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Nase, Ilir; van Assendelft, Nick; Remøy, Hilde

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Rent Premiums and Vertical Sorting in Amsterdam's Multi-Tenant Office Buildings

Ilir Nase [1] · Nick van Assendelft [2] · Hilde Remøy [1]

Abstract

This paper investigates the impact of vertical location and tenant sorting on commercial office rents within the tall office towers of Amsterdam. In economic geography and urban economics' approach to productivity tall buildings constitute an important, density-increasing typology that fosters agglomeration. Through econometric modelling of 627 office rent transactions in 33 tall office buildings in Amsterdam rented during the period 2000–2016, this paper provides empirical evidence to the growing body of knowledge on the economics of height. This paper is the first to decompose the vertical rent premium whereby 27% is related to view, 3% to industry-level differences and the remaining 70% to firm-level signalling and other factors. The results indicate positive rent premiums for higher floor locations consistent across a wide range of specifications, strong premiums associated with the top output-per-job industry sectors and a weak presence of vertical sorting. Additional sorting evidence shows clear differences among industry sectors for height preference (law firms and consultancy & management practices), or lack of it despite high productivity (ICT sector). Relative price differentials for view and status were consistent across the various industry sectors with the exception of insurance carriers who seem to prefer status over the view aspect of height. The good performance of the OLS model with submarket fixed effects indicates the strong delineation of office submarkets in Amsterdam.

Keywords Vertical rent gradients · Vertical sorting · Commercial office sector · Spatiotemporal modelling · STAR

✉ Ilir Nase
  i.nase@tudelft.nl

  Nick van Assendelft
  Nick.vanassendelft@cushwake.com

  Hilde Remøy
  H.T.Remoy@tudelft.nl

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Introduction

Over the past five decades urban economic theory has focused on analysing urban spatial structure based on the Alonso (1964), Mills (1967), Muth (1969) framework of monocentric cities. This framework concentrates on land prices' impact on horizontal spatial structure and land use. Consequently, mainstream urban economics is characterised by an implicit assumption that treats cities as flat, with little or no consideration of the vertical spatial structure (see Duranton and Puga 2015 for a recent review). In economic geography and urban economics' approach to productivity tall buildings constitute an important, density-increasing typology that fosters agglomeration. Additionally, building height is strongly influenced by competition for status among developers, investors and cities (Helsley and Strange 2008). Tall buildings can therefore be considered a strategic component of urban economic development and are predicated on a variety of factors namely economic cycles, local land use regulations, a city's global positioning and the search for status/prestige that stakeholders aim to achieve through these developments (Barr 2012; Garza and Lizieri 2016). Notwithstanding their importance, empirical research on tall buildings, rents and vertical spatial structure is still embryonic.

There has been a surge of skyscraper development across the globe particularly in the last two decades as a result of major technological advancements. This, coupled with concentration of wealth in particular world regions, has led to a competition for building higher. The Council of Tall Buildings and Urban Habitat (CTBUH) reports that by the end of 2016 the number of buildings taller than 200 m amounted to 1168 globally (CTBUH 2017a). In the Netherlands, considering also local land use regulations, six out of ten buildings above 100 m and eight out of the ten tallest structures have been constructed in this millennium. The Dutch market is experiencing an increase in high-rise constructions, as there are currently 51 high-rise buildings proposed or under development (CTBUH 2017b). The above figures point to a renewed global skyscraper construction boom and a growing importance of tall buildings in the Netherlands, which calls for further in-depth research on the economic aspects underpinning skyscraper development.[1]

This paper contributes to the growing body of knowledge on the economics of tall buildings by investigating the rent premiums associated with higher floor location and different industry sectors that occupy commercial office space. The study is part of an embryonic body of knowledge that analyses exact, within building location to estimate vertical rent gradients and assess tenants' willingness to pay to locate on higher floors. To the best of our knowledge, it is the first that assesses height premiums after holding view constant. In their quest for height firms are driven by a search for status – 'showing off' by being on top of others; demand for view amenities that raise profit rather than directly reflect their utility function; signalling the quality of their product and other factors (Liu et al. 2018). Our empirical analysis shows that after holding view constant firms still pay significant premiums – which are roughly 70% of the initial amount – to be located on higher floors. These we mainly attribute to signalling and other, firm-level differences among office tenants.

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[1] Throughout the paper the terms 'tall building' and 'skyscraper' are used interchangeably.

The empirical analysis uses a dataset of 627 office transactions in thirty-three multi-tenant buildings of ten floors or taller rented during the period 2000–2016. It employs standard hedonic models to investigate rent premiums and various aspects of vertical sorting of different industries. We additionally use spatiotemporal models based on widely accepted approaches to spatial econometric analysis of real estate data (Pace et al. 2000; Tu et al. 2004; LeSage and Pace 2009; Nappi-Choulet and Maury 2009; Dubè and Legros 2014; Nase et al. 2016, among others). Spatial econometric literature indicates addressing estimation bias or inconsistency and improved model fit over OLS estimates as the typical rationale for this model choice, given that real estate data are of spatial character. Our empirical estimates point towards more plausible spatiotemporal estimates based on theoretical expectations for a limited number of variables. However, model performance was considerably lower compared to the OLS estimates with spatial (expert delineated submarket) fixed effects indicating the efficiency of submarket delineation in the Amsterdam office market. The remainder of this paper is organized as follows. The next section starts by analysing the theoretical underpinnings of the economics of tall buildings and subsequently focuses on rent premiums, vertical sorting and the willingness to pay for locating on higher floors. Section three provides an overview of the data and variables used in the analysis and section four describes the methodological approach. The fifth section provides a detailed account of the empirical findings in two parts. The first part focusses on the rent premiums for various industry sectors and different aspects of height (vertical location). The second part concentrates on the vertical sorting of different industries based on preferences for view and/or status. Section six draws conclusions to this study.

Height Determinants, Rent Premiums and Vertical Sorting in Tall Office Buildings

Tall buildings can be considered a way to signal economic strength for builders, developers, international corporations, government entities and cities, making building height an important strategic component in urban economics (Barr 2012). The average global building height has significantly increased during the past fifteen years. While the tallest 100 buildings in the world had an average height of 286 m in 2001, this has since risen to 362 m by the end of 2016 (CTBUH 2017a). These figures are indicative of the surge in high-rise buildings and point to the increasing importance of their role in urban development. The literature on skyscraper development is characterized by a small number of prevailing theoretical approaches summarized by Garza and Lizieri (2016). The key theories are namely the traditional microeconomic model, the game theoretic approach, the business cycle behaviour model and the global cities influence.

The traditional microeconomic theory is based on the monocentric city model, where competition for scarce land in the city centre among different sectors drives up land prices and subsequently determines the optimal building height and shows height increases as a function of economic activity within a city. One of the earliest studies on the economics of building height uses these principles to investigate profit maximisation based on costs and income flows for various height levels of a hypothetical building considering excessive height as a response to increasing land values (Clark and Kingston 1930). However, many contemporary cities are not characterized

by the monocentric model and building height does not monotonically decrease with distance from the CBD but shows considerable variations (Duranton and Puga 2015). The waves of different building height within the CBD are mainly caused by the coexistence of multiple production centres with their own gravity centres and the endogenous relationship between land value and agglomeration (Barr 2012).

The game theoretic approach developed by Helsley and Strange (2008) focuses on the competition of developers in reaching 'the tallest' building heights. This contest explains overbuilding, as every game participant chooses building heights which exceed profit maximization heights and result in the tallest building being much higher in comparison to the surrounding buildings. Record breaking buildings show some cyclicality over time, exceeding each other in rapid succession within the 1920s, 1970s and 2000s. This model explains status, overbuilding and the dynamics within the skyscraper race concluding that excessive height is a result of the competition for status/power/ego. Ahlfeldt and McMillen (2018) investigate historical land prices and building height in Chicago and find evidence that excessively tall buildings are less likely to be constructed at the same location or in the same or subsequent decade than other tall buildings indicating support for the game theoretical model.

The work of Barr (2010, 2012, 2013) on the economic determinants of building height stands somehow at the intersection of these two theories. The author finds that skyscraper height is primarily determined by local and national economies, land use regulations and taxation (Barr 2010). Record breaking height and the quest for status are only driven by the right combination of ego and economics and occur only when the opportunity costs for both is relatively low. Subsequent research considered ego as an important factor for building height (Barr 2012). Results showed the search for status had increased building height by approximately 15 floors at the end of the twentieth century. Height competition increases significantly during times of economic growth, due to the lower opportunity costs for seeking social status. Additionally, economic factors and land use regulation were important determinants of building height. In a comparative study of building height determinants for the cities of Chicago and New York, Barr (2013) finds that general economic and policy variables are mainly responsible for the variation in height between the cities. However, each city responded differently demonstrating that local factors have an important influence on building height.

Theory on global cities has focused on economic and sociological aspects analysing capital flow, transaction volumes and communication networks to show that these areas are able to attract high skilled labour due to their concentration of advanced producer services. This has implications for the traditional economic model, as the economic size of the city alone is not a determining factor for building height but should also consider global connectivity and world city status. The business cycle approach is based on the Skyscraper Index which links record breaking tall buildings (considered as overinvestment or capital accumulation into bricks and mortar) to global economic downturns in 1929, 1974, 1998 and 2008 (Thornton 2005). This approach does not provide a causal relationship among the two phenomena and has found little application in academic research. More recently, Barr et al. (2015) showed that popular beliefs related to the use of the Skyscraper Index to predict global business cycles do not hold. The authors used cointegration analysis and Granger causality tests to conclude that GDP (a proxy for national income) Granger causes skyscraper height while there is no evidence of

reverse causality among the two. This is more in line with rational economic behaviour of income (wage) capitalization into various real estate amenities (height in this case) as outlined by Roback (1982).

These theories depict skyscraper height as a function of income in general (demand side) and developer competition for status (supply side). Particularly the evidence based empirical work on the demand side seems to favour mainly the hypothesis that skyscraper height is generally an outcome of rational economic behaviour. According to these studies the non-economic drivers of height such as developer ego tend to happen only in boom times (Barr 2012; Barr et al. 2015). The demand side theories and related evidence hypothesize that excessively tall buildings can be only explained by a contest of developer's egos since they are overbuilt (exceed optimal height) in the narrow economic sense (Helsley an Strange 2008; Ahlfeldt and McMillen 2018). Our research is positioned on the demand side theories of building height through its concerted analysis of explaining and estimating tenants' willingness to pay for locating on higher floors, the possible existence of sorting along different floor levels and its causes across various industry sectors.

A theoretical framework for the vertical spatial structure and systematic sorting[2] of industry sectors based on the tension between vertical access costs and amenities has been proposed by Liu et al. (2018). It predicts that higher productivity, higher amenity-oriented industries tend to locate on higher floors. These predictions are supported by empirical evidence which also shows the existence of a non-monotonic vertical rent gradient. Throughout the paper the authors unveil three hypotheses in attempting to explain why firms are willing to pay more to be on higher floors. First, the upper floors offer better views which to commercial tenants are important only if they increase profits. In this context, the authors offer mixed relations to both increased productivity and reduced HR costs. Second, firms tend to locate on higher floors to demonstrate their (powerful) status by positioning themselves 'above the others'. This behaviour is very similar to the ego-driven developers who build higher to dissipate competition. In the recent years of increased corporate social responsibility this hypothesis might not hold across the wide spectrum of industries. Third, by using height firms tend to signal quality of their product to customers. Consequently, a higher location is assumed to be worth more to high-productivity tenants.

In the light of the above evidence, our first goal it to test for the existence of vertical rent premiums and investigate their nature. Liu et al. (2018) show that vertical rents are independent of the within building and nearby employment and increase approximately 0.58% on average per floor although accessibility decreases with height. The sector

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[2] Generally we agree with the theoretical framework of demand and supply equilibrium developed by Liu et al. (2018). However, we point out two key departures from that framework based also on the focus of the current paper. The first concerns the joint analysis of ground floor retail and other (higher) floor level retail and office properties to conclude that there is a 'non-monotonic' rent gradient. We explicitly focus on the office sector as we believe that office and retail are two different asset/property classes that should be analysed separately. Consequently, our empirical analysis shows that the within sector rent gradient while upward increasing is not truly monotonic. The second point concerns the claim that view and status related 'perks' associated with higher floor location might incite workers of 'prestigious' companies to accept lower wages resulting in cost reduction. We find no evidence of such claim in the literature and turn to the literature on workplace that supports the idea of such perks being associated with increased employee satisfaction and performance that should eventually lead to increased productivity which in turn should translate in increased profits and eventually higher willingness to pay. We find this more plausible than the former claim.

persistently seen on higher floor levels was law firms. Within the Dutch context, Koster et al. (2014) found significant positive rents in taller buildings across four submarkets in the Netherlands including Amsterdam. Their results indicated 4% rent premiums on average for a 10-m building height increase which is attributed to building agglomeration economies due to the increase in productivity, landmark effects and panoramic views. Our second goal is to investigate rent differentials among different industry sector office tenants to test for the existence of productivity-related, higher wages' capitalization into prices consistent with the hedonic price theoretical framework of Lancaster (1966) Rosen (1974) and Roback (1982).

