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Agglomeration Economies and Capitalization Rates: Evidence from the Dutch Real Estate Office Market

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Abstract

Agglomerations of economic activity result in higher rents for users. However, these benefits do not necessarily carry over to real estate investors because higher rents might also come with higher investment amounts and risks. We address this by testing whether the effects of agglomeration economies, as observed in office rents, carry over to capitalization rates as a theoretically more refined measurement of productivity externalities. Using transaction-based data for the period 1996-2011 in the Netherlands, we show that agglomeration economies result in capitalization rates that are 4.6 percent, or 40 basis points, lower.

Keywords capitalization rates · agglomeration economies · commercial real estate · office market

Introduction

Agglomeration economies, or the benefits associated with the geographical clustering of economic activity, have been widely discussed in the literature. Essentially, agglomeration economies lead to a productivity advantage associated with sharing of information, availability of labor, of technology, and proximity to suppliers.[1] The

[1] Studies on agglomeration economies show a positive relationship between firm productivity and agglomeration economies (Henderson, 1986, 2003; Rosenthal and Strange, 2008; Greenstone et al., 2010; Koster et al., 2014).

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literature indicates that agglomeration economies are characterized by higher wages and higher labor productivity.[2] For real estate markets, agglomeration economies are inferred from higher asset prices (Gyourko et al., 2010) or higher rents (Drennan and Kelly, 2011; Koster et al., 2014). The findings of Koster et al. (2014), for instance, suggest a positive effect from agglomeration economies on rents for offices clustered within large central business districts (CBDs) of 5 percent, so that tenants in clusters benefit from agglomeration economies. Agglomeration economies in rents, however, do not necessarily benefit real estate investors in terms of returns since asset prices play a role as well. The question we address is to what extent agglomeration economies are reflected in capitalization rates.[3]

Investors may benefit from agglomeration economies due to better tenant pooling in ways similar to labor market pooling (cf. Glaeser et al., 1992).[4] Tenant pooling lowers the risks of vacancy and associated fluctuations in operating income. Other potential sources of agglomeration benefits include cheaper and faster supply of property management operation and maintenance services, which makes investors willing to pay a higher price or, equivalently, a lower rent-to-price ratio (i.e. capitalization rate). We examine how these capitalization rates of real estate investments vary within local markets. While both positive and negative externalities may be at work, we consider the net effect of agglomeration economies on capitalization rates. Our paper connects to the work of Gunnelin et al. (2004), who claim that appraisers see capitalization rates as varying across properties within markets. They show that appraisers use higher capitalization rates for properties outside a CBD than for properties within it. Whether these cross-sectional differences in transaction-based capitalization rates can be explained by local agglomeration externalities has not yet been studied and thus forms the central question of our research.

We aim to contribute to the empirical literature in two ways. First, we examine transaction-based, property-specific capitalization rates, which allows us to better control for heterogeneity and amenities in commercial real estate markets. These property-specific capitalization rates are a more refined measurement for identifying agglomeration economies than aggregate market-level rates. Also, transaction-based, property-specific capitalization rates are preferable to using appraisal-based data, since the latter risks misstating depreciation or appreciation rates (Darrat and Glascock, 1993; Chaney and Hoesli, 2015).

Second, we identify local job clusters by year to allow for the formation of local clusters within our sample period. We use geocoded employment data at establishment-level to determine the boundaries of the job clusters because these boundaries

[2] For studies on agglomeration economies, see, among others, Glaeser and Mare (2001), Amiti and Cameron (2007), Arzaghi and Henderson (2008), Glaeser (2008, 2010), Melo et al. (2009) and Greenstone et al. (2010).

[3] A similar argument on what measurement to use can be found in the literature on agglomeration externalities and productivity. Our approach basically follows Henderson (1986), where, rather than using simple partial measurements of productivity, more refined multifactor productivity measurements were used to measure the presence of agglomeration externalities. For real estate markets, capitalization rates can be considered as a more refined approach for assessing the presence of agglomeration economies.

[4] We use tenant pooling as analogue to labor market pooling, where there are many tenants within an office cluster, so that tenants can change location without moving out of the cluster.

do not follow the boundaries of zip codes or cities (For a discussion on enterprise zone boundaries, see Neumark and Kolko, 2010; for city boundaries, see Henderson et al., 2019). The literature has traditionally used aggregate data at city, metropolitan, or state level (Rosenthal and Strange, 2004). These levels of spatial data produce fairly coarse measurements of job clusters, making it difficult to interpret the geographical extent of agglomeration economies (Billings and Johnson, 2016). Also, and similar to what Neumark and Kolko (2010) point out for enterprise zones, these approximations introduce measurement error by incorrectly assigning observations as inside of outside clusters. We apply point-based time-varying cluster density mapping techniques to determine the boundaries of the job clusters. In our empirical approach, we use information on whether a property transaction is located within the boundary of an area that is or ever will be a job cluster, in order to distinguish between unmeasured differences across properties and agglomeration economies. We will show that agglomeration economies in job clusters result in significantly lower cap rates.

The main finding of this paper is that capitalization rates are lower for offices within an economically significant cluster. The results show that investors require a lower capitalization rate by approximately 4.6 percent or 40 basis points if the property is within such a job cluster.

This paper is organized as follows. In the next section, we specify a stylized capitalization rate model of commercial real estate to assess the effect of agglomeration economies on capitalization rates. In Section 3, we describe the empirical framework and data. In Section 4, we discuss the results. Finally, in Section 5, we reflect on the results and offer suggestions for further research.

