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Research Paper

The financial impact of street-level greenery on New York commercial buildings

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HIGHLIGHTS

- Street-level greenery adds value to commercial buildings as evidenced by transaction price and rental premiums in NYC.
- In addition to residential buildings, we identify the financial impact of visual green density for commercial buildings.
- Demonstrates the use of image recognition algorithms to include street greenness into commercial building valuation in the US.
- Investments in urban landscape are further aligned with corporate and institutional investments in office buildings.

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ABSTRACT

Urban street-level greenery is empirically documented to improve mental and physical health, increase productivity, increase urban environmental equality and reduce carbon footprints. In addition, these benefits raise residents' welfare, which has been correlated with increases in residential house prices. We measure street-level greenness in New York City through a novel Green View Index (GVI) using Google Street View images, and assess the impacts of greenness on commercial real estate prices. Using a sample of office transactions, we spatially correlate Google Street View Images for New York City over the 2010 to 2017 period. We find an 8.9% to 10.5% statistically, economically and positive transaction premium and a 5.6% to 7.8% rent premium for offices with low to high street-level greenness relative to those building transactions spatially correlated with very low greenness. Estimations are robust t with proximity to parks, subway stations, sidewalk widths, household income levels and investments by Building Improvement Districts, as well as other vital and standard office valuation features. By documenting the role of greenery in commercial building valuations, our results give a more complete understanding of the value of greenness in urban environments, as well as the economic role that urban landscape architecture, planning and development has upon cities.

1. Introduction

Street-level greenery and parks provide numerous benefits for urban occupants and the environment. Increased greenery is correlated with a decreased urban carbon footprint (Chen, 2015) and increased oxygen generation (Nowak et al., 2007). More urban greenery boosts residents' thermal comfort in a city (Norton et al., 2015) and the provision of more greenery has been tied to increased equity between neighborhoods and satisfaction (Ambrey & Fleming, 2014). These outcomes have led to a quantitative improvement in environmental justice across cities globally (Kabisch & Haase, 2014; Wolch et al., 2014; Lin et al., 2015; You, 2016), but authors document there is still work to be done. Most importantly, greenery is most closely aligned with public health and wellness, which is leading to enhanced cognition, increased perceived mental health and decreased all cause-mortality (Bratman et al., 2015; Perini & Magliocco, 2014; Van Dillen et al., 2012; Van den Berg et al., 2015; Kang et al., 2020a). These urban-scale impacts for occupants are also enhancing their utility, which is empirically correlated with increased residential

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property values. Residential and commercial asset valuation models are based on measuring differentiated preferences for neighborhood and building level features and amenities. Access to parks has been correlated with higher residential property values (Nicholls & Crompton, 2005) and results already documented that street-level greenery had a positive value impact (Morancho, 2003). More recently, advances in image recognition algorithms have led to the development of a Green View Index (GVI), starting with the seminal work by Yang et al. (2009), and shifting to a more efficient workflow developed by Li et al. (2015). Ultimately, these advances have shown that street-level greenery and access to parks results in higher residential values, ceteris paribus (Ye et al., 2019b; Zhang & Dong, 2018; Fu et al., 2019).

Yet, little work has documented the impact of street-level greenery on commercial real estate values. Within the urban context, commercial real estate comprises approximately 38 to 74% of urban space, is 50% of buildings, 33% of assessed property value and average of 56% of local property tax revenues (Bishop-Henchman, 2012; Lang, 2000). Consequently, the economic impact of street-level greenery upon commercial building values is necessary for aligning and developing a more holistic context of the impact of urban street-level greenery. In this way, we measure the value implications of street-level greenery upon commercial office spaces in New York City (NYC).