Following from the first two goals, our third goal is to test the existence and explain the causes of vertical sorting. Liu et al. (2018) found evidence that sales per worker and employment in industries are positively correlated to floor number, indicating that the highest floors contain the most productive industries. Additionally, larger firms have established headquarters on higher floor levels. It is argued that the location of these 'trophy' tenants is based on strong amenity orientation and corresponding status. An interesting finding in this context relates to the association of within building relative location with 'social power' (Dorfman et al. 2017). The authors perform a series of experiments to conclude, among others, that information about people's floor location signals their social power. We consider the concept of individual social power to be closely related to the concept of firm-level status described earlier.

As evidence points to three key attributes associated with higher floor location, in the remaining parts of this paper, we focus particularly on these aspects when explaining the causes of vertical sorting among different industry sector tenants. This research adds to the embryonic body of knowledge on the economics of height in two ways. First, it improves upon previous findings about the Dutch office market by providing floor level and industry sector rent premiums, factors which have not been previously measured due to lack of related information. Second, it provides the first evidence to date on the causes of vertical sorting through a concerted and laborious process of variable design and subsequent econometric analysis. These particular features of variable design and more general information about the data used in this study are explained in detail in the next section.

Data and Variable Description

The database used in this research is constructed from a variety of sources. Their combination enables the analysis of commercial rent transaction values, the related industry sector and location within a building for each transaction, in addition to the common hedonic characteristics such as size, age etc. The market transaction data are sourced from Cushman & Wakefield (C&W). Their general market database, rental contracts and rent roll records of office building transactions provide information regarding rent prices, transaction date, size, building age, renovation date (when applicable), building height (in floors), number of parking spaces in a building, and the ratio Net/Gross area. The latter we use as a proxy for building design efficiency, particularly considering that in tall buildings competition among developers might lead to unused physical space mainly on the top levels (following Helsley and Strange 2008). Rent rolls and rental contracts furthermore specify the exact vertical location of tenants within the building.

The variable list was further enriched with information from *Vastgoeddata,* an online commercial real estate data provider. The database combines several data sources from the Dutch Land Registry, Strabo, *Ruimtelijke Plannen* and Creditsafe. The Creditsafe's data is used to identify and categorize the tenants according to their corresponding business classification code and industry sector. The industry sectors categorization follows that of the Dutch Chamber of Commerce, which employs the SIB 2008 code *Standaard Bedrijfsindeling* 2008 (in Dutch).

The tall commercial office buildings within this study are selected based on data acquired from the website www.emporis.com that provides technical information on tall structures. This dataset provides accurate information about high-rise structures across the globe and has been employed in previous studies of Manhattan and Chicago (Ahlfeldt and McMillen 2018; Barr 2012). The website adopts a context-based definition of tall buildings, and the threshold for Amsterdam stands at forty meters (ten floors on average). We use this threshold for our subsequent data collection whereby from the initial database we select only transactions registered on multi-tenant office buildings of ten floors or more. Additionally, we omit all entries classified as retail to obtain a final database of 627 transactions located in thirty-three buildings across Amsterdam transacted during the period 2000Q1 – 2016Q3 (Fig. 1). Building heights were verified with the 3D-GIS information on the cadastral system of the Netherlands (BAG - *Basisregistraties Adressen en Gebouwen*).

Table 1 provides an overview of the variables generated in the data collection process indicating, with the appropriate rationale, the ones which were not used in the empirical analysis. To ensure that the data is comparable across the analysis timespan the dependent variable (the only economic variable) is corrected for currency exchange rates and inflation. All rental contracts in guldens (Dutch currency before
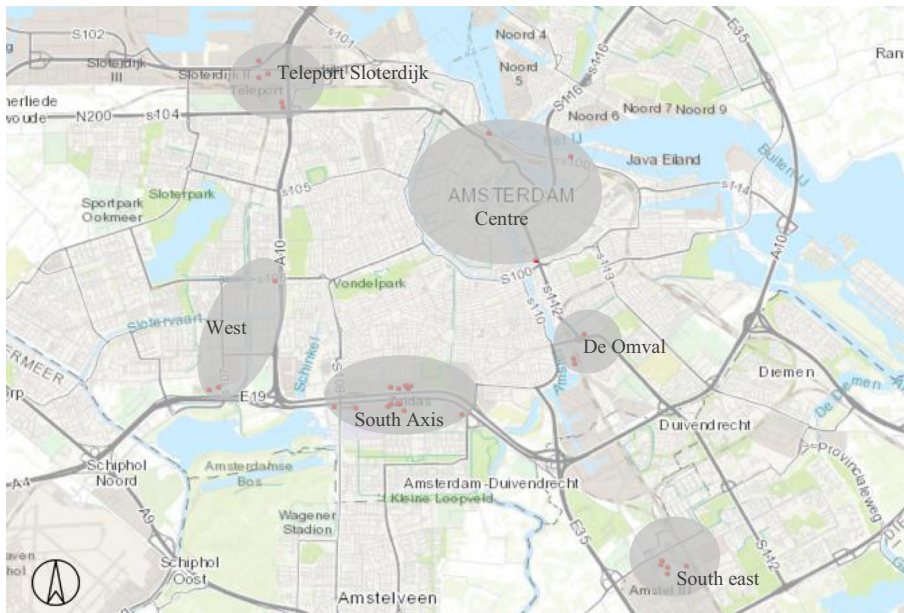

Fig. 1 Building locations and their spatial clustering into submarkets

Table 1 Variable names, statistics, description and sources

Variable name	Mean	Std. Dev.	Min.	Max.	Description	Source
Rent2016[a]	323.99	87.38	126.23	627.42	Rent per square meter in year 2016 Euros	C&W
LnRent2016	5.74	0.30	4.84	6.44	Natural log of the above (dep. variable)	C&W
Area[a]	960.28	1335.12	200	10,000	Lettable floor area of transaction in sq. m	C&W
LnArea	6.41	0.85	5.30	9.21	Natural log of the above (Area)	BAG
Age[a]	12.29	5.29	2	22	Building age since latest renovation year	BAG
LnAge	2.36	0.62	0.69	3.09	Natural log of the above (Age)	BAG
Floors	20.02	7.597	10	35	Number of floors excluding basements	C&W + Emporis
High Floor	11.21	6.62	0	31	Highest floor on transaction record	C&W
Ln(HighFL+1)	2.33	0.64	0	3.47	Natural log of the above	C&W
Ln(View Area)	11.95	0.77	8.32	15.02	View (potential) of transacted property	C&W + ArcScene
RelativeFL	0.614	0.25	0	1	Given as: HighFloor/Floors (status proxy)	C&W
Penthouse	0.0733	0.26	0	1	Dummy for penthouse offices	C&W
Ground Floor	0.04	0.20	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 1 to 5[d]	0.22	0.41	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 6 to 10	0.29	0.45	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 11 to 15	0.25	0.43	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 16 to 20	0.13	0.34	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 21 to 25	0.08	0.27	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Floor 26 to 31	0.02	0.16	0	1	Within building (vertical location) dummy	C&W + Fieldwork
Tenants	35.25	25.85	4	88	Number of tenants in the building	C&W + Fieldwork
Elevators[b]	5.26	2.311	2	10	Total number of elevators in the building	C&W + Fieldwork
ParkingNo	282.78	107.94	40	484	Number of parking places in the building	C&W
Net/Gross	0.77	0.07	0.61	0.93	Ratio of net to gross area of the building	C&W

Table 1 (continued)

Variable name	Mean	Std. Dev.	Min.	Max.	Description	Source
LnParcel	8.86	0.89	6.94	9.82	Parcel size in natural log form	BAG
EPC	1.08	0.24	0	1.80	Energy performance score of the building	C&W + epconline.nl
Dstat[a]	350.86	407.01	101.23	2187.71	Distance to the nearest train station in m	C&W + BAG
LnDstat	5.54	0.68	4.62	7.69	Natural log of the above (Dstat)	C&W + BAG
Dhigh[a]	1091.39	660.46	69.67	3561.39	Distance to the nearest highway exit in m	C&W + BAG
LnDhigh	6.84	0.61	4.24	8.18	Natural log of the above (Dhigh)	C&W + BAG
Financial Services	0.24	0.43	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Insurance carriers	0.03	0.16	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Real Estate	0.10	0.31	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Business services	0.13	0.33	0	1	Industry Sector Dummy	C&W + Vastgoeddata
ICT Services	0.11	0.31	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Law offices	0.06	0.24	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Consult& Management	0.13	0.34	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Other[d]	0.22	0.41	0	1	Industry Sector Dummy	C&W + Vastgoeddata
Y2000[c]	0.02	0.15	0	1	Transaction Year Dummy	C&W
Y2001[c]	0.02	0.15	0	1	Transaction Year Dummy	C&W
Y2002[d]	0.03	0.18	0	1	Transaction Year Dummy	C&W
Y2003	0.02	0.15	0	1	Transaction Year Dummy	C&W
Y 2004	0.04	0.21	0	1	Transaction Year Dummy	C&W
Y2005	0.05	0.22	0	1	Transaction Year Dummy	C&W
Y2006	0.08	0.27	0	1	Transaction Year Dummy	C&W
Y2007	0.07	0.25	0	1	Transaction Year Dummy	C&W
Y2008	0.06	0.24	0	1	Transaction Year Dummy	C&W
Y2009	0.04	0.19	0	1	Transaction Year Dummy	C&W

Table 1 (continued)

Variable name	Mean	Std. Dev.	Min.	Max.	Description	Source
Y2010	0.08	0.27	0	1	Transaction Year Dummy	C&W
Y2011	0.07	0.25	0	1	Transaction Year Dummy	C&W
Y2012	0.12	0.33	0	1	Transaction Year Dummy	C&W
Y2013	0.05	0.22	0	1	Transaction Year Dummy	C&W
Y2014	0.07	0.25	0	1	Transaction Year Dummy	C&W
Y2015	0.11	0.31	0	1	Transaction Year Dummy	C&W
Y2016	0.07	0.25	0	1	Transaction Year Dummy	C&W
De Omval	0.11	0.31	0	1	Submarket (horizontal location) Dummy	C&W + BAG
South-Axis[d]	0.63	0.48	0	1	Submarket (horizontal location) Dummy	C&W + BAG
South-East	0.09	0.29	0	1	Submarket (horizontal location) Dummy	C&W + BAG
Teleport Sloterdijk	0.06	0.24	0	1	Submarket (horizontal location) Dummy	C&W + BAG
Centre	0.07	0.26	0	1	Submarket (horizontal location) Dummy	C&W + BAG
West	0.04	0.19	0	1	Submarket (horizontal location) Dummy	C&W + BAG
N = 627						

[a] variable for descriptive purpose, not used in analysis; [b] dropped due to high correlation with 'Floors'; [c] observations in this category need to be discarded for the spatiotemporal process; [d] category baseline

2002) have been transformed to Euros using exchange rates from CBS (Dutch central bureau for statistics). Subsequently, all dependent variable values are corrected for inflation and reported in 2016 Euros. The average property in the database has a rental transaction price of €324/ m^2 /year with an area of 960 m^2, located in buildings approximately 20 floors tall that host on average 35 tenants. It was constructed or renovated approximately 12 years ago and has a EPC score of 1.08 which corresponds to energy label B. The relatively high number of tenants to number of floors may be attributed to the presence of the World Trade Centre Amsterdam transactions in the database.[3] The Centre hosts some of the largest multi-tenant office towers in the Netherlands, with tenant numbers varying from 37 in tower D to 88 in tower A, and is located in the South Axis submarket (Fig. 1). This submarket is considered the top office location in the Netherlands with the highest transaction activity. Such a dominance in transaction volume is also reflected in the composition of our database as approximately 63% of the entries are registered in this submarket.