Background

We start by modeling the asset price of a specific property at the time of purchase following seminal contributions by Fisher (1930) and Gordon (1962). The asset price model implies that the asset price of property i at time t of purchase, P_{it} is determined by the discounted sum of expected future rent, that is, net operating income NOI_{it}, and the expected selling price at the end of the investment horizon $PS_{i,t+T}$. This is reflected in the following asset pricing equation for property i at the time t of purchase:[5]

$$P_{it} = \frac{NOI_{i,t+1}}{(1+r_{it})} + \frac{NOI_{i,t+1}(1+g_{i,t+2})}{(1+r_{it})^2} + \frac{NOI_{i,t+1}(1+g_{i,t+3})}{(1+r_{it})^3} + \\ + \frac{NOI_{i,t+1}(1+g_{i,t+T})+PS_{i,t+T}}{(1+r_{it})^T}, \quad (1)$$

where g_{it} is the property-specific expected growth rate in NOI_{it}, T is the investment horizon of a property, r_{it} is the property-specific discount rate at time t of purchase, and $PS_{i,\,t+T}$ is the expected selling price of the property at t+T.

Key determinants in this model are *NOI,* the expected selling price, and the property-specific discount rate. If we assume that the expected growth rate of net

[5] For the notational glossary, see Appendix A.

operating income g_{it} is constant over time, $g_{it} = g_{i,t+1} = \ldots = g_{i,t+T}$, and that $PS_{i,t+T}$ is a fixed multiple of *NOI* (see Geltner et al., 2007; Clayton et al., 2009), then the asset price can be expressed as:

$$P_{it} = \frac{NOI_{i,t+1}}{r_{it} - g_{it}}. \tag{2}$$

The capitalization rate CAP_{it}, defined as $NOI_{i,t+1}$ divided by P_{it}, equals the discount rate minus the expected growth rate of net operating income:

$$CAP_{it} \equiv \frac{NOI_{i,t+1}}{P_{it}} = r_{it} - g_{it} = RFI_t + EI_t + RP_{it} - g_{it}, \tag{3}$$

where the discount rate r_{it} can be expressed as the sum of the risk-free real interest rate RFI_t, the expected inflation EI_t, and a property specific risk premium RP_{it}, so $r_{it} = RFI_t + EI_t + RP_{it}$.

Equation (3) can be interpreted as follows. First, the capitalization rate is higher for investments which require greater compensation, i.e., a higher discount rate, r_{it}. Higher discount rates may be driven by higher interest rates, higher inflation rates, or higher risk premia. We assume that the risk-free real interest rate and the expected inflation are independent of the property and location (Sivitanidou and Sivitanides, 1999). The implication is that variation in property-specific discount rates is captured in the risk premium. Second, the capitalization rate is lower for investors who have a more positive market outlook on expected rental growth rates (g_{it}). These investors will assess the current value of an investment as higher and therefore be willing to pay a higher price relative to the rent (Sivitanidou and Sivitanides, 1996; Plazzi et al., 2010).

Also, Eq. (3) explains why investors accept a lower capitalization rate, and thus are willing to pay a higher price conditional on rental income, for properties in a job cluster where rents are higher. Investors may consider risks in job clusters to be lower due to tenant pooling, in which case tenants can relocate without moving out of the job cluster. In such situations, vacancy rates tend to be lower and rental growth rates tend to be higher, since tenants perceive this as the best location for their businesses (Jennen and Brounen, 2009). [6] Next, job clusters may come with highly skilled labor and associated efficiency gains in terms of production of real estate management services (Archer and Smith, 2003). Furthermore, liquidity risks in job clusters may be lower and expected selling prices higher. Liquid assets have an advantage over less liquid assets in terms of future investment opportunities, in that they are less costly to convert into cash (Lusht, 2001). Correspondingly, job clusters attract more institutional investors, who tend to favor prime (high rent) markets. Given that institutional investors have longer investment horizons, this further reduces risk (Cheng et al., 2013).

The conceptual framework above provides a testable hypothesis regarding the question why investors require lower capitalization rates and, conditional on cash

[6] This seems to be supported by anecdotal evidence that larger markets have seen higher rent increases than smaller markets.

flow, are willing to pay a higher asset price for properties in locations associated with agglomeration economies.

Data and Empirical Methodology

Data

Data on capitalization rates was obtained from Strabo, a real estate consultancy firm that tracks rental and asset transactions for the Netherlands (for details, see Appendix B). Our data cover the period from January 1996 to March 2011 and include periods of both boom and bust in the Dutch commercial real estate market. The data include information on the gross capitalization rate at the time of purchase, the annual rent (cash-flow income), and the asset price.[7] Furthermore, information is provided about structural characteristics, such as the total square meters of office space, and whether the building is new or existing.[8] Furthermore, the rate on ten-year Dutch government bonds is used as a measurement of the risk-free interest rate.

Agglomeration and jobs clusters

We operationalize and measure agglomeration economies based on data on number of jobs of all establishments in the Netherlands for each year from 1996 to 2011. The data come from administrative business records and includes, for each establishment, information about the geographical location, SBI sector classification, and number of employees.[9] One of the attractive attributes of the data is that it includes longitude and latitude, allowing us to accurately measure the geographical clustering of jobs.

We use GIS to delineate boundaries of job clusters based on geographical clustering of numbers of jobs. For each year, we first calculate the spatial density of jobs using GIS point density-tool techniques. We calculate the density of number of jobs on a 50x50-meter raster grid with an 800-meter radius from the grid centroid. [10] Next, we compare each grid to its neighboring grids. If the density of number of jobs exceeds or equals a pre-determined threshold, then the grids are merged to form a cluster.[11] This pre-determined threshold is based on the empirical distribution of

[7] Investors typically buy a property, given the existing contractual rental agreements.

[8] Note that we miss information on building year for several observations. We therefore omitted building year from the set of control variables. While so, Bokhari and Geltner (2018) show that the impact of building year on capitalization rates is relatively small compared to that of rental income.

[9] For 2011, we have 1,049 million firms and establishments, or 6.815 million jobs across the nation.

[10] In terms of the Imperial system, this is identical to a 0.031 x 0.031 mile raster grid and a half-mile radius from the grid centroid.