In this research, we build off the body of work using Google Street View images and assess the visual density of greenness for a composite set of images spatially correlated with office buildings in a 50-meter radius. From these images, we operationalize a GVI to identify very low, low, medium, and high visual density of greenness, respectively. We then pair this data with commercial office transactions from Real Capital Analytics (RCA, 2019) and commercial office leases from CompStak (2019) in the market place over the 2010 to 2017 period. We find that the supply of dense street-level greenery is scarce for the NYC office market. The percentage of buildings with High GVI values (ranging from 0.84% to 7.97%) is just 0.23 (259 building samples). This implies that the positive and economically significant finding is suggestive of a scarce street-level greenery supply for office building occupants in the NYC market. Given the advantageous impact to cognition and mental health, as well as the economic benefit to enhancing the urban streetscape with greenery, there is strong justification for enhancing the value of commercial office spaces for the building owner, as well as for the productivity gains for the office employees within.

Statistically, the null hypothesis is that street-level greenery has zero financial impact on real estate rents 50 or transaction prices. To test, we deploy a multi-variate regression model to - determine whether we can accept or reject the null hypothesis with statistical confidence levels equal to 0.01, 0.05, or 0.10.

2. Literature review

2.1. Measuring urban greenery using qualitative approaches

Despite the benefits of urban greenery, the lack of data on both its quantity and quality has limited measurement from a human street-level viewpoint. Qualitative research relies on questionnaires, surveys, interviews and(or) professional audits to assess and qualify opinions, attitudes and perceptions towards urban greenness (Sugiyama et al., 2008; Tilt et al., 2007; Hipp et al., 2016). Numerous studies show that the perception of street-level greenery contributes positively to psychological and behavioral effects, such as promoting the mental and physical health of people (De Vries et al., 2003; Grahn & Stigsdotter, 2010; Ellaway et al., 2005; Ulrich, 1979; Takano et al., 2002). However, qualitative methods can be costly to execute from a time and labor perspective, and may be susceptible to bias (Downs & Stea, 1977; Meitner, 2004; Hoehner et al., 2005; Lu, 2019; De Vries et al., 2013; Van Dillen et al., 2012).

On the other hand, quantitative measures of greenness can be more efficient and impartial. These include land cover characterization (Speak et al., 2015), the percentage area of green spaces through remote sensing imagery or air photos (Blaschke et al., 2000; Chen et al., 2006; Charreire et al., 2014; Gupta et al., 2012), visual extrapolation from GIS (Speak et al., 2015), and tree identification and counting (Speak et al., 2015; McPherson et al., 2016). Among these methods, remote sensing is the most used technique due to its large land area coverage and comprehensive perspective. An earlier definition of a Green Index (GI) is based on the Normalized Difference Vegetation Index (NDVI), originating from remote sensing images which discriminates between vegetated and non-vegetated areas (Schöpfer & Lang, 2006; Tilt et al., 2007; Hur et al., 2010; Saied et al., 2005).

However, quantitative measures based on NDVI also have limitations, such as insensitivity to the vertical dimension and spatial arrangement within the study area (Gupta et al., 2012) and failure to capture more granular street greenery elements such as shrubs or lawns (Li et al., 2015). Remote sensing data taken from the above does not describe the street-level, human perception of urban greenery (Kang et al., 2020a). Transitioning to the street-level, Yang et al. (2009) were the first to develop the Green View Index (GVI), which used color images captured from four directions as representative of human perception from the street-level, to measure the visibility of surrounding urban greenery.

2.2. Measuring greenness using Google street view images and image processing

A recent emergence in urban data and the development of computer vision techniques expanded ways to measure and assess urban greenery. The emergence of street view images in the last decade provides a novel data source in characterizing the urban landscape (Anguelov et al., 2010; Badland et al., 2010). Users can navigate the virtual urban environment remotely as if they were traveling in the real world using such services. For researchers, street view images have been widely used in measuring the quantity and quality of street greenery associated with increased recreational green physical activity (Li et al., 2015, 2018; Lu, 2019). Large-scale street view images are easily accessed, cost-effective, and not labor intensive. Researchers are able to investigate the urban landscapes through these near real-scenery images at eye-level. New analytical tools such as image processing algorithms and space syntax tools also allow for efficient processing of much larger and more complex data sets at unprecedented scales (Fu et al., 2019; Kang et al., 2020b). Integration of street view images at a big data scale and image recognition algorithms allow for a new approach to human-scale measurement of spatial features in the urban environment at full urban and even at a state or national scale.

