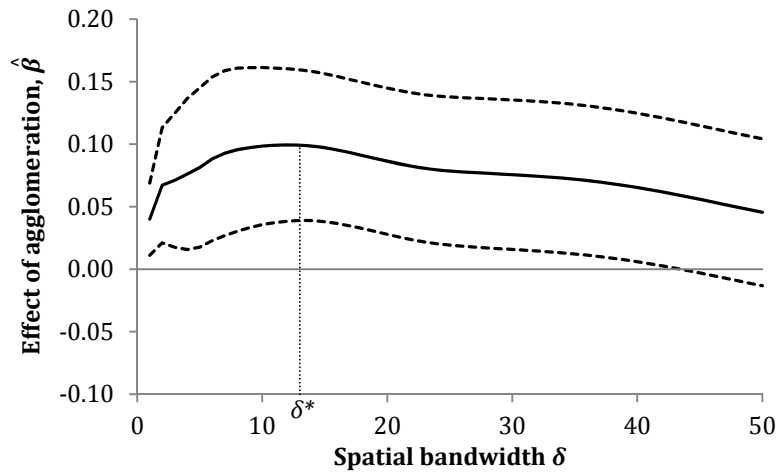FIGURE B1 — CROSS-VALIDATION SCORES FOR SPECIFICATION (3)

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

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, $\hat{n}_{it}$ ($\delta = 15$) SBI2	182,760	135,400	128,006	3,314	573,250
Agglomeration shift-share, $\hat{n}_{it}$ ($\delta = 15$) 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	IV– FE	IV – FE	IV – FE	IV – FE
	Population density	SBI two-digit instrument	SBI five-digit instrument	Political instruments	Political instruments
Population density 1830 *(log)*	-0.077				
	(0.008) ***				
Distance to station 1870	-0.032				
	(0.003) ***				
Agglomeration shift-share, $\hat{n}_{jt}$		0.761	0.766		
		(0.013) ***	(0.014) ***		
Share voters liberal party				-0.026	-0.022
				(0.004) ***	(0.004) ***
Share voters socialist party				0.090	0.053
				(0.008) ***	(0.006) ***
Share voters Christian party				-0.003	-0.012
				(0.005)	(0.005) **
Share voters liberal party, maximum				-0.004	0.009
				(0.003)	(0.003) ***
Share voters socialist party, maximum				-0.025	-0.009
				(0.003) ***	(0.004) **
Share voters Christian party, maximum				-0.004	0.010
				(0.003)	(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 bandwidth δ^* *(in km)*	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, given a uniform distribution of employment and $\delta = 13$, 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. Figure D2 presents the cross-validation scores for three specifications with different kernel functions and highlights that the bandwidth is very similar for different kernel functions.
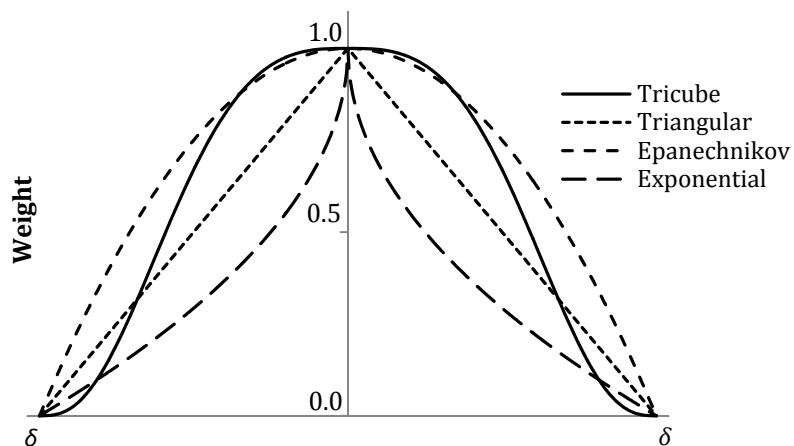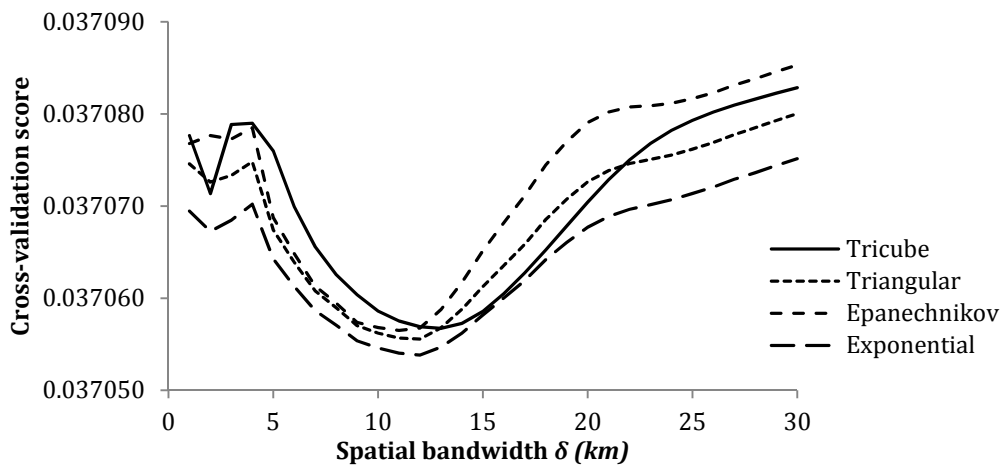
FIGURE D1 — KERNEL FUNCTIONS

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