[11] A similar density-cluster methodology has been applied to delineate attractive nature in a study on housing (Daams et al., 2016). In fact, their methodology includes an overlay of grid-based density clusters with various land use data, in which case the intersection of sets defines clusters of attractive natural space.

job density across the nation. [12] This in turn gives the boundaries of the job clusters, which enables us to match properties to job clusters and identify whether properties are inside or outside clusters.

Clusters are dynamic in nature, and it is this specific feature of the data that we are exploiting to identify agglomeration effects in transaction-based capitalization rates. We repeat the above procedure for each year to determine how job clusters develop over time (see Appendix B). For instance, an office building, which initially is not located inside a cluster, may become part of a cluster as the job cluster expands. Thus, we can identify whether properties are in an area that is or ever will be a job cluster. In the empirical modeling approach, we exploit the dynamics of clusters to identify whether properties are inside or outside clusters, and before or after the job cluster emerged. [13]

Descriptive statistics

The data cover 1996 to 2011. We exclude observations for which no information is available on asset price, rent, property characteristics, or transaction-type details, restricting the sample to 1,936 observations (for further details, see Appendix B).

Table 1 shows descriptive statistics. It shows that the mean capitalization rate between 1996 and 2011 is 8.18 percent (0.0818), with a median capitalization rate of 8.00 percent. So investors pay on average 12.5 times the annual rent at the time of purchase. In total, 16 percent of observations involve office properties located in the Amsterdam Metropolitan Area. Next, 7 percent of observations involve sale and leaseback transactions, while 8 percent of observations involve new properties. We have four types of transactions: between private seller and private buyer (26 percent), private seller and institutional buyer (28 percent), institutional seller and private buyer (15 percent) and, institutional seller and institutional buyer (31 percent).

Capitalization rates show temporal and cross-sectional variation. Figure 1 shows distributions for the capitalization rate, rent and asset price. Figure 2 shows the capitalization rate and the interest rate by year (left panel) and the rent by asset price (right panel). The left panel shows a declining pattern for both the capitalization rate and the interest rate from 1996 up to 2005. After 2005, the capitalization rate and the interest rate tend to move in opposing directions. The right panel reflects cross-sectional variation in capitalization rates as reflected in the bivariate relationship of asset prices and rents.

The number of nearby jobs varies as well. Table 1 shows that the mean number of jobs per sq. km is 6,816, with a standard deviation of about 6,000, while Fig. 3 shows the distribution of number of jobs. Figure 3 shows that transactions relate to properties in areas associated with relatively large numbers of jobs compared to the national average.

[12] In the empirical analysis, we consider various thresholds to assess the robustness of our findings (see Appendix B for number of clusters and descriptive statistics).

[13] The empirical modeling approach is akin to Been et al. (2016).

Table.1 Summary statistics

Variable	Description	median	mean	sd
Capitalization rate	initial yield or rent-to-price ratio	0.080	0.0824	0.017
Rent	annual rent per sq. m in euros, current	133.83	140.60	41.69
Price	asset price per sq. m in euros, current	1,656	1,791	788
Size	size of office building in sq. m.	3,040	6,529	10,733
Interest rate	the rate on ten-year Dutch government bonds in percent		4.47	0.75
New building	new office building (1=yes)		0.08	
Amsterdam	office building located in greater Amsterdam Metropolitan Area (1=yes)		0.16	
Sale-leaseback	sale-leaseback (1=yes)		0.07	
S private ×B private	private investor seller × private investor buyer		0.26	
S private × B institutional	private investor seller × institutional investor buyer		0.28	
S institutional × B private	institutional investor seller × private investor buyer		0.16	
S institutional × B institutional	institutional investor seller × institutional investor buyer		0.30	
Job density	total number of jobs per sq. km.	4,753	6,811	6,011
DJC 500	property is in Cluster ever with ≥ 500 jobs per sq. km		0.99	
DOC_{it} 500	property is in Cluster currently with ≥ 500 jobs per sq. km		0.98	
DJC 1500	property is in Cluster ever with ≥ 1,500 jobs per sq. km		0.94	
DOC_{it} 1500	property is in Cluster currently with ≥ 1,500 jobs per sq. km		0.90	
DJC 2000	property is in Cluster ever with ≥ 2,000 jobs per sq. km		0.88	
DOC_{it} 2000	property is in Cluster currently with ≥ 2,000 jobs per sq. km		0.82	
DJC 5000	property is in Cluster ever with ≥ 5,000 jobs per sq. km		0.55	
DOC_{itf} 5000	property is in Cluster currently with ≥ 5,000 jobs per sq. km		0.48	
Number of observations			1,936	

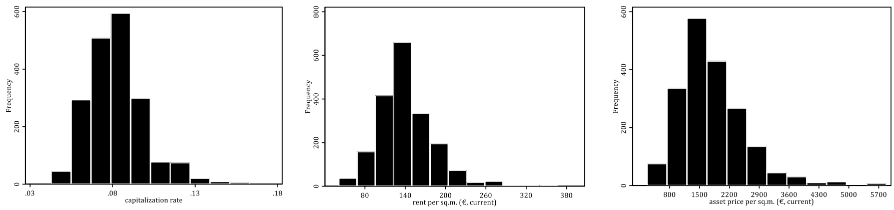


Fig. 1 Distribution of capitalization rates (left panel) rents (center panel) asset prices (right panel). The panels show the distributions over the 1996-2011 period for individual transactions