With regard to the variable groupings of interest, we assign a vertical location to each observation based on the highest floor on which it is situated (High Floor) to capture better the view amenity premium and status/power associated with height (Liu et al. 2018). Following evidence on 'social power' (Dorfman et al. 2017), we calculate a 'Relative floor' variable by dividing the floor on which a transaction is located by the total number of (above ground) floors in the respective building. This variable has a range from zero, for ground floor located offices, to one for offices located on top of their buildings (penthouses). We further isolate penthouse transactions in a variable that takes the value of one for all observations that have a 'Relative floor' value of 1 and zero otherwise. These two variables proxy for the prestige/status (or 'social power') aspect of height as they have been constructed disregarding view potential or height of surrounding buildings. However, as we will show in the following sections it is difficult to completely isolate/separate the two factors. Using the vertical location variable (High Floor) we additionally specify categories of five floors whereby more than half of the observations are located between floors one and ten. A further 25% are located between floors eleven and fifteen and only 10% of the transactions occupy floors higher than level twenty (Table 1).

In order to investigate view premiums for different industry sectors we construct a 'view potential' variable (View) based on the visible area from each floor level in all the thirty three buildings figuring in our transaction database. The necessary data in the form of shape files and geodatabases with feature classes is obtained from the cadastral system of the Netherlands (BAG database). This is in turn verified (and when necessary amended) with the 3D ArcGIS scenes provided by ESRI Netherlands, site inspections and Google Street view analysis. We emphasise here the 'potential' dimension of view and restrict our analysis only to its 'quantitative' aspect (visible area) due to the fact that the C&W database does not include information about the exact location of each transaction within a particular floor. In other words, we do not know which side of their building any given transaction is facing. This does not allow for the analysis of

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[3] Considering this, we have additionally estimated the key OLS & ST models presented in the Empirical Analysis section after omitting the records located in the WTC and find that the results are consistent with those of the whole database. We have not included these outcomes in the paper to save space, these estimates are available from the authors upon request.

more qualitative aspects of view including price differentials for different view types namely, river/water feature, (historic) city scape, park etc. considering that the BAG 3D data enables such differentiation. There have been applications of such analysis in computer and built environment related research areas for descriptive purposes. However, to the best of our knowledge, this is the first paper to employ such a variable to estimate rent premiums for views. Appendix gives a detailed description of how this variable is constructed including screenshot examples of the Line of Sight 3D analyst tool in ArcScene.

Methodology

The methodological approach of this paper is based on the Lancaster (1966), Rosen (1974), Roback (1982) hedonic price theory for the analysis of height and view related premiums and the understanding of different reasons for industries' vertical sorting. Spatiotemporal modelling routines of real estate data are additionally used as described in Pace et al. (2000) and further extended to the office sector by Tu et al. (2004), Nappi-Choulet and Maury (2009) via Bayesian estimation and Chegut et al. (2015) via GMM estimation. We particularly exploit the properties of the spatiotemporal model specification that aid Maximum Likelihood computation and follow the estimation line of Pace et al. (2000).

The baseline hedonic model is given in matrix notation in Eq. 1 below

$$Y = \alpha\iota + X\beta + D\delta + \varepsilon$$
$$\varepsilon \rightarrow iid\left(0, \sigma^2 I\right) \tag{1}$$

where, $\mathbf{Y}$ is the $n \times 1$ vector of observations on the dependent variable, ι is an $n \times 1$ vector of ones related to the constant α to be estimated. $\mathbf{X}$ is an $n \times k$ matrix of hedonic property characteristics (in this case including also spatial fixed effects – submarket dummies), β is a $k \times 1$ vector of parameters to be estimated associated with these characteristics, $\mathbf{D}$ is a $n \times (t-1)$ matrix of time period dummies and δ is a $(t-1) \times 1$ vector of time dummy parameters to be estimated.[4] The $n \times 1$ vector ε of error terms is assumed to be independent and identically distributed (iid) with mean zero and variance σ^2. In the presence of spatial autocorrelation this assumption is violated and OLS estimates become inefficient.

Spatiotemporal modelling of real estate data address this issue by accounting for the spatial dependence among observations and the fact that only past transactions can influence any given transaction in the dataset. The general spatiotemporal model shown in Eq. 2 conditions all property sales on previous neighbouring transactions and a property's own hedonic characteristics.

$$\mathbf{Y}_t = \rho \mathbf{W}\mathbf{Y}_{(t-1)} + \alpha\iota + X_t\beta + \mathbf{D}\delta + \varepsilon_t \tag{2}$$

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[4] In this notation n is the number of observations, k is the number of variables in $\mathbf{X}$, t is the number of time periods (in years) and $\mathbf{I}$ is the identity matrix of size $n \times n$.

W is the n x n spatial weight matrix that models the spatial dependence structure in the data and ρ is the spatial autoregressive parameter vector of dimensions $n \times 1$. The spatiotemporal modelling approach starts by decomposing W into a spatial matrix S which specifies spatial interactions among all observations[5] and a temporal matrix T that specifies temporal relations among previous observations only. For the specification of the elements s_{ij} ($i = 1...n; j = 1...n$) of the spatial matrix S we use a negative exponential weighting scheme based on the spatial distance d_{ij} (in kilometres) between any two observations (i, j) (Eq. 3).[6] The main rationale behind this choice is a theoretical one informed by the nature of the data. Negative exponential functions do not suffer from the point discontinuity problem encountered with the more common inverse distance weighing schemes for the case $d_{ij} = 0$. This happens when any two transactions are recorded in the same building (same x and y coordinates) which is a common phenomenon in our dataset considering we have 627 transactions in 33 buildings.

$$s_{ij} = \begin{cases} \exp(-d_{ij}) & \forall \ i > j \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

For the specification of the elements τ_{ij} ($i = 1...n; j = 1...n$) of the temporal weight matrix we use an inverse distance weighting scheme (Eq. 4) to give more weight to observations happening closer in time. We chose the inverse time distance weighing scheme based on applications of related spatiotemporal studies since the literature does not suggest specific functional forms for both space and time matrixes. In the next section we discuss results with different weight matrix specification both in weighing functions (inverse space distance and negative exponential for time), and in the fine tuning of the above specified functions.

$$\tau_{ij} = \begin{cases} t_{ij}^{-1} & \text{if } t_{ij} > 1, \forall i > j \\ 1 & \text{if } 1 \geq t_{ij} > 0, \forall i > j \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where t_{ij} is the temporal distance (in months) between two observations. The conditioning $i > j$ in both S and T and the temporal ordering of the data ensures dependence

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[5] Elhorst (2001) points out that spatial sample data do not follow any particular order and any two spatial units should mutually affect each other. In this context, the author questions the lower triangular nature of the weight matrix specified by Pace et al. (1998). We follow this logic in stating that the (purely) spatial weight matrix specifies interaction among all observations. It is the temporal dimension of real estate data that imposes the ordering and the subsequent lower triangular nature of the matrix (via the $i > j$ conditioning). This structure appropriately models the behaviour of economic actors in the real estate market.

[6] This provides a combined building and neighbourhood effect matrix where observations in the same building are given a weight of 1 (since the distance between them is zero) and other observations follow the distance decay weight. Tu et al. (2004) have further partitioned S into building and neighbourhood matrices. This approach has a specific appeal to the focus of our study and we construct the building effect matrix following the weighting scheme applied by Tu et al. (2004) to avoid rank deficiency in the matrix (input weights of the nearest building transactions in the previous quarter for entries missing previous observations in the same building – row sums to zero). However, the resulting lagged dependent variables by building and neighbourhood effect matrices had a very high correlation (.87) which led us to adopt a single spatial matrix as described in the main text.

only on past observations resulting in lower triangular matrices with zeros on the diagonal. This is consistent with the unidirectional nature of temporal dependence.

In combining the two effects into one spatiotemporal matrix $\boldsymbol{\Phi}$ we use the unit by unit (Hadamard) matrix production ($\boldsymbol{\Phi} = \mathbf{S} \quad \mathbf{T}$) which also ensures the strict lower triangular nature of $\boldsymbol{\Phi}$ that enables all conditioning only on past sales. Based on a priori information about market activity and the economic behaviour of market actors[7] we specify $\mathbf{S}$ for the five nearest spatial neighbours, $\mathbf{T}$ with a cut-off point of two quarters and $\boldsymbol{\Phi}$ for the ten nearest spatiotemporal neighbours. The final form of W is thus a linear combination of the spatial, temporal and spatiotemporal weights as shown in Eq. 5 where ρ, ν and ψ are the n ×1 vectors of the respective parameters to be estimated.

$$W = \rho\boldsymbol{S} + \nu\boldsymbol{T} + \psi\boldsymbol{\Phi} \tag{5}$$

The final spatiotemporal autoregressive model is given in Eq. 6

$$Y = \rho SY + \nu TY + \psi\boldsymbol{\Phi}Y + \alpha\iota + X\beta + \varepsilon \tag{6}$$

Where, the spatial multiplier used in the maximum likelihood estimation is given by: $(\boldsymbol{I} - \rho\mathbf{S} - \nu\mathbf{T} - \psi\boldsymbol{\Phi})$ and $\mathbf{X}$ is a general matrix of all independent variables. In the literature multiple versions of the maximum likelihood function appear. To ensure continuity of the estimation procedure we adopt the concentrated log likelihood function explained in Pace et al. (2000) which depends on two terms, the log determinant of the spatial multiplier $\ln|(\boldsymbol{I} - \mathbf{W})|$ and the Squared Sum of Errors (SSE). For model specifications conditional upon previous observations (first period in time series/spatial panels) the so called 'conditional likelihood' has a great computational appeal since the value of the determinant of the spatial multiplier is one and its log is zero. This 'disappearance' of the spatial multiplier term from the equation shifts the focus from that of maximizing the log likelihood function to that of minimizing the SSE, essentially an OLS approach (Ripley 1981; Upton and Fingleton 1985; Pace et al. 2000; Elhorst 2001; LeSage and Pace 2009). A typical assumption of this approach is the impossibility of instantaneous/contemporaneous interaction among the phenomena under investigation (Upton and Fingleton 1985). In real estate data analysis the temporal resolution is on a day (transaction date basis) however, time is represented as a discrete process, generally on a monthly/quarterly basis. This provides further methodological opportunities to test the existence of such interactions based on this specification of the temporal unit (see Thanos et al. 2016 for an example). The next section proceeds with the empirical analysis of the data based on the framework outlined above.

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[7] Considering market activity we rely on practitioners' evidence of applying a cut-off threshold of six months when selecting comparables. The spatiotemporal approach is particularly effective in this regard as it accurately models the behaviour of valuers. In a valuation assignment valuers start by defining a 'neighbourhood' radius for the subject property, apply the temporal cut-off point and, based on spatial and temporal closeness, end up with a shortlist of 5–15 comparables from which to determine the value of the subject property. We did test the various weight specifications for this range of nearest neighbours and find no significant differences among the model outcomes. This is consistent with recent claims of no sensitivity of effect estimates to weight matrix specification (LeSage and Pace 2014).

Empirical Analysis

Rent Premiums

The modelling procedure begins with the standard hedonic model described in Eq. 1 with space (submarket) and time (year) fixed effects as outlined in Table 1. The results are shown in Table 2 for six different models and are indicative of a good model performance with relatively high R^2 levels and relatively low SEE values. Models 1–3 employ a continuous variable for vertical location (High Floor) and model 1 controls for all height-related variables including View and proxies for status namely 'Relative Floor' and 'Penthouse'. The results indicate significant positive premiums for vertical location and view only while the status proxies have also negative signs. We attribute this mainly to the relatively high correlations particularly between the variables High Floor and Relative Floor ($r = 0.7$). This is indicative of the relatively low separable nature of the height related amenities of status and view considering that the correlation between the variables Relative Floor and View is 0.4. The negative sign of the variable Penthouse can be related to the fact that most penthouse transactions are in relatively older buildings with low view potential as most new buildings have their topmost floors occupied by other uses namely hotel and retail (restaurant).[8]

The above findings on respective (or lack of) premiums for height-related aspects are consistent across specifications 2 and 3. The vertical location premium is between 0.7–1% (see also Table 3), which is very similar to the premiums between 0.6–0.9% reported by Liu et al. (2018). Building height premiums (variable Floors) are between 0.7–1.3% (see also Table 6) which is close to the findings by Koster et al. (2014) at 4% per 10 m height or, roughly 1.33% per floor. This seems to be also in line with some anecdotal evidence that we have on average construction costs increase of approximately 0.8% per floor in the Netherlands. The price elasticity of the overall visible area from any transacted property to its payable rent is roughly 3.5% (consistent across various specifications). This outcome is both statistically and economically significant indicating the importance of view on premiums paid for locating on higher floors.