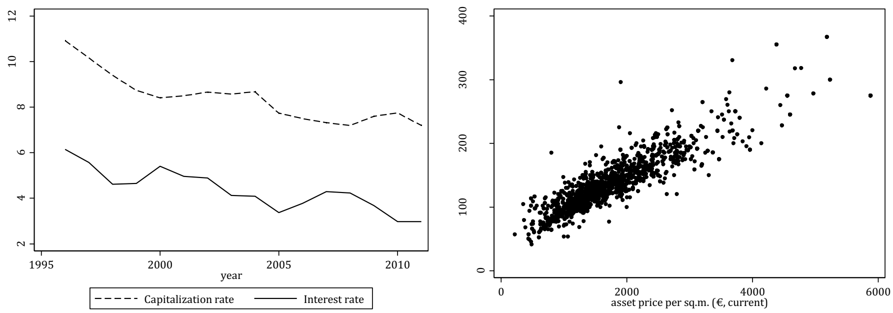


Fig. 2 Capitalization rates and interest rate by year (left panel) and rent by asset price (right panel). The left panel shows the mean capitalization rate and the interest rate over the 1996-2011 period. In the right panel, we plot the asset prices against rents for individual transactions

[14] The lower panel of Table 1 gives information on job clusters. Recall that boundaries of job clusters are determined by a threshold for numbers of jobs. The thresholds are 500, 1,500, 2,000, and 5,000 per sq. km. These are the statistics listed in Table 1. Naturally, the higher the threshold the smaller the number of job clusters, and the lower the percentage of transactions that falls within a job cluster (for details, see Appendix B). Table 1 shows that for a threshold equal to 2,000 jobs per sq.km, 87.6 percent of the transactions are located in an area that is or ever will be a job cluster (or DJC_2000=1), and 81.4 percent are in a job cluster at the time of the transaction (or DOC_it_2000=1).

Empirical methodology

The empirical approach aims to identify the effect of agglomeration on the capitalization rate. Identifying the causal effect of agglomeration is challenging because of

[14] The average job density per sq. km in the Netherlands for 2000 is 118, or 3.8 million jobs over 32,000 sq.km. For 2011 it is 213 or 6.815 million jobs over 32,000 sq. km. Amsterdam has 546,000 jobs in 2011or an average job density per sq. km of about 2,000 jobs per sq. km.

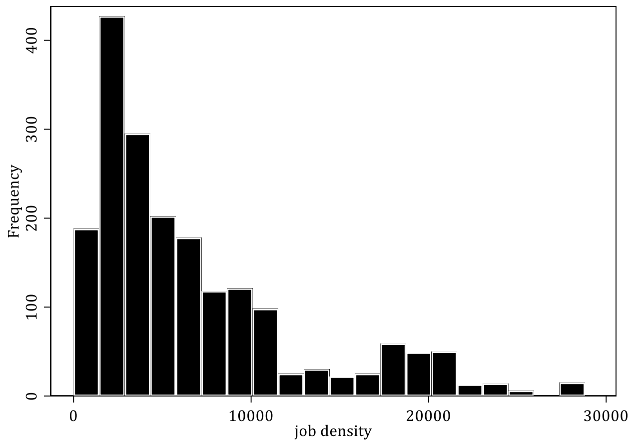


Fig. 3 Local job density per sq. km in the sample. Figure plots the local job-density measurement for individual transactions in the sample

endogeneity of job clusters (see Glaeser, 2010). When developers, in terms of site selection and new construction of offices, built specific properties of higher quality as a landmark in job centers, for instance, rather than agglomeration we could find lower capitalization rates because of unobserved property characteristics.

A natural starting point would be a regression model of the natural log of capitalization rates on property characteristics and a dummy variable indicating whether an office is inside a job cluster. Such an approach yields lower capitalization rates inside job clusters when agglomeration economies are present. As endogeneity of agglomeration is a real concern, instrumenting for agglomeration to restore consistency of the Ordinary Least Squares estimator is typically required (Wooldridge, 2002). In modeling agglomeration effects on rents, Koster et al. (2014) follow Ciccone and Hall (1996) in using instruments such as population in 1830 by municipality and distance to nearest railway station in 1870. Glaeser (2010) argues that instruments on current administrative boundaries may create an inherent bias. This suggests that distance to nearest railway station in 1870 is perhaps a better instrument than the population in 1830 by municipality. From a spatial equilibrium perspective, initial conditions will play a role and endogeneity remains a concern (cf. Glaeser, 2008). In addition, agglomeration may affect capitalization rates in other and unmeasured ways.

We estimate a regression model, in which the logarithm of the capitalization rate at the time of purchase for a specific property at time t is related to a linear function of property characteristics, interest rates, and agglomeration economies. We exploit time-varying information on job clusters and include whether a property is in an area that is or ever will be a job cluster. Specifically, we estimate:

$$\log\ CAP_{irt} = \beta_x X_{it} + \beta_1 IR_t + \beta_2 DJC_i + \beta_3 DJC_i \times DOC_{it} + \delta_r + \mu_t + \varepsilon_{irt}, \quad (4)$$

where CAP_{irt} is the gross capitalization rate for a specific property i in city r at the time of purchase t; X_{it} is a vector of the relevant property characteristics, including the log rent level; IR_t is a measurement for the risk-free interest rate at time t; DJC_i is a dummy variable indicating whether the subject property is in or ever will be in a cluster; and $DJC_i \times DOC_{it}$ is the interaction between DJC_i and DOC_{it}, a dummy variable indicating whether the property is in an office cluster at time t. The terms δ_r and μ_t are city and year fixed effects, respectively.

The variable, DJC_i, which indicates whether the property is in a cluster ever, captures any unobserved time-invariant heterogeneity associated with the specific location. The variable of interest is $DJC_i \times DOC_{it}$ and captures the effect of agglomeration on capitalization rates inside a job cluster. If agglomeration effects are present, we expect β_3 to be negative.[15]

Estimation Results

Main Results

The main results are presented in Table 2. Models include year and city fixed effects, and a threshold of 2,000 jobs per sq. km to determine the boundaries of job clusters. The estimates for property characteristics are as one would expect. On average, new properties have a capitalization rate that is about 10 percent lower than existing properties and is consistent with existing literature (Bokhari and Geltner, 2018). Next, larger properties, in terms of office space, have lower capitalization rates. Also, the interest rate is positively associated with the capitalization rate, a finding consistent with earlier literature (see Clayton et al., 2009; Chaney and Hoesli, 2015). Generated cash flow of rents per square meter is negatively associated with capitalization rates and reveals that properties with the lowest capitalization rates have the highest rents. These are the properties that thus have the highest asset values.[16]

The coefficient on *DJC* in column (1) is -0.0108 and indicates that properties located in an area that is or ever will be a job cluster, on average, sell for lower cap rates than properties outside those areas. Nevertheless, given the large standard error, the coefficient is not statistically significant.

The key parameter is the coefficient on $DJC_i \times DOC_{it}$. This coefficient captures the average effect of agglomeration in a job cluster at the time of buying. The estimate of -0.0512 reveals a negative and statistically significant effect (at the five percent level) for high concentrations of jobs on capitalization rates. So our results suggest a 5 percent lower capitalization rate for properties in locations with a high concentration of jobs, and corresponds to an average reduction in capitalization rates of 40 basis points. We have also estimated the model in which DJC_i is interacted with job

[15] On the other hand, if $\beta_3 \geq 0$,this would be inconsistent with the conceptual framework, since it would indicate that investors assess properties in agglomeration economies as riskier.

[16] We include rent to encompass any unobserved characteristics related to the specific property. However, measurement error in rents may affect our findings. We therefore estimated the models without log of rent also. These findings did not alter the qualitative findings of our paper.

Table 2 Estimation results, 1996-2011

Threshold density in jobs per sq.km.:	2,000			
	(1)		(2)	
DJC_i	-0.0108		-0.265	
	(0.0326)		(0.183)	
$DJC_i \times DOC_{it}$	-0.0512	**	0.447	***
	(0.0259)		(0.143)	
Job density (log)			-0.0188	
			(0.0227)	
DJC_i × Job density (log)			0.0369	
			(0.0253)	
$DJC_i \times DOC_{it}$ × Job density (log)			-0.0630	***
			(0.0184)	
Rent (log)	-0.120	***	-0.112	***
	(0.0374)		(0.0359)	
Size (log)	-0.0287	***	-0.0272	***
	(0.00761)		(0.00710)	
New building (1=yes)	-0.0979	***	-0.106	***
	(0.0177)		(0.0173)	
Interest rate (%)	0.0934	***	0.0997	***
	(0.0151)		(0.0155)	
City fixed effects	yes		yes	
Year fixed effects	yes		yes	
Adjusted R-squared	0.45		0.46	
RMSE	0.15		0.15	
Observations	1,936		1,936	

dependent variable is capitalization rate (log). Standard errors are clustered at the zip-code level and reported in parentheses. DJC in column (1) is based on a threshold of job density greater than or equal to 2,000 jobs per sq. km. $DJC_i \times DOC_{it}$ is based on DJC and a dummy DOC indicating the current job cluster at the time of the transaction. Variable description is given in Table 1. *** p<0.01, ** p<0.05, * p<0.1

density (log). Model (2) shows similar results and a negative effect for high concentration of jobs on capitalization rates.

The obvious question arises as to what extent our coefficient on $DJC_i \times DOC_{it}$ depends on the threshold used to define the boundaries of local job clusters. By changing the threshold level, we basically manage the number of different job clusters. So, if the threshold level is high, few locations are classified as job cluster. Here we examine the robustness of our main finding, using various threshold values. These results are given in Table 3. Our results reveal sensitivity in the effect size of agglomeration on capitalization rates. Nevertheless, the results indicate that earlier findings hold for a range of threshold levels. So, in job clusters for 1,500, or 5,000 jobs per sq. m, we find lower capitalization rates for offices.

Table 3 Estimation results for various threshold levels, 1996-2011

Threshold density in jobs per sq.km.:	500 (1)		1,500 (2)		5,000 (3)	
DJC_i	-0.140	*	-0.051	*	0.019	
	(0.076)		(0.038)		(0.036)	
$DJC_i \times DOC_{it}$	0.047		-0.036		-0.069	*
	(0.058)		(0.030)		(0.038)	
Property controls	yes		yes		yes	
City fixed effects	yes		yes		yes	
Year fixed effects	yes		yes		yes	
Adjusted R-squared	0.45		0.45		0.46	
RMSE	0.15		0.15		0.15	
Number of observations	1,936		1,936		1,936	

dependent variable is capitalization rate (log). Standard errors are clustered at the zip-code level and reported in parentheses. DJC in column (1) is based on a threshold of job density greater than or equal to # jobs per sq. km, as indicated in the specific column. $DJC \times DOC_{it}$ is based on DJC and the dummy DOC indicating current job cluster at the time of the transaction. Property controls refer to identical set of explanatory variables as shown in Table 2. Variable description is given in Table 1.*** p<0.01, ** p<0.05, * p<0.1.

Heterogeneity in transactions

We subsequently explore whether our main findings depend on heterogeneity in transactions. The robustness tests relate to i.) variation in submarkets, ii.) whether a transaction is a sale and leaseback, iii.) heterogeneity in sellers and buyers, and iv.) whether a transaction refers to a foreclosed property. Table 4 provides results, which suggest that the main findings are not driven by these sources of heterogeneity. The results show that capitalization rates are between 4.3 and 5.0 percent lower if the property is within a job cluster.

First, the question arises as to whether submarkets may explain the observed patterns in capitalization rates. Core markets are known to behave differently from non-core markets (Shilling et al., 2017). To explore this, we divide the sample into Amsterdam (greater Amsterdam Metropolitan Area) and otherwise. [17] Table 4, column (1) reports similar agglomeration effects as reported in Table 2.

Second, heterogeneity in sale and leaseback may explain observed patterns of lower capitalization rates in clusters. Sale and leaseback deals are known for lower capitalization rates (Sirmans and Slade, 2010). If sale and leasebacks were over-represented in clusters, this would invalidate our main findings and interpretation. We use information on whether the transaction involves a sale and leaseback and

[17] Amsterdam refers to the greater Amsterdam Metropolitan Area and is a major European gateway city (CBRE, 2017).