Models 4–6 use vertical location dummies of 5-floor categories to investigate the vertical rent gradient beyond the linear relationship implied by the continuous variable High Floor. Similarly to the approach used earlier, we control for view and/or status across these three specifications. Parameter estimates show strong consistency across all six models and with categorical vertical location variables we observe the same tenant behaviour of no preference for status/power and willingness to pay for view. Vertical location dummies in combination show the expected upward increasing (although not completely monotonic) rent gradient. Figure 2 indicates that premiums for going up to floor level categories 6–10, 16–20 and 25–31 from the respective lower categories are higher than the rest. Moving to the topmost category (floors 25–31) is associated with the highest premiums as indicated by the graph slope. This finding reinforces those about the

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[8] In addition to the within-building, purely physical definition of the relative height/penthouse concept we specify these variables as a combination of geographical and property sector characteristics to test whether the 'showing-off' hypothesis is more restricted in nature. More specifically, we investigate whether there are premiums for being above/on top of *competition* within a given industry in a particular submarket. Notably, in this model the sign of the variable penthouse is positive however, both variables are not statistically significant reinforcing the findings from the models given in the main text.

Table 2 OLS model estimates for various height-related variables

Models (OLS)	(1)		(2)		(3)		(4)		(5)		(6)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
Constant	4.8415**	14.8991	4.8433**	14.9134	5.1299**	16.0115	4.9035**	15.0918	5.1382**	16.1342	4.9014**	15.1079
Control Variables												
LnArea	-0.0281**	-3.2728	-0.0271**	-3.1986	-0.0144	-1.8904	-0.0270*	-3.0829	-0.0149	-1.9465	-0.0269**	-3.0867
LnAge	0.0058	0.3782	0.0058	0.3752	0.0073	0.4699	0.0050	0.3275	0.0068	0.4421	0.0051	0.3289
Floors	0.0064**	2.8264	0.0076**	5.5579	0.0079**	3.5870	0.0077**	3.9045	0.0085**	4.2741	0.0079**	5.8102
Tenants	0.0008	1.8672	0.0008	1.8267	0.0009*	2.1408	0.0008	1.8693	0.0009*	2.0750	0.0008	1.8661
Parking	0.0002*	2.4791	0.0002*	2.4573	0.0002*	2.1803	0.0002*	2.2390	0.0002*	2.0793	0.0002*	2.2364
Net/Gross	0.0377	0.3214	0.0406	0.3462	0.0854	0.7265	0.0345	0.2949	0.0735	0.6279	0.0346	0.2958
EnergyCoeff	0.0094	0.2899	0.0088	0.2725	0.0063	0.1936	0.0047	0.1440	0.0051	0.1565	0.0046	0.1422
LnDStat	0.0520**	2.6674	0.0525**	2.6878	0.0546**	2.7702	0.0526**	2.6998	0.0554**	2.8286	0.0525**	2.6971
LnDHighw	0.0373	1.9254	0.0366	1.8915	0.0317	1.6266	0.0370	1.9086	0.0332	1.7063	0.0370	1.9079
Industry sector dummies												
Finance	0.0482**	2.9533	0.0485**	2.9796	0.0466**	2.8338	0.0481**	2.9503	0.0450**	2.7505	0.0481**	2.9487
Insurance	0.0266	0.7509	0.0307	0.8708	0.0350	0.9807	0.0328	0.9328	0.0385	1.0878	0.0329	0.934
Real Estate	0.0404*	1.9775	0.0416*	2.0376	0.0373	1.8097	0.0457*	2.2184	0.0429*	2.0699	0.0457*	2.2171
Business	0.0351	1.7940	0.0352	1.7946	0.0332	1.6807	0.0327	1.6738	0.0305	1.5522	0.0327	1.6754
ICT	0.0305	1.5373	0.0302	1.5194	0.0259	1.2966	0.0295	1.4875	0.0246	1.2403	0.0295	1.4899
Law	0.0754**	3.0099	0.0769**	3.0745	0.0754**	2.9879	0.0788**	3.1683	0.0769**	3.0748	0.0787**	3.1665
Consult & Manag.	0.0663**	3.4592	0.0673**	3.5160	0.0654**	3.3913	0.0682**	3.5636	0.0663**	3.4444	0.0682**	3.5645
Vertical location & view variables												
High Floor	0.0090**	2.8639	0.0071**	5.3855	0.0089**	2.8802	–	–	–	–	–	–

Table 2 (continued)

Models (OLS)	(1)		(2)		(3)		(4)		(5)		(6)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
View	0.0384**	3.4247	0.0353**	3.3340	–	–	0.0325**	2.8229	–	–	0.0322**	2.8570
Relative FL	−0.0393	−0.5470	–	–	0.0205	0.3141	−0.0073	−0.1197	0.0275	0.4559	–	–
Penthouse	−0.0193	−0.8163	–	–	–	–	–	–	–	–	–	–
Ground Floor	–	–	–	–	–	–	0.0328	0.5534	0.0317	0.5308	0.0351	0.6234
Floor6_10	–	–	–	–	–	–	0.0634**	2.6580	0.0796**	3.4078	0.0615**	3.4269
Floor11_15	–	–	–	–	–	–	0.0735**	2.0659	0.0916**	2.5971	0.0701**	3.3684
Floor16_20	–	–	–	–	–	–	0.1322**	2.8671	0.1516**	3.2975	0.1277**	4.9830
Floor21_25	–	–	–	–	–	–	0.1373**	2.4539	0.1591**	2.8488	0.1318**	4.2015
Floor26_31	–	–	–	–	–	–	0.2346**	3.4019	0.2536**	3.6686	0.2280**	5.4576
Submarket dummies												
De Omval	−0.2386**	−9.0083	−0.2398**	−9.0479	−0.2365**	−8.8597	−0.2420**	−9.0541	−0.2374**	−8.8527	−0.2422**	−9.0702
South East	−0.5533**	−18.3375	−0.5528**	−18.3134	−0.5478**	−18.0798	−0.5521**	−18.3410	−0.5472**	−18.1535	−0.5520**	−18.348
Tel. Sloterdijk	−0.6295**	−18.8767	−0.6283**	−18.8454	−0.6249**	−18.6406	−0.6094**	−18.1820	−0.6037**	−17.9924	−0.6096**	−18.223
Centre	−0.3542**	−7.9540	−0.3521**	−7.9123	−0.3306**	−7.4640	−0.3529**	−7.9658	−0.3348**	−7.6090	−0.3527**	−7.9682
West	−0.4482**	−9.0216	−0.4457**	−8.9889	−0.4285**	−8.6279	−0.4436**	−8.9289	−0.4288**	−8.643	−0.4430**	−8.9647
Year dummies												
Y2003	−0.0879	−1.9356	−0.0862	−1.9106	−0.0792	−1.7337	−0.0953*	−2.1097	−0.0878	−1.9337	−0.0946*	−2.1113
Y2004	−0.0595	−1.5674	−0.0605	−1.5992	−0.0550	−1.4415	−0.0678	−1.7954	−0.0626	−1.6492	−0.0675	−1.7914
Y2005	−0.0978**	−2.5947	−0.0987**	−2.6230	−0.1013**	−2.6643	−0.1039**	−2.7678	−0.1063**	−2.8115	−0.1038**	−2.7659
Y2006	−0.0990**	−2.8311	−0.1010**	−2.8901	−0.0982**	−2.7872	−0.1093**	−3.1315	−0.1084**	−3.0857	−0.1091**	−3.1293
Y2007	−0.1455**	−4.0507	−0.1467**	−4.0932	−0.1429**	−3.9527	−0.1527**	−4.2760	−0.1489**	−4.1461	−0.1525**	−4.2748

Table 2 (continued)

Models (OLS)	(1)		(2)		(3)		(4)		(5)		(6)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
Y2008	-0.1761**	-4.8316	-0.1768**	-4.8468	-0.1782**	-4.8391	-0.1853**	-5.0840	-0.1887**	-5.1457	-0.1851**	-5.0827
Y2009	-0.1387**	-3.4318	-0.1380**	-3.4423	-0.1319**	-3.2502	-0.1447**	-3.6100	-0.1367**	-3.3987	-0.1444**	-3.6090
Y2010	-0.1213**	-3.4299	-0.1227**	-3.4720	-0.1242**	-3.4800	-0.1312**	-3.7199	-0.1327**	3.7381	-0.1310**	-3.718
Y2011	-0.1742**	-4.8042	-0.1760**	-4.8537	-0.1724**	-4.7148	-0.1826**	-5.0646	-0.1811**	-4.9907	-0.1826**	-5.0632
Y2012	-0.1997**	-5.9765	-0.2009**	-6.0155	-0.1972**	-5.8577	-0.2069**	-6.2186	-0.2052**	-6.1298	-0.2067**	-6.2244
Y2013	-0.2532**	-6.5836	-0.2550**	-6.6300	-0.2563**	-6.6045	-0.2590**	-6.7766	-0.2601**	-6.7621	-0.2588**	-6.7760
Y2014	-0.2218**	-6.0533	-0.2252**	-6.1587	-0.2220**	-6.0170	-0.2329**	-6.3980	-0.2315**	-6.3204	-0.2329**	-6.3970
Y2015	-0.2036**	-5.8660	-0.2073**	-5.9964	-0.2017**	-5.7877	-0.2137**	-6.2160	-0.2113**	-6.1095	-0.2136**	-6.2159
Y2016	-0.1880**	-5.2068	-0.1893**	-5.2483	-0.1871**	-5.1429	-0.1974**	5.4909	-0.1967**	-5.4360	-0.1972**	-5.4918
Model fit Statistics												
R-squared	0.8170		0.8166		0.8131		0.8194		0.8170		0.8194	
Log-likelihood	-676.225		-676.902		-682.411		-672.245		-676.229		-672.252	
SSE	9.5986		9.6204		9.7993		9.4717		9.5988		9.4719	
Median |e|	0.0578		0.0552		0.0579		0.0538		0.0547		0.0537	
k	40		38		38		44		43		43	
N	598		598		598		598		598		598	

Dependent variable is Ln [rent price (in year 2016 €)/m² /year]; SRD's are signed root deviances (which can be interpreted as t-values) from OLS estimations that mimic spatial routines as explained in Pace et al. (2000) to ensure compatibility with spatiotemporal models for later comparison; * and ** denote 95% and 99% significance levels respectively

lack of a significant penthouse effect among the offices in our database as this vertical location category does not include any penthouse offices. Our category-based rent gradient from Model 6 estimates is very similar (albeit not directly comparable) to the non-parametric estimate, floor-level-based rent gradient by Liu et al. (2018, p.111). Both gradients have the same peaks in floor ranges 6–10 and 26–30+ and the same trough in the floor level range 1–5. The large difference in the ground floor rent level relates to the inclusion in their analysis of the retail sector which we have excluded for the reasons explained in footnote 2. One slight difference relates to floor level range 21–25 for which rents are steadily increasing in the US study whereas they are only slightly increasing in Amsterdam. We attribute this to contextual differences among the two studies.

Industry sector related results show that Law Firms, Consultancy and Management, Finance and Real Estate sectors pay significantly higher rents than the benchmark 'Other sectors'. This outcomes are quite consistent across the six models in Table 2 preserving also the same order in premiums paid as indicated by the parameter estimates. We further analyse this outcome in the light of the productivity hypothesis that more productive (wealthier) industry sectors are willing to pay higher premiums. We calculated output per job for different industry sectors with the 2014 national employment data from the CBS. The outcomes in decreasing order are as follows; Law firms ≈ €23.500/Full Time Equivalent (FTE), ICT ≈ €19.500/FTE, Consultancy & Management ≈ €19.000/FTE, Real Estate ≈ €12.000/FTE, Other Sectors ≈ €8.500/FTE. Information on the remaining categories used in this paper was not available. What is immediately clear from the respective parameter estimates is the higher rents paid by the first, third (and to some extent fourth), most productive sectors – Law, Consultancy & Management and Real Estate respectively. Whereas ICT, the second most productive sector pays the second lowest rents after the control group 'Other industries'. This is a clear exception from the consistent vertical sorting pattern of high productivity, high amenity oriented office firms locating high up reported by Liu et al. (2018).[9] In the next section we further investigate whether these preference patterns carry across the search for amenities (view) or status.

In order to assess the impact of view (and other aspects) on height premiums we compare the coefficient estimates for the vertical location variable 'High Floor' from Model 2 and its three variants namely 2a, 2b and 2c presented in Table 3. The four models in combination provide different scenarios that help assess the view and other (non-view) premiums related to willingness to pay of office tenants for locating on higher floors. Model (2a) is the same as Model (2) but in this case we do not control for view. Models 2b and 2c do not control for industry sectors and model 2b additionally controls for view. By and large, the coefficient estimates are relatively stable across the four models and this is particularly true for space and time fixed effects and the other height control namely Floors (number of floors in a building that controls for building height). When holding view constant, we see that there is approximately a 27% decrease in the value of the coefficient estimate for the vertical location variable High Floor. The results are consistent for models with and without industry sector controls (model pairs 2–2a and 2b–2c respectively).[10]

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[9] It must be pointed out that Liu et al. (2018) do not control for this industry sector in their analyses.