Table.4 Estimation results accounting for heterogeneity in deals, 1996-2011

Threshold density in jobs per sq.km.:	2,000							
	(1)		(2)		(3)		(4)	
DJC_i	-0.0108		-0.0148		-0.0110		-0.0103	
	(0.0326)		(0.0316)		(0.0307)		(0.0328)	
$DJC_i \times DOC_{it}$	-0.0512	**	-0.0477	*	-0.0471	*	-0.0444	*
	(0.0259)		(0.0243)		(0.0240)		(0.0267)	
Transaction controls								
Amsterdam	-0.080	**	-0.079	**			-0.0684	**
	(0.0342)		(0.0339)				(0.0341)	
Sale-leaseback			-0.0381				-0.0465	
			(0.0421)				(0.0443)	
Seller institutional × Buyer institutional					-0.0355	**	-0.0343	*
					(0.0177)		(0.0180)	
Seller institutional × Buyer private					0.0171		0.0235	
					(0.0195)		(0.0198)	
Seller private × Buyer institutional					-0.0420	**	-0.0397	*
					(0.0205)		(0.0213)	
Property controls	yes		yes		yes		yes	
City fixed effects	yes		yes		yes		yes	
Year fixed effects	yes		yes		yes		yes	
Adjusted R-squared	0.45		0.45		0.46		0.46	
Number of observations	1,936		1,936		1,936		1,852	

dependent variable is capitalization rate (log). Standard errors are clustered at the zip-code level and reported in parentheses. DJC in column (1) is based on a threshold of job density greater than or equal to 2,000 jobs per sq. km, as indicated in the specific column. $DJC_i \times DOC_{it}$ is based on DJC and the dummy DOC indicating current job cluster at the time of the transaction. Property controls refer to identical set of explanatory variables as shown in Table 2. Variable description is given in Table 1.*** p<0.01, ** p<0.05, * p<0.1.

augment our model accordingly. The results in Table 4, column (2) again show similar results.

Third, we address the issue of whether our results are driven by heterogeneity in the type of buyer and seller.. From the literature we know that type of investor is an important moderator in explaining variation in deals (Bokhari and Geltner, 2011). Our data provide information on a large list of buyer and seller types, which we classify into private and institutional investors. These results are reported in Table 4, column (3).

Last, we check whether our results depend on foreclosures. To explore this, we now remove all transactions which include Banking either as buyer or seller. If foreclosures were driving our results, no such effects of agglomeration should remain. The results in Table 4, column (4) reveal that our parameter of interest is robust to limiting the number of observations to non-banking and that our main results remain valid.

Table.5 Estimation results with measurement of expected rental growth

Threshold density in jobs per sq.km.:	2,000	
DJC_i	0.0068	
	(0.0306)	
$DJC_i \times DOC_{it}$	-0.0695	***
	(0.0248)	
Expected rental growth (%)	-0.0005	
	(0.0006)	
Property controls	yes	
Transaction controls	yes	
City fixed effects	yes	
Year fixed effects	yes	
Adjusted R-squared	0.43	
Number of observations	1,832	

dependent variable is capitalization rate (log). Standard errors are clustered at the zip-code level and reported in parentheses. DJC in column (1) is based on a threshold of job density greater than or equal to 2,000 jobs per sq. km $DJC_i \times DOC_{it}$ is based on DJC and the current job density at the time of transaction. Expected rental growth is 100 * (job $density_{it}$ - job $density_{t-1}$)/ (job $density_{t-1}$). Property controls refer to identical set of explanatory variables as shown in Table 2. Transaction controls refer to set of explanatory variables as shown in Table 4. Variable description is given in Table 1.*** p<0.01, ** p<0.05, * p<0.1

Expected Rental Growth

The outcomes presented so far do not explicitly control for the expected rental growth rate, g_{it}, as originally proposed in the conceptual model. To include a property-specific measurement of expected rental growth, we augment our model and include a measurement of change in local job density to capture expected rental growth.[18] These results are provided in Table 5. Table 5 shows that our main findings still hold and that agglomeration lowers capitalization rates. Finally, expected rental growth is negative, but given the relatively large standard error, is not statistically significant at any conventional level of significance.

Conclusions

This paper studies the impact of agglomeration economies on real estate markets by examining transaction-based capitalization rates for offices in the Netherlands. Theoretically, agglomeration economies are reflected in higher rents, since tenants benefit from being situated within a cluster. Also, having other office structures in

[18] Specifically g_{it} = 100 * (job $density_{it}$ - job $density_{t-1}$)/ (job $density_{t-1}$).

the vicinity suggests efficiency gains in terms of production and services. The question arises as to whether these agglomeration economies are reflected in lower capitalization rates. We use the gross capitalization rate at time of buying and relate this to whether a property is situated within a job cluster. In examining this, we use a dataset with transaction-based capitalization rates for which we have unique information on local job densities over time. We use GIS to delineate the boundaries of job clusters over time, and are able to identify whether a transaction is in an area that is or ever would be inside a job cluster. Our results indicate that investors require a lower capitalization rate by approximately 4.6 percent or 40 basis points if the property is within such a job cluster.

While our work extends earlier studies on agglomeration economies in commercial real estate markets, we recognize a number of directions for further research. First, the modeling of expected rental growth could be carried out in more detail using information on underlying drivers and feedback mechanisms. Also, rather than considering the total number of jobs, future research could focus on co-agglomeration and associated linkages across industries by exploiting information on SBI industry classification. Finally, further refinement could be considered when addressing nearness to clusters. What we have used here is a dichotomous classification of inside or outside a job cluster, irrespective of the distance from the nearest cluster. A more refined way would include rings or some distance decay function approach. These topics await future research.