[10] We test the results for a variant of the View variable based on the visible area from only the highest floor in every given transaction (to exactly match the High Floor variable) and we find that the results are very similar, albeit slightly higher, to the ones we report in the paper with the view-related vertical location premium at roughly 30%. The impact of variations at industry level is also slightly higher at 4%.

Table 3 Vertical location premium differentials (before and after view & industry control)

Models (OLS)	(2a)		(2b)		(2c)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
Constant	5.1427**	16.1761	4.8691**	14.8262	5.1577**	16.0753
Control Variables						
LnArea	−0.0144	−1.8904	−0.0272**	−3.1662	−0.0150	−1.9449
LnAge	0.0073	0.4685	0.0087	0.5560	0.0098	0.6251
Floors	0.0074**	5.3280	0.0081**	5.8686	0.0078**	5.6328
Tenants	0.0010*	2.1777	0.0008	1.8546	0.0010*	2.1772
Parking	0.0002*	2.1785	0.0002*	2.5181	0.0002*	2.2523
Net/Gross	0.0857	0.7283	0.0400	0.3384	0.0811	0.6839
EnergyCoeff	0.0058	0.1788	0.0190	0.5898	0.0165	0.5071
LnDStat	0.0546**	2.7742	0.0593**	3.0243	0.0611**	3.0899
LnDHighw	0.0317	1.6267	0.0318	1.6484	0.0271	1.3971
Industry sector dummies						
Finance	0.0467**	2.8466	–	–	–	–
Insurance	0.0341	0.9579	–	–	–	–
Real Estate	0.0369	1.7938	–	–	–	–
Business	0.0332	1.6783	–	–	–	–
ICT	0.0259	1.2958	–	–	–	–
Law	0.0755**	2.9918	–	–	–	–
Consult & Manag.	0.0654**	3.3883	–	–	–	–
Vertical location & view variables						
High Floor	0.0098**	9.1238	0.0073**	5.4813	0.0100**	9.1994
View	–	–	0.0337**	3.1534	–	–
Relative FL	–	–	–	–	–	–
Penthouse	–	–	–	–	–	–
Submarket dummies						
De Omval	−0.2363**	−8.8542	−0.2355**	−8.8830	−0.2319**	−8.6951
South East	−0.5478**	−18.0788	−0.5570**	−18.4693	−0.5525**	−18.2593
Tel. Sloterdijk	−0.6251**	−18.6492	−0.6376**	−19.0491	−0.6350**	−18.8782
Centre	−0.3306**	−7.4652	−0.3511**	−7.8012	−0.3307**	−7.3868
West	−0.4291**	−8.6419	−0.4613**	−9.2858	−0.4446**	−8.9542
Year dummies						
Y2003	−0.0805	−1.7687	−0.0834	−1.8377	−0.0779	−1.7034
Y2004	−0.0554	−1.4535	−0.0672	−1.7613	−0.0631	−1.6412
Y2005	−0.1018**	−2.6801	−0.1012**	−2.6843	−0.1049**	−2.7605
Y2006	−0.0982**	−2.7858	−0.1039**	−2.9781	−0.1022**	−2.9052
Y2007	−0.1432**	−3.9610	−0.1500	−4.1874	−0.1472**	−4.0775
Y2008	−0.1781**	−4.8352	−0.1808**	−4.9200	−0.1823**	−4.9189
Y2009	−0.1329**	−3.2880	−0.1294**	−3.2148	−0.1254**	−3.0908
Y2010	−0.1244**	−3.4863	−0.1330**	−3.7662	−0.1350**	−3.7941
Y2011	−0.1722**	−4.7093	−0.1888**	−5.2043	−0.1853**	−5.0701

Table 3 (continued)

Models (OLS)	(2a)		(2b)		(2c)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
Y2012	−0.1972**	−5.8567	−0.2053**	−6.0882	−0.2018**	−5.9443
Y2013	−0.2563**	−6.6018	−0.2564**	−6.6385	−0.2583**	−6.6315
Y2014	−0.2215**	−6.0089	−0.2359**	−6.4245	−0.2332**	−6.3051
Y2015	−0.2012**	−5.7791	−0.2147**	−6.2058	−0.2094**	−6.0160
Y2016	−0.1872**	−5.1445	−0.1931**	−5.3200	−0.1915**	−5.2347
Model fit statistics						
R-squared	0.8131		0.8109		0.8077	
Log-likelihood	−682.460		−685.989		−690.961	
SSE	9.8009		9.9173		10.0836	
Median |e|	0.0576		0.0557		0.0578	
k	37		31		30	
N	598		598		598	

Dependent variable is Ln [rent price (in year 2016 €)/m² /year]; SRD's are signed root deviances; * and ** denote 95% and 99% significance levels respectively. Relative FL and Penthouse not included due to statistical insignificance (see Model 1)

In contrast, for a similar analysis undertaken with the industry sector control variables, we observe roughly a ten times smaller decrease (at approximately 2.7%) in the value of the coefficient estimate for the variable High Floor, which is consistent for models with and without view controls (model pairs 2–2b and 2a–2c respectively). The low impact of industry-level variations is mainly due to the relatively small number of industries that pay statistically significant higher rents to locate on higher floors. These are namely Law, Consultancy and Management, Finance and to some extent Real Estate. These outcomes are indicative of the strong impact that view has on the willingness to pay to be on higher floors and the relatively weak ability of industry sector dummies to capture productivity differences at the firm level which has been linked to the signalling part of height premiums.

Overall, these analyses show that roughly 70% of the premium for locating on higher floors is non-view related (High Floor coefficient difference for models 2 and
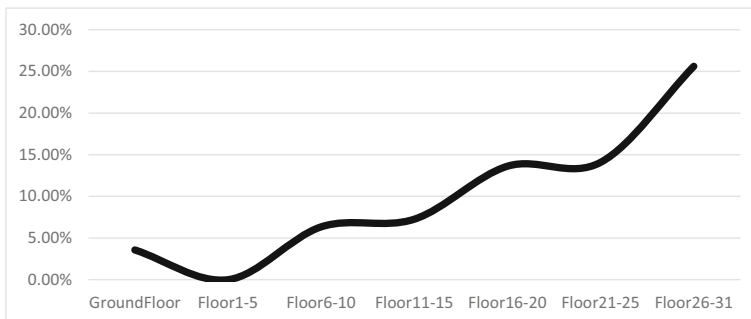
Fig. 2 Vertical rent gradient with Model 6 coefficients from the formula exp.(β)-1

2c) and can be attributed to willingness-to-pay variations at the firm level for factors such as signalling or status. Given the statistical insignificance of the variable 'Relative Floor' (status proxy) in Model 1, the outcomes point mainly to product quality signalling and other unobserved factors. In trying to capture the signalling part of the height premium, it is probably the variations across individual firms that play a more important role. To control for these variations Liu et al. (2018) use the 'sales-per-worker' proxy which appears to be a good predictor of firm vertical location. In the absence of such information in our database, in the subsequent analyses in Section 5.2, we use productivity figures as detailed above mainly for ranking purposes.

It is important to note the very high SRD values of all the submarket dummies indicating the presence of strong clustering in the Amsterdam office market. Clear delineation of submarkets seems to be a typical feature of the Dutch property markets as indicated by high explanatory power of hedonic models with spatial fixed effects in some residential studies and one office study (Koster et al. 2014). Following unexpected outcomes regarding the signs of some of the control variables we perform the Moran's I test[11] and find statistically significant spatial autocorrelation in the residuals of Model 6 which motivates our spatiotemporal autoregressive modelling in the next step of the analysis.

The spatiotemporal procedure is given in Eq. 6 and its application follows the theoretical discussion in the previous section. To avoid the poor performance of the spatiotemporal estimator in the estimation of the first observations due to lack of previous comparables we retained some initial observations (29 in total, which correspond to the first two years in the database). As reported in Tables 2 and 3 (and all the subsequent tables), estimates are with the resulting database of $N = 598$ for comparative purposes. Spatiotemporal estimates are given in Table 4 whereby we observe strong positive spatial and spatiotemporal autocorrelation and negative temporal autocorrelation, consistent with the sign of the time dummies. To ensure model stationarity we use temporally differenced dependent and independent variables using the weight matrix **T** resulting in variables of the form $(I\text{-}T)Y$ and $(I\text{-}T)X$ respectively for all three Models 7–9. The strong negative temporal dependence (consistent with the time trend in the previous OLS models) is evident in the high value of the parameter ν and its relatively high SRD value. However, the temporal dependence governing parameter does not exceed parameter space boundaries and its SRD value is not excessively high in relation to those of the other estimates in the model. Notably, the signs of the variables Age and EPC have reverted back to the a priori expectations.

The variables of interest – height and industry sector – show clear consistency across estimates with a decrease in premiums (from the OLS estimates) for floor levels 21–25 compared to levels 16–20. Additionally, it can be observed that only vertical location variables are statistically significant. Among industry sector premiums there is also consistency of estimates albeit with the overall decrease in value. This phenomenon is generally referred to in the literature as the overestimation of OLS methods compared to the spatial or spatiotemporal (ST) estimates. However, we observe an overall decrease across all three indicators of model fit

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[11] The test is performed with a weight matrix with 10 spatiotemporal nearest neighbours, Φ in our equations in the text. The results are as follows: Moran's $I = 0.0156$, Moran's I-statistic $= 3.09427217$, $p = 0.0019$; indicating the presence of spatial autocorrelation in the OLS residuals.

Table 4 Spatiotemporal model estimates for various height-related variables

Models (ST)	(7)		(8)		(9)	
Variables	Coeff.	SRD	Coeff.	SRD	Coeff.	SRD
Constant	0.2190	0.8269	0.2166	0.8183	0.1674	0.6272
Control variables						
LnArea	−0.0212**	−2.6219	−0.0249**	−2.7024	−0.0278**	−3.1067
LnAge	−0.0329*	−2.3480	−0.0343*	−2.4305	−0.0365**	−2.5881
Floors	0.0024	1.8084	0.0025	1.8280	0.0023	1.6970
Tenants	0.0016**	3.4156	0.0015**	3.3583	0.0016**	3.5166
Parking	0.0001	0.7870	0.0001	0.7984	0.0001	0.8488
Net/Gross	0.1679	1.4198	0.1501	1.2507	0.1717	1.4285
EnergyCoeff	−0.0867**	−2.6826	−0.0876**	−2.7095	−0.0858**	−2.6580
LnDStat	0.0020	0.1478	−0.0010	−0.0714	−0.0002	−0.0173
LnDHighw	0.0292*	2.0128	0.0293*	2.0230	0.0302*	2.0648
Industry sector dummies						
Finance	0.0451**	2.5822	0.0460**	2.6297	0.0486**	2.7746
Insurance	0.0433	1.1602	0.0413	1.1044	0.0394	1.0499
Real Estate	0.0612**	2.7619	0.0621**	2.8007	0.0552*	2.5017
ICT	0.0387	1.8553	0.0394	1.8870	0.0402	1.9187
Business	0.0302	1.4126	0.0317	1.4781	0.0332	1.5417
Law	0.1089**	4.0836	0.1095**	4.1062	0.1091**	4.0553
Consult & Manag.	0.0782**	3.7898	0.0788**	3.8165	0.0775**	3.7419
Vertical location & view variables						
GroundFloor	0.0562	0.9483	0.0595	1.0033	–	–
Floor6–10	0.0750**	4.5174	0.0667**	3.4663	–	–
Floor11–15	0.0878**	4.9087	0.0764**	3.4176	–	–
Floor16–20	0.1407**	6.2953	0.1271**	4.6069	–	–
Floor21–25	0.1245**	4.5527	0.1085**	3.2607	–	–
Floor26–31	0.2161**	5.4174	0.1998**	4.5195	–	–
View	–	–	0.0101	0.8414	0.0179	1.5980
High Floor	–	–	–	–	0.0057**	4.0617
ST model parameters						
Space (ρ)	0.3108**	6.8265	0.3108**	6.8305	0.3241	7.0853
Time (ν)	−0.8919**	−14.7396	−0.8936**	−14.7620	−0.8992	−14.7226
Spatiotemporal (ψ)	0.5332**	9.8623	0.5353**	9.8929	0.5358	9.8104
Model fit statistics						
R2	0.7553		0.7556		0.7505	
Log-likelihood	−743.7966		−743.4426		−749.6061	
SSE	12.0325		12.0183		12.2686	
k	26		27		22	
N	598		598		598	

The dependent variable is Ln [rent price (in year 2016 €)/m2/year]; in models 7–9 the dependent variable vector and the independent variables' matrix are time differenced of the form (**I-T)Y** and (**I-T)X** respectively to ensure model stationarity over time. SRD's are signed root deviances; * and ** denote 95% and 99% significance levels respectively. Relative FL and Penthouse not included due to statistical insignificance (see Model 1)

statistics and an increase in the median absolute error in all the three ST models.[12] This leads us to conclude that submarket delineation in Amsterdam is a strong indicator of rent levels. In this regard, it has been pointed out that a difference between OLS and ST models is the trade-off between 'surveyability' and 'plausibility' of the estimation results (Elhorst 2001).[13] Consistent outcomes across models 1–9 emphasise the existence of a clear upward vertical rent gradient which is not typically monotonous. The impact of view potential on prices is positive although not significant in the ST models. Wealthier, more productive industry sectors pay higher rents with the exception of ICT services. This is an interesting finding which needs further investigation with regard to each sector's preference for (various aspects of) height. In the next part of this section we explore this starting with a descriptive analysis of vertical sorting, proceeding with models that employ different height-related dependent variables and conclude with models of industry height interactions for a deeper insight on view or status preferences.

(Causes of) Vertical Sorting among Industry Sectors

In analysing concentration of particular sectors along different levels of a building we use the tabulation of floor levels across typical sample percentiles. Table 5 shows this vertical sorting whereby 'All Sample' and 'Other Industries' (the second and last column respectively) are used for benchmarking. We analyse these outcomes in combination with the relative rent levels paid and output per FTE of the sectors as indicated in the previous section. The strongest evidence on vertical sorting comes from Law Firms as the sector that has the highest output per FTE, pays the highest relative rents and shows higher concentration on the upper floor levels. For the 75th percentile grouping 'Law Firms' show concentration along the 19th floor which is four floors higher than both benchmarks. While 'ICT' (second highest output-per-FTE sector) floor levels are slightly higher than both benchmarks across the percentiles, their paid rent prices are the second lowest suggesting inconclusive results with regard to vertical sorting for prestige/status and view premiums. The figures in Table 5 indicate a relatively steady floor level increase across sectors with the exception of 'Insurance Carriers'. There is a leap of fifteen floor levels (from 8th to 23rd floor) in location concentration from the 50th to the 75th percentile of this sector. Similar to the results for the ICT sector, these figures do not support the claim that sectors that pay relatively high rent levels locate on higher floors.

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[12] Previous research building upon the Pace et al. (1998) and Pace et al. (2000) framework reports error percentile levels of model estimates and focuses specifically on median absolute error values. Despite the increase compared to the OLS estimates, these are very low across all our ST models and are very low compared to the ones reported in previous office sector studies (Tu et al. 2004; Nappi-Choulet and Maury 2009) and even lower than those reported in residential sector studies (Pace et al. 1998; Pace et al. 2000).

[13] Spatial econometric models are criticised for being sensitive to researcher-specified weight matrices and considering ST model performance in our empirical study we further experiment with a wide range of weight matrix specification. In addition to the fine tuning tests described in Footnote 7 we tested for different weighing schemes namely inverse spatial distance square $(1/d_{ij}^2)$ and negative exponential time distance $(\exp(-t))$. The findings are quite consistent across these specifications with slightly higher model fit statistics for the weighing schemes reported in the paper. These estimates are available from the authors upon request.

Table 5 Floor levels for typical percentile values across industry sectors

Percentiles	All Sample	Financial Services	Insurance Carriers	Real Estate	Business Services	ICT Services	Law Firms	Consultancy & Management	Other Industries
5	2.0	3.5	2.0	2.0	1.05	2.0	2.95	1.0	2.0
10	3.0	5.0	2.7	2.0	3.1	4.0	3.0	2.9	3.0
25	6.0	7.5	5.5	4.0	5.0	8.0	6.0	6.0	6.0
50	10.0	11.0	8.0	8.0	8.5	12.0	11.5	11.0	10.0
75	15.0	15.5	23.0	13.0	13.0	16.0	19.0	15.25	15.0
90	21.0	21.0	30.0	22.4	18.0	22.0	24.5	25.0	19.0
95	24.0	26.0	30.0	23.7	21.0	24.5	31.0	25.0	20.0

By and large, these findings are indicative of a relatively weak vertical sorting in the office towers of Amsterdam[14] with the exception of 'Insurance Carriers' who for the 75th 90th and 95th percentiles show vertical concentration that is between 6 and 11 floors higher compared to the benchmarks used. Slightly weaker evidence of sorting is observed among 'Law firms' with concentration generally 4–5 floors higher than the benchmarks. When considered in combination with relative paid rent prices and output per FTE in each sector, sorting and signalling evidence is consistent only for 'Law firms'. These results should be treated with care considering the relatively smaller sample sizes of these sectors compared to the other categories (Table 1). Additional weak evidence of top floor clustering relates to the tenants operating in the 'Consultancy and Management' sector (second highest sector for rents paid and third highest sector for output/FTE). The 90th percentile of this sector locates around the 25th floor which is six floors higher than the 'Other sectors' benchmark and four floors higher than the 'All sample' benchmark.

The above findings in combination with those of the previous sub-section provide evidence on the existence of height premiums and weak vertical sorting related to specific industry sectors. Preferences for different aspects of height are not directly observable from these findings. In order to address this issue we analyse various determinants of vertical location by regressing building and tenant features on different height related dependent variables. Table 6 summarises the outcomes of models 10–13, each with a different height-related dependent variable by also controlling for submarket location. Model 10 uses the continuous dependent variable High Floor and model 11 uses the logarithm of this variable. In addition to the variables employed earlier, we include the number of elevators/10 m of building height as a measure of building vertical transport service and the parcel size (in logarithm form) as a control for height. The latter follows the logic that for the same FAR (in the Netherlands referred to as Floor Space Index hence, FSI), smaller parcels would result in taller buildings, assuming that developers would build to maximise FAR allowance and that there are no height restrictions.

Parameter estimates across models 10 and 11 seem to be fairly consistent with one notable outcome regarding Law firms locating significantly higher than the baseline category. The primacy of law firms is also observable in the models with view and power

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[14] This is particularly the case when compared with finding from the US market in the study by Liu et al. (2018) who investigated significantly taller buildings.

Table 6 Models with various height-related dependent variables

Models (OLS)	(10) dep.var. High Floor		(11) dep.var. Ln(High Floor+1)		(12) dep.var. View		(13) dep.var. Relative Floor	
Variables	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Constant	29.3119*	12.591	4.4603**	1.3070	12.1722**	1.3722	1.1451**	0.4385
Building features								
LnAge	1.0844	0.7811	0.0289	0.0902	−0.1178	0.0960	−0.0699*	0.0316
Tenants	−0.0055	0.0208	0.0013	0.0024	−0.0013	0.0025	0.0013	0.0010
Elv/10 m	−3.5648*	1.8125	−0.3824	0.2167	−1.2272**	0.1934	−0.2473**	0.0861
Parking	−0.0007	0.0060	−0.0006	0.0006	−0.0003	0.0007	−0.0002	0.0002
Lnparcel	−1.7089*	0.7176	−0.0678	0.0736	0.0637	0.0840	0.0767*	0.0307
EnergyCoeff	−8.2671**	0.9588	−0.9470**	0.1259	−0.8281**	0.1142	−0.1366*	0.0537
LnDStat	−2.6128**	0.8090	−0.2847**	0.0844	−0.2597*	0.1035	−0.0595	0.0327
LnDHighw	3.3263**	0.7950	0.2241*	0.0886	0.0672	0.0991	−0.0446	0.0338
Tenant features								
LnArea	−0.5228	0.3656	−0.0429	0.0365	0.3424**	0.0455	−0.0176	0.0150
Finance	0.6226	0.6985	0.0920	0.0678	0.0021	0.0870	−0.0013	0.0307
Insurance	2.0722	1.8767	0.1177	0.1617	0.2721	0.1865	0.0449	0.0721
Real Estate	−1.0243	0.9174	−0.1585	0.0975	−0.1838	0.1069	−0.0906*	0.0393
Businesss	−0.0686	0.7929	−0.0244	0.0902	−0.0269	0.0898	−0.0419	0.0388
ICT	0.1594	0.8526	0.0399	0.0836	−0.0705	0.0978	0.0061	0.0368
Law	2.3537*	1.0470	0.2303*	0.0920	0.1797	0.1058	0.0576	0.0406
Consult& Manag	0.6247	0.8117	0.0226	0.0880	0.0081	0.0776	0.0134	0.0374
Submarket dummy								
De Omval	3.4202*	1.5960	0.2771	0.1501	0.2483	0.1586	0.0086	0.0491

Table 6 (continued)

Models (OLS)	(10) dep.var. High Floor		(11) dep.var. Ln(High Floor+1)		(12) dep.var. View		(13) dep.var. Relative Floor	
Variables	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
South East	0.8778	1.4150	0.1253	0.1534	0.1477	0.1782	−0.0136	0.0550
Tel. Sloterdijk	5.9208**	1.0403	0.4897**	0.1212	0.4481**	0.1217	0.1545**	0.0536
Centre	−1.0932	2.3574	0.1288	0.2439	0.8524**	0.2958	0.2844**	0.0961
West	6.3012**	1.7166	0.5345*	0.2177	0.8411**	0.2229	−0.0274	0.0839
Model fit statistics								
R^2	0.3085		0.2506		0.3515		0.1228	
σ^2	32.0614		0.3224		0.4111		0.0604	
Log likelihood	−1873.6260		−498.3076		−570.9851		2.2883	
N	598		598		598		598	

SE are White-corrected, robust standard errors; * and ** denote 95% and 99% significance levels respectively

Table 7 Estimating industry sector relative price differentials for different aspects of height

Models (OLS)	14		15		16		17	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Constant	5.2039**	0.2616	4.8993**	0.3029	4.6433**	0.2886	4.8791**	0.3017
Control variables								
LnArea	−0.0156	0.0096	−0.0287*	0.0116	−0.0424**	0.0109	−0.0271*	0.0114
LnAgecomb	0.0068	0.0164	0.0051	0.0162	0.0032	0.0166	0.0059	0.0163
Floor	0.0077***	0.0015	0.0080**	0.0014	0.0102**	0.0014	0.0077***	0.0014
High_Floor	–	–	–	–	–	–	0.0071**	0.0014
View	–	–	0.0367*	0.0159	–	–	–	–
No.Ten	0.0010*	0.0005	0.0009	0.0005	0.0009	0.0005	0.0008	0.0005
No.Parking	0.0002	0.0001	0.0002*	0.0001	0.0002*	0.0001	0.0002*	0.0001
Net.Gross	0.0827	0.1080	0.0358	0.1088	0.0067	0.1111	0.0412	0.1078
EI	0.0117	0.0281	0.0150	0.0281	−0.0023	0.0285	0.0090	0.0278
LnDStat	0.0553***	0.0193	0.0529**	0.0191	0.0469*	0.0195	0.0523**	0.0195
LnDHigh	0.0280	0.0196	0.0326	0.0198	0.0393*	0.0194	0.0367	0.0196
Industry*Height*View interactions								
Finance*HighFL	0.0102**	0.0013	0.0073**	0.0015	–		–	
Insurance*HighFL	0.0093***	0.0019	0.0060**	0.0022	–		–	
RealEstate*HighFL	0.0095**	0.0016	0.0067**	0.0017	–		–	
Business*HighFL	0.0089**	0.0017	0.0060**	0.0019	–		–	
ICT*HighFL	0.0085**	0.0014	0.0058**	0.0017	–		–	
Law*HighFL	0.0130**	0.0014	0.0103**	0.0016	–		–	
Cons&Man*HighFL	0.0116**	0.0015	0.0089**	0.0017	–		–	
Other*HighFL	0.0080**	0.0014	0.0050**	0.0017	–		–	

Table 7 (continued)

Rent Premiums and Vertical Sorting in Amsterdam's Multi-Tenant...