Appendix A - Glossary of model notation

Variable definitions

P_{it}	= Asset price for property *i* at time *t* (EUR, current).
NOI_{it}	= Net operating income for property *i* at time *t* (EUR, current).
g_{it}	= Rental growth expectation for property *i* at time *t*.
r_{it}	= Discount rate for property *i* at time *t*.
PS_{it+T}	= Expected selling-price for property *i* at time *t*+*T*.
T	= Investment horizon.
CAP_{it}	= Capitalization rate for property *i* at time *t*.
RFI_t	= Risk-free nominal interest rate at time *t*.
EI_t	= Expected inflation at time *t*.
RP_{it}	= Risk premium for property *i* at time *t*.

Appendix B - Data appendix

Data sources

The data combines various sources: transaction data, all-parcel files, and data on jobs and establishments (for details, see Schoenmaker, 2016).

A. Transaction data

The data were drawn from the Strabo transaction database covering all publicly reported asset transactions in the Netherlands. The total number of asset transactions includes 14.3 million sq. m of office space. Total office space in the Netherlands in 2011 amounted to 50 million sq. m office space (Bak, 2014). The records contain information on the size of the property, asset price, rental income, and whether the property is newly built. Furthermore, the records include addresses on which basis we geocoded the data. We use data between 1996 and 2011 as our sample for estimation. We have office transactions across 137 cities or 852 zip-codes (6-digits street-level).

We exclude transactions for which we do not have information on asset value and rent at the time of asset purchase. This reduces the sample to 2,649 observations. We further exclude transactions for which we have no information on the property characteristics, including location. This reduces the sample size to 1,955. Next, we exclude transactions for which we have no information on transaction-type details. This leaves us with 1,948 observations. Lastly, we removed the top 1% of the distribution of capitalization rates, resulting in 1,936 observations which will be used in the empirical analysis.

B. All-parcel file

The all-parcel file includes all parcels in the Netherlands in 2012 and come from the Dutch Department of Infrastructure and Environment. We map all office buildings as well as the geocoded transaction data of offices. Figure 4 maps all office buildings.

Fig. 4 Office buildings in the Netherlands, 2012. This figure shows all office buildings in the Netherlands. Black dots represent office buildings

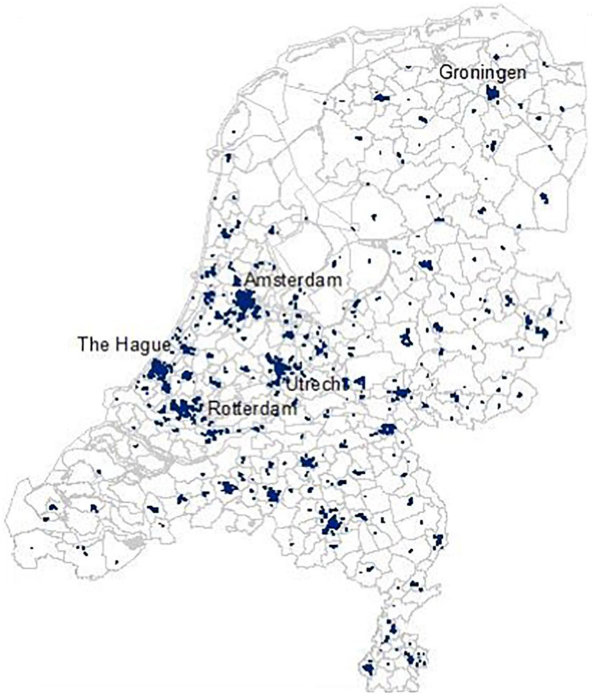
C. Jobs data

The data on jobs come from administrative records based on the Chambers of Commerce and include, for each establishment, information about address, SBI sector classification, and number of employees. We have annual data from 1996 onwards. We use the address to geocode total number of jobs.

Data management

The data was used as follows. First, we prepare the jobs data. For each year, we first calculate the density of jobs using GIS density-tool techniques, calculating the job density on a 50 x 50 meter raster grid with 800-meter search radius from the grid centroid. Next, each grid is compared with its neighboring grids. If the number of jobs exceeded or equaled the cut-off value, then the grids are merged to form a cluster. We set a threshold on number of jobs per sq. km to identify a cluster on the basis of the empirical distribution of job density across the nation. Figure 5 maps shows the resulting clusters with a threshold of 2,000 jobs per sq.km, for the year 2000.

Fig. 5 Job clusters in the Netherlands. This figure shows all job clusters in the Netherlands with 2,000 jobs per sq.km for year 2000



The number of job clusters varies with the threshold. This is summarized in Table 6 for the year 2000.

Table.6 Descriptive statistics for job clusters by threshold, for year 2000

Threshold in jobs per sq.km	1	500	1,500	2,000	5,000
Number of job clusters	753,601	1,009	597	504	155
Number of jobs per cluster	9	6,442	8,270	8,435	11,476
		(29,210)	(27,598)	(25,940)	(21,420)
Cluster size (in sq.km)	0.04	3.18	2.04	1.66	1.09
		(9.91)	(5.25)	(3.99)	(1.95)
Job density (number per sq.km)	118	1,512	4,310	5,945	12,488
		(4,264)	(7,686)	(13,433)	(15,729)

Clusters are based on GIS density tool procedures based on a 50 x 50 meter raster grid with 800-meter search radius from the grid centroid. Total number of firms in year 2000 is 753,601 for 3,777,811 jobs. Jobs include (unweighted) part-time and fulltime jobs. Total surface for the Netherlands is set at 32,000 sq.km.

We repeat this procedure for each year to identify how clusters develop over time. Figure 6 illustrates the dynamics for the region of Utrecht. Next, we merged this data with the transaction data to form our sample for estimation between 1996 and 2011.