Models (OLS)	14		15		16		17	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Finance*View	–	–	–	–	0.0715**	0.0129	0.0363*	0.0159
Insurance*View	–	–	–	–	0.0704**	0.0127	0.0347*	0.0161
RealEstate*View	–	–	–	–	0.0707**	0.0133	0.0358*	0.0162
Business*View	–	–	–	–	0.0704**	0.0130	0.0352*	0.0160
ICT*View	–	–	–	–	0.0704**	0.0130	0.0348*	0.0161
Law*View	–	–	–	–	0.0746**	0.0129	0.0388*	0.0160
Cons&Man*View	–	–	–	–	0.0735**	0.0130	0.0379*	0.0160
Other*View	–	–	–	–	0.0676**	0.0127	0.0325*	0.0157
Finance*RltvFL	–	–	–	–	–	–	–	–
Insurance*RltvFL	–	–	–	–	–	–	–	–
RealEstate*RltvFL	–	–	–	–	–	–	–	–
Business*RltvFL	–	–	–	–	–	–	–	–
ICT*RltvFL	–	–	–	–	–	–	–	–
Law*RltvFL	–	–	–	–	–	–	–	–
Cons&Man*RltvFL	–	–	–	–	–	–	–	–
Other*RltvFL	–	–	–	–	–	–	–	–
Fin*View*RltvFL	–	–	–	–	–	–	–	–
Ins*View*RltvFL	–	–	–	–	–	–	–	–
RE*View*RltvFL	–	–	–	–	–	–	–	–
Business*View*RltvFL	–	–	–	–	–	–	–	–
ICT*View*RltvFL	–	–	–	–	–	–	–	–
Law*View*RltvFL	–	–	–	–	–	–	–	–

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Table 7 (continued)

Models (OLS)	14		15		16		17	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Cons&Man*View*RltvFL	–	–	–	–	–	–	–	–
Other* View*RltvFL	–	–	–	–	–	–	–	–
Fin*View*HighFL	–	–	–	–	–	–	–	–
Ins*View*HighFL	–	–	–	–	–	–	–	–
RE*View*HighFL	–	–	–	–	–	–	–	–
Business*View*HighFL	–	–	–	–	–	–	–	–
ICT*View*HighFL	–	–	–	–	–	–	–	–
Law*View*HighFL	–	–	–	–	–	–	–	–
Cons&Man*View*HighFL	–	–	–	–	–	–	–	–
Other*View*HighFL	–	–	–	–	–	–	–	–
Year dummies								
Y2003	−0.0876	0.0621	−0.0943	0.0619	−0.0962	0.0628	−0.0872	0.0612
Y2004	−0.0502	0.0507	−0.0552	0.0498	−0.0542	0.0501	−0.0604	0.0493
Y2005	−0.1038*	0.0475	−0.1008*	0.0467	−0.0900	0.0469	−0.1001*	0.0462
Y2006	−0.0951*	0.0439	−0.0976*	0.0435	−0.0975*	0.0443	−0.1013*	0.0436
Y2007	−0.1437**	0.0449	−0.1474**	0.0441	−0.1508**	0.0447	−0.1469**	0.0443
Y2008	−0.1803***	0.0521	−0.1791***	0.0497	−0.1740***	0.0482	−0.1776***	0.0492
Y2009	−0.1321***	0.0470	−0.1376***	0.0468	−0.1413***	0.0491	−0.1385***	0.0475
Y2010	−0.1280***	0.0434	−0.1261***	0.0426	−0.1141**	0.0428	−0.1237***	0.0427
Y2011	−0.1747***	0.0449	−0.1785***	0.0438	−0.1821***	0.0432	−0.1767***	0.0439
Y2012	−0.1974***	0.0436	−0.2012***	0.0428	−0.2040***	0.0426	−0.2012***	0.0428
Y2013	−0.2539***	0.0519	−0.2524***	0.0508	−0.2627***	0.0498	−0.2552***	0.0505

Table 7 (continued)

Models (OLS)	14		15		16		17	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Y2014	−0.2240	0.0439	−0.2273	0.0431	−0.2367	0.0430	−0.2258	0.0429
Y2015	−0.2019	0.0426	−0.2083	0.0417	−0.2170	0.0416	−0.2076	0.0417
Y2016	−0.1871	0.0448	−0.1893	0.0438	−0.1895	0.0435	−0.1899	0.0439
Submarket dummies								
D.Omval	−0.2387**	0.0273	−0.2426**	0.0264	−0.2394**	0.0276	−0.2396**	0.0272
D.ZuidOost	−0.5502**	0.0236	−0.5561**	0.0234	−0.5579**	0.0243	−0.5524**	0.0238
D.TelSlot	−0.6250**	0.0255	−0.6283**	0.0260	−0.6120**	0.0262	−0.6279**	0.0264
D.Centre	−0.3270**	0.0401	−0.3492**	0.0417	−0.3584**	0.0407	−0.3513**	0.0416
D.West	−0.4340**	0.0444	−0.4522**	0.0456	−0.4570**	0.0449	−0.4454**	0.0449
Model fit statistics								
R²	0.8114		0.8151		0.8072		0.8163	
adj.R²	0.7993		0.8029		0.7949		0.8042	
σ²	0.0176		0.0173		0.0180		0.0172	
N	598		598		598		598	

Models (OLS)	18		19		20		21	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Constant	5.0665**	0.2623	4.8020**	0.2991	5.0960**	0.2617	5.2280**	0.2607
Control variables								
LnArea	−0.0161	0.0094	−0.0291**	0.0112	−0.0194*	0.0095	−0.0186	0.0097
LnAgecomb	0.0080	0.0166	0.0065	0.0164	0.0079	0.0166	0.0066	0.0164

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Table 7 (continued)

Models (OLS)	18		19		20		21	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Floor	0.0132**	0.0013	0.0119**	0.0014	0.0130**	0.0013	0.0078**	0.0015
High_Floor	–	–	–	–	–	–	–	–
View	–	–	0.0363	0.0160	–	–	–	–
No.Ten	0.0009	0.0005	0.0008	0.0005	0.0009	0.0005	0.0010	0.0005
No.Parking	0.0002	0.0001	0.0002*	0.0001	0.0002	0.0001	0.0002	0.0001
Net.Gross	0.0957	0.1092	0.0495	0.1099	0.0892	0.1097	0.0813	0.1080
EI	0.0117	0.0284	0.0132	0.0283	0.0135	0.0284	0.0124	0.0281
LnDStat	0.0542**	0.0197	0.0522**	0.0195	0.0543**	0.0198	0.0552**	0.0192
LnDHigh	0.0289	0.0194	0.0337	0.0196	0.0302	0.0194	0.0284	0.0196
Industry*Height*View interactions								
Finance*HighFL	–	–	–	–	–	–	–	–
Insurance*HighFL	–	–	–	–	–	–	–	–
RealEstate*HighFL	–	–	–	–	–	–	–	–
Business*HighFL	–	–	–	–	–	–	–	–
ICT*HighFL	–	–	–	–	–	–	–	–
Law*HighFL	–	–	–	–	–	–	–	–
Cons&Man*HighFL	–	–	–	–	–	–	–	–
Other*HighFL	–	–	–	–	–	–	–	–
Finance*View	–	–	–	–	–	–	–	–
Insurance*View	–	–	–	–	–	–	–	–
RealEstate*View	–	–	–	–	–	–	–	–
Business*View	–	–	–	–	–	–	–	–

Table 7 (continued)

Models (OLS)	18		19		20		21	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
ICT*View	–	–	–	–	–	–	–	–
Law*View	–	–	–	–	–	–	–	–
Cons&Man*View	–	–	–	–	–	–	–	–
Other*View	–	–	–	–	–	–	–	–
Finance*RltvFL	0.2128**	0.0292	0.1502**	0.0339	–	–	–	–
Insurance*RltvFL	0.2243**	0.0449	0.1464**	0.0494	–	–	–	–
RealEstate*RltvFL	0.1991**	0.0393	0.1356**	0.0412	–	–	–	–
Business*RltvFL	0.1829**	0.0364	0.1197**	0.0415	–	–	–	–
ICT*RltvFL	0.1812**	0.0324	0.1194**	0.0370	–	–	–	–
Law*RltvFL	0.2679**	0.0353	0.2032**	0.0399	–	–	–	–
Cons&Man*RltvFL	0.2345**	0.0351	0.1725**	0.0395	–	–	–	–
Other*RltvFL	0.1602**	0.0316	0.0938*	0.0380	–	–	–	–
Fin*View*RltvFL	–	–	–	–	0.0166**	0.0023	–	–
Ins*View*RltvFL	–	–	–	–	0.0164**	0.0035	–	–
RE*View*RltvFL	–	–	–	–	0.0155**	0.0031	–	–
Business*View*RltvFL	–	–	–	–	0.0142**	0.0028	–	–
ICT*View*RltvFL	–	–	–	–	0.0141**	0.0025	–	–
Law*View*RltvFL	–	–	–	–	0.0212**	0.0028	–	–
Cons&Man*View*RltvFL	–	–	–	–	0.0184**	0.0028	–	–
Other* View*RltvFL	–	–	–	–	0.0124**	0.0025	–	–
Fin*View*HighFL	–	–	–	–	–	–	0.000792**	0.0001
Ins*View*HighFL	–	–	–	–	–	–	0.000647***	0.0001

Table 7 (continued)

Models (OLS)	18		19		20		21	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
RE*View*HighFL	–	–	–	–	–	–	0.000743**	0.0001
Business*View*HighFL	–	–	–	–	–	–	0.000696***	0.0001
ICT*View*HighFL	–	–	–	–	–	–	0.000664***	0.0001
Law*View*HighFL	–	–	–	–	–	–	0.001021**	0.0001
Cons&Man*View*HighFL	–	–	–	–	–	–	0.000908***	0.0001
Other*View*HighFL	–	–	–	–	–	–	0.000621**	0.0001
Year dummies								
Y2003	–0.0675	0.0628	–0.0780	0.0625	–0.0689	0.0630	–0.0883	0.0624
Y2004	–0.0443	0.0511	–0.0509	0.0502	–0.0459	0.0511	–0.0515	0.0509
Y2005	–0.0924	0.0484	–0.0911	0.0474	–0.0934	0.0484	–0.1049*	0.0476
Y2006	–0.0923*	0.0453	–0.0951*	0.0447	–0.0942*	0.0454	–0.0967*	0.0441
Y2007	–0.1366**	0.0464	–0.1416**	0.0454	–0.1381**	0.0464	–0.1447**	0.0450
Y2008	–0.1783**	0.0523	–0.1768***	0.0498	–0.1783***	0.0524	–0.1802**	0.0523
Y2009	–0.1185*	0.0492	–0.1272*	0.0486	–0.1214*	0.0493	–0.1342**	0.0473
Y2010	–0.1216**	0.0451	–0.1208***	0.0440	–0.1218***	0.0452	–0.1280**	0.0435
Y2011	–0.1722**	0.0461	–0.1760***	0.0448	–0.1734***	0.0461	–0.1755**	0.0450
Y2012	–0.1946**	0.0448	–0.1988***	0.0439	–0.1950***	0.0449	–0.1975**	0.0438
Y2013	–0.2530**	0.0526	–0.2520***	0.0514	–0.2537***	0.0526	–0.2543**	0.0519
Y2014	–0.2267	0.0459	–0.2290	0.0445	–0.2284	0.0459	–0.2254	0.0441
Y2015	–0.2047	0.0440	–0.2098	0.0429	–0.2052	0.0441	–0.2024	0.0427
Y2016	–0.1834	0.0456	–0.1861	0.0445	–0.1845	0.0457	–0.1873	0.0450
Submarket dummies								

Table 7 (continued)

Models (OLS)	18		19		20		21	
Variables	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
D.Omval	-0.2375**	0.0281	-0.2401	0.0272	-0.2387	0.0279	-0.2412	0.0273
D.ZuidOost	-0.5486**	0.0240	-0.5541**	0.0238	-0.5508**	0.0239	-0.5526**	0.0236
D.TelSlot	-0.6165**	0.0259	-0.6206**	0.0264	-0.6192**	0.0260	-0.6285**	0.0254
D.Centre	-0.3243**	0.0399	-0.3465**	0.0414	-0.3327**	0.0403	-0.3340**	0.0403
D.West	-0.4261**	0.0453	-0.4455**	0.0464	-0.4314**	0.0456	-0.4370**	0.0444
Model fit statistics								
R^2	0.8093		0.8125		0.8094		0.8114	
adj.R^2	0.7970		0.8001		0.7972		0.7993	
σ^2	0.0178		0.0176		0.0178		0.0176	
N	598		598		598		598	

Dependent variable is Ln [rent price (in year 2016 €)/m²/year]; SE are White-corrected, robust standard errors; * and ** denote 95% and 99% significance levels respectively

proxy as dependent variable albeit not statistically significant. It is important to point out that while rents are highest in the South Axis submarket (baseline category), almost all other submarkets provide higher vertical location possibilities with Sloterdijk and the West being significantly higher than the South Axis. Also relatively smaller tenants tend to locate on higher floors, although this variables parameter was not statistically significant. The parcel size variable has the expected sign based on the logic explained above while the elevator variable is unexpectedly negative. This might be explained by the presence of a height related indicator in the denominator (height in 10 m).

Model 12 analyses the determinants of view potential of a transaction whereby the most important features are location and tenant size. The latter is related to the construction of the variable View (accounting for the area visible from all floors in a transaction record – see Appendix). Submarket related evidence indicates that all locations offer better view potential compared to the South Axis and Sloterdijk, Centre and the West have significantly higher view potentials. Status proxy (Relative floor) related results are given in model 13 with the most notable outcome being the significant and negative coefficient of the industry dummy for Real Estate companies.

Following the relatively mixed evidence coming from regressions on the different aspects of height we turn our attention again to the industry-level rent premiums. In Table 7 we present model estimates where we interact the height-specific continuous variables with the industry sector dummies. This provides insights into the causes of vertical sorting by analysing the relative price differential among industries related to the aspects of height that we are able to control for in our data. Model 14 analyses the rent differentials of overall vertical location, model 15 additionally controls for view, Model 16 investigates the premiums for view related perks and model 17 does the same while also controlling for vertical location. Model 18 gives industry sector premiums for the status aspect of height and model 19 repeats this analysis by holding view constant. Model 20 interacts industry sector dummies with View and Relative Floor while Model 21 interacts these dummies with View and High Floor to compare parameter estimates with those from model 14 for overall vertical location premiums.
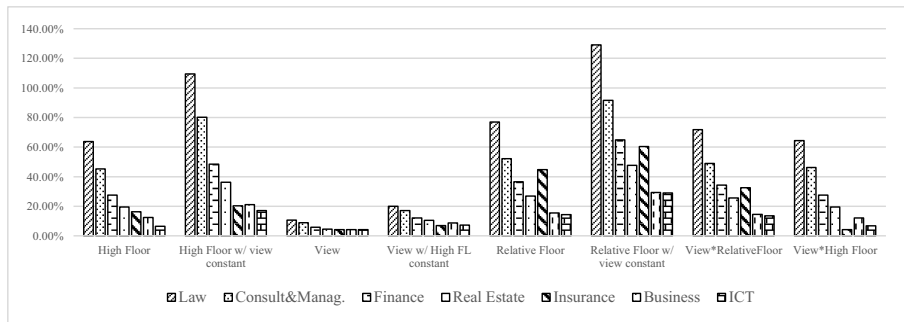
Table 8 Industry sector relative price differentials for various aspects of height[a]

	High Floor	High Floor[b]	View	View[c]	Relative Floor	Relative Floor[b]	View* Relative Floor	View* High Floor
Law	63.81%	109.46%	10.64%	20.02%	76.88%	129.14%	71.85%	64.43%
Consult&Manag.	45.30%	80.12%	8.96%	17.10%	52.17%	91.52%	49.03%	46.19%
Finance	27.55%	48.46%	5.89%	12.05%	36.54%	64.82%	34.32%	27.50%
Real Estate	19.48%	36.22%	4.61%	10.42%	26.83%	47.72%	25.68%	19.55%
Insurance	16.35%	20.29%	4.28%	6.90%	44.76%	60.41%	32.56%	4.24%
Business	12.37%	21.17%	4.23%	8.75%	15.56%	29.33%	14.59%	12.07%
ICT	6.52%	17.09%	4.18%	7.29%	14.37%	29.00%	13.60%	6.84%

[a] Calculated as premiums relative to the baseline category 'Other' from Table 7's respective model coefficients, the latter with the formula exp.(β)-1

[b] Results from model estimated by holding View constant

[c] Results from model estimated by holding High Floor constant

Fig. 3 Industry sector relative rent differentials for various aspects of height

Using parameter estimates from all interaction terms across models 14–21 we calculate industry sector price differentials relative to the baseline category 'Other sectors'. We use the formula exp.(β)-1 which is widely accepted to be a more accurate estimation in semi-log models than the direct use of β-parameters. In all models the baseline category 'Other' is associated with the lowest premiums and relative price differentials are calculated as *[(exp(β)-1'Industry') – (exp(β)-1'Other')]/ (exp(β)-1'Other')*. We have summarized rent differentials for each height aspect and their cumulative interaction in Table 8 and Fig. 3.

It can be inferred that Law firms and Consultancy & Management services show consistently the highest rent differential compared to all investigated sectors across all aspects of height namely overall vertical location, status features, view related perks and the interaction of the latter with the first two. The lowest differentials are observed in the ICT services despite this sector being the second most productive which reinforces previous findings in both OLS and ST models.

By and large, the ranking of sectors by price differentials is quite consistent across various aspects of height with the exception of Insurance carriers. Figure 3 clearly indicates their preference for 'Relative Floor' (status proxy) and a disregard for the amenities of view. Insurance carriers show the third highest rent differential for power (fourth after view is held constant in Model 19) and have a very low differential for view which is more evident when it is also controlled for vertical location (Model 17). In this model, Insurance carriers are associated with the lowest rent differential. All other sectors show strong consistency in rent differential rankings for vertical location aspects of view and status. Law firms and Consultancy & management services are top of the charts, Business services and ICT services show the least willingness to pay for height related perks with Financial services and Real estate sectors sitting in the middle of the table. It can be concluded from the above evidence that Law and Consultancy & Management firms locate on higher floors driven by both view and status benefits whereas Insurance carriers see height primarily as a means to signal status.

Conclusions

The vertical structure of cities is an important economic aspect that mainstream urban economics has neglected for the past five decades. This paper contributes to an emerging body of knowledge on the economics of tall commercial office buildings

through empirical evidence about rent premiums, vertical sorting across different industry sectors and their willingness to pay for either view amenities or status benefits of height. This is the first paper that analyses vertical location premiums after holding view constant and finds that the non-view, firm-level signalling and other factors constitute roughly 70% of the vertical premium while view and industry-level variations account for 27% and 3% of the vertical location respectively. Other key findings relate to a strong vertical rent gradient within buildings that is even stronger for the top five floors in the office market of Amsterdam. Individual industry sector outcomes point to significant rent premiums paid by 'Law Firms', tenants operating in the 'Consultancy & Management' and 'Finance' sectors compared to the benchmark of 'Other Sectors'. Evidence of vertical sorting across industries was relatively weak with strong and consistent evidence only related to 'Law Firms' located in higher floor levels and this sector having the highest output per FTE among the analysed categories. 'Consultancy & Management' firms have consistent outcomes related to rent premiums and sector productivity while evidence on their vertical sorting on higher floor levels was relatively weak. Results regarding 'Insurance Carriers' located on top floors and the 'ICT' sector having the second highest output per job were not further supported by their paid rent levels which is an outcome that calls for further research.

Additional findings on willingness to pay for either view or status aspects of height shed further light on sector economic strength deriving from productivity and marginal prices of the two respective height perks. 'Law' and 'Consultancy & management' firms consistently showed the highest willingness to pay for both view and status while also being the first and third most productive sector respectively. This is well in line with the Roback model of wage capitalization into prices. In contrast, ICT firms showed the lowest willingness to pay for benefits deriving from locating on higher floors despite being the second most productive sector. This finding is a notable exception to the hypothesis forwarded by Liu et al. 2018 that high-productivity firms consistently locate on higher floors. Insurance carriers on the other hand, show preference for status over view in their vertical sorting. An interesting feature emerging from the research is the very strong delineation of submarkets in the Amsterdam office market with horizontal sorting/clustering into submarkets being a very important predictor of headline commercial office rents. Future research should focus on investigating the nature of the non-view premium attributable to variations at the firm level and whether the results on wage capitalisation into rents and causes of vertical sorting among industries can be replicated with effective rents. This is an important feature in the commercial office market which can also be used to test the performance of spatiotemporal models in the light of this study's outcomes.

The findings of this study are of significance to practitioners and policy makers involved in designing urban development policies related, among others, to zoning, land use planning and property-taxation-based financing. Real estate practitioners will find the insights on the causes of vertical sorting, floor level and industry sector-related premiums of high importance during the rental contract negotiation process. In this context, this paper provides additional evidence that improves transparency in the bargaining process among two interested parties. The contribution to the related academic fields is twofold through empirical evidence on the economics of tall buildings, and

spatiotemporal modelling of commercial office properties. From the economics of tall buildings perspective particularly the decomposition of the height premium according to prevailing theories and the causes of vertical sorting of industries are notable contributions. Both fields represent exciting areas of research calling for novel, more comprehensive data mining techniques and methodological approaches.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Appendix: Constructing the 'View' variable

The data for constructing this variable is obtained from the BAG 3D database available at https://www.pdok.nl. The geodatabases included here consist, among others, of 3D feature classes for buildings, terrain, roads and water features. These were used as existing multipatch features or to construct raster images necessary for the analysis of barriers and view potentials from a set of observation points representing each floor level across the 33 buildings in the transactions database. This analysis is undertaken with the Line of Sight 3D analyst tool available in the ArcScene version 10.5.1 software of ArcGIS from ESRI.

To specify an observation point we use the centroid of each building under investigation and give it a height (along the Z-coordinate axis) respective of the floor level

Fig. 4 LOS analysis for floor 30 of the Rembrandt Tower
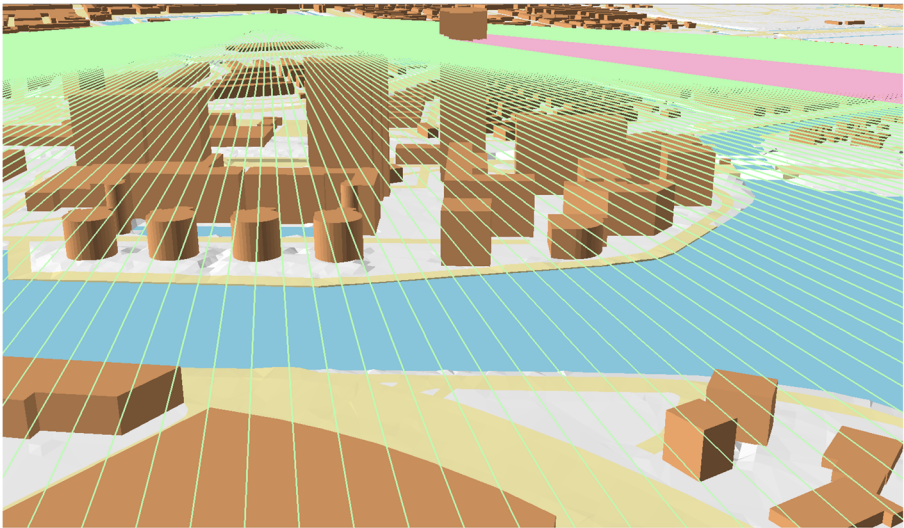
Fig. 5 Details from the 30th floor LOS analysis for the Rembrandt Tower

recorded in the transaction. Consequently, we specify an area for which to perform the line of sight (LOS) analysis and the most common way of doing so is by drawing circles around the observation point. For the purpose, a radius of 1 km is specified and the main reason for this is that the LOS is particularly influenced by nearby obstruction points (e.g. tall buildings). In the case of dense built up areas and clear office submarkets (local concentration of tall buildings), obstruction features in the immediate vicinity are of crucial importance as any feature beyond the 750–1000 m range would in turn be part of the skyline. Following specification of this radius, the LOS analysis is undertaken with standard modelling in ArcScene and selected outputs are shown in Figs. 4 and 5. Figure 4 shows the LOS analysis for floor 30 of the Rembrandt Tower where 3D buildings are in brown, water features in blue, terrain in grey and roads are in pale yellow. The red line bounds the 1 km radius circle, green lines depict the visible area and magenta lines depict the obstructed area form this level. Figure 5 gives details from the 30th floor LOS analysis for the Rembrandt Tower showing how large parts of the Amstel River are visible and how the adjacent Mondriaan Torren obstructs parts of the view (the Rembrandt Tower 3D feature object itself has to be deleted for this analysis).

The output of the LOS analysis is a feature class that records shape lengths for two different visualisation codes. For each LOS output we extract the sum of lengths of the lines depicting the visible area (green lines in the figures above). When the radius around each observation point and the sampling distance[15] between the lines are kept constant for all LOS, the variation in sum of line lengths directly gives the variation in the visible area from each floor under consideration. We use this logic to construct the view potential variable which is given as the logarithm of the sum of line lengths depicting the visible area – green lines in the figures below or visualisation code 1 in the LOS feature classes.

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[15] The individual LOS analysis is a laborious process and in order to save time with the task of computing each floor's LOS, we specify a sampling distance of 20 instead of the default one which is set at 1.

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Affiliations

Ilir Nase [1] · **Nick van Assendelft** [2] · **Hilde Remøy** [1]

[1] Department of Management in the Built Environment, Faculty of Architecture and the Built Environment, TU Delft, Building 8, Julianalaan 134, 2628 BLDelft, The Netherlands

[2] Cushman & Wakefield Valuation and Advisory Services, Gustav Mahlerlaan 362-364, 1082 MEAmsterdam, The Netherlands