Fig. 6 Illustration of a zoom-in of clusters near the city of Utrecht based on job clusters in 1996 (top panel), and 2011 (lower panel). Cluster based on jobs 1996 (light), and 2011 (dark). Black dots represent office asset transactions in our sample. Utrecht is one of the main cities in the Netherlands

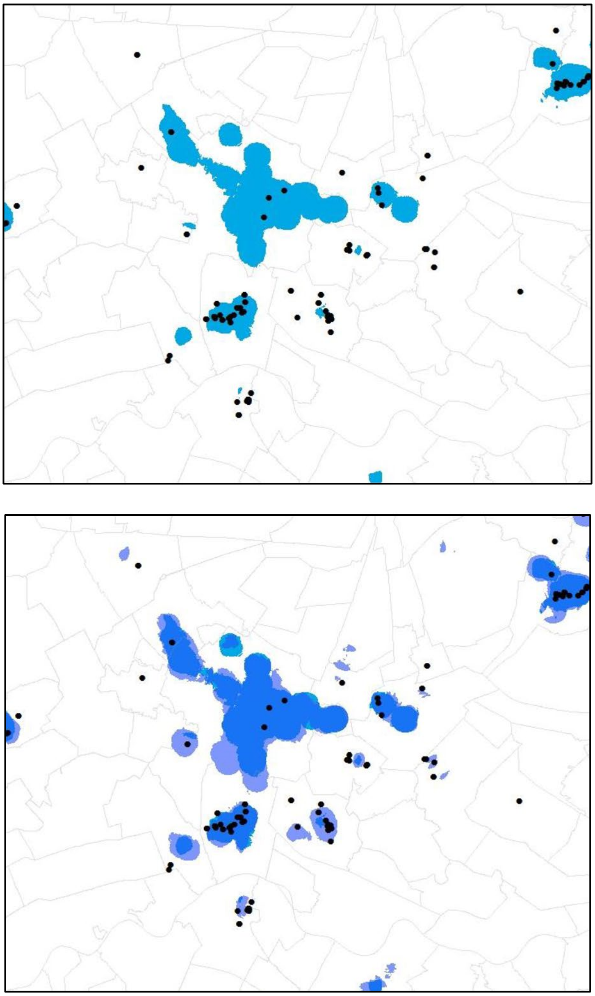


Table 7 shows the correlations among the variables of interest. The results reveal that the capitalization rate is negatively correlated with the rent per sq. m (cash flow), the office size, and new properties. Observe the high correlation between rents and asset prices. These univariate statistics indicate that higher cash flows are associated with lower capitalization rates, and larger properties, and new properties have lower capitalization rates. In addition, we find that job density is negatively correlated with the capitalization rate. The estimates for the baseline hedonic models are provided in Table 8.

Table.7 Correlation matrix

	Cap	Rent	Price	500Size	Job density	DJC				DOC_it		
						500	1,500	2,000	5,000	500	1,500	2,000
Rent	-0.41											
Price	-0.71	0.90										
Size	-0.21	0.17	0.24									
Job density	-0.20	0.22	0.26	0.34								
DJC 500	-0.06	0.06	0.06	0.06	0.01							
1,500	-0.15	0.12	0.14	0.13	0.07	0.24						
2,000	-0.16	0.18	0.19	0.19	0.12	0.35	0.66					
5,000	-0.15	0.21	0.23	0.23	0.24	0.67	0.27	0.42				
DOC_it 500	-0.07	0.02	0.03	0.03	-0.01	0.14	0.34	0.23	0.10			
1,500	-0.17	0.14	0.16	0.16	0.11	0.33	0.73	0.77	0.36	0.38		
2,000	-0.16	0.18	0.19	0.19	0.14	0.44	0.52	0.79	0.51	0.27	0.71	
5,000	-0.17	0.20	0.25	0.25	0.23	0.73	0.24	0.36	0.87	0.12	0.33	0.46

Table gives correlations. Variable description is given in Table 1.

Table.8 Estimation results of baseline models

	(1)	(2)	(3)	(4) 500	(5) 1,500	(6) 2,000	(7) 5,000	(8) Job density
Job cluster				0.0309	-0.053	-0.0614	-0.0503	-0.0237
				(0.0520)	(0.0227)	(0.0173)	(0.0188)	(0.010)
Rent (log)	-0.231	-0.174	-0.122	-0.123	-0.121	-0.115	-0.121	-0.115
	(0.0285)	(0.0312)	(0.0366)	(0.0368)	(0.0367)	(0.0358)	(0.0347)	(0.0359)
Size (log)	-0.0203	-0.0243	-0.0278	-0.0277	-0.0279	-0.0276	-0.0272	-0.0274
	(0.00866)	(0.0080)	(0.0076)	(0.0076)	(0.00759)	(0.00755)	(0.00722)	(0.00736)
New building (1=yes)	-0.0866	-0.08	-0.089	-0.009	-0.0875	-0.094	-0.093	-0.09
	(0.0191)	(0.0166)	(0.0176)	(0.0176)	(0.0176)	(0.0173)	(0.0176)	(0.0176)
Interest rate (%)	0.053	0.0452	0.051	0.051	0.052	0.0513	0.0459	0.0487
	(0.0103)	(0.0137)	(0.0136)	(0.0136)	(0.0137)	(0.0138)	(0.0145)	(0.0138)
City FE	no	no	yes	yes	yes	yes	yes	yes
Province FE	no	yes	no	no	no	no	no	no
Year FE	no	yes	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.249	0.353	0.442	0.442	0.445	0.449	0.451	0.450
Observations	1,936	1,936	1,936	1,936	1,936	1,936	1,936	1,936

dependent variable is capitalization rate (log). Standard errors are clustered at the zip-code level and reported in parentheses. DOC_{it} is a dummy indicating inside current cluster at time of transaction. Columns (4)-(8) give results for different thresholds of current job cluster DOC_{it}: 500, 1,500, 2,000, 5,000 and 10,000 jobs per sq. km. Column (9) uses job density (log). Variable description is given in Table 1.

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