To enhance this method, Li et al. (2015) optimized the research method of Yang et al. (2009) by using eighteen Google Street View (GSV) images at different view angles rather than four images taken manually. The work by Li et al. (2015) is the first to use GSV as a street-level, urban greenery assessment tool. After conducting a case study assessment of street-level greenery using GSV images in the East Village in Manhattan New York, Li et al. (2015) concludes that the new GVI proves to be well-suited for assessing street-level greenery through an accuracy assessment, using 33 randomly selected samples. The results indicate high correlation coefficients (0.96) between the values of the calculated GVIs and the corresponding values that were calculated manually using Photoshop. Further, the GVI may accurately represent the amount of greenness that pedestrians can see on streets because the GSV images take panorama views into consideration at different view angles: horizontal (0 degree), up-look (45 degree), and down-look (-45 degree) (Li et al., 2015; Ye et al., 2019a). Rather than replacing prior methods, which used high resolution remote sensing imagery or intensive field surveys, this new method provides an additional layer of data to enrich the urban green information from the human viewpoint.

Building upon the method proposed by Li et al. (2015), researchers began to employ a similar methodology to conduct applied research on the relationship between street-level greenery and various urban outcomes globally. Zhang and Dong (2018); Ye et al. (2019b), and Fu et al. (2019) assessed street-level greenery using Baidu Street View images and documented the positive impacts on housing prices in Beijing and Shanghai. Lu (2019) assessed street-level greenery using GSV images in Hong Kong and found that the quantity and quality of street-level greenery were positively associated with the likelihood of engaging regular physical activity. In this research, we employ the methodology of Li et al. (2015) to calculate the GVI and assess street-level greenery impacts on the commercial office stock of New York City.

2.3. The value of urban greenery

A nascent literature examines the impact of urban greenery on the housing market. Researchers have found that proximity to green spaces results in an increase in residential property values ranging from 3% to above 20% depending on the specific types of green space and the urban context in comparison (Ye et al., 2019b; Arvanitidis et al., 2009; Crompton, 2001; Crompton et al., 2001; Crompton & Nicholls, 2019; Fu et al., 2019; Hamidi et al., 2020).

In earlier studies, using qualitative methods of measuring greenery, Crompton (2001) estimated urban parks may yield a positive impact of up to 20% to adjacent properties compared to the average price in the same area (Crompton, 2001). Hamilton and Quayle (1999); Lindsey et al. (2002) assessed impacts of greenways by examining responses to surveys of residents whose properties were proximate to an urban greenway (Hamilton & Quayle, 1999; Lindsey et al., 2002). According to Arvanitidis et al. (2009), good quality urban greenery improves the quality of life in cities enhancing their attractiveness to residents, employees, tourists, investors and firms (Arvanitidis et al., 2009).

Since the early 2000s, quantitative research through hedonic analysis documented results in line with previous qualitative research. Crompton (2005) documented urban greenway's positive impacts ranging from 5.3% to 20.2% on property values in multiple residential areas in Austin, Texas (Crompton, 2005). Lindsey et al. (2003) documented pricing premiums due to urban greenways ranging from 2.4% to 14%, using 2,157 samples in Indianapolis, Indiana (Lindsey et al., 2003). Morancho (2003) concludes that only the distance from a green area is significant rather than the green area's geographic size as far as environmental variables are concerned and according to the estimates from this study, every 100 m further away from a green area equates to a drop of 300,000 pesetas (approximately USD 2,000) in the average home's price (Morancho, 2003).

More nascent research has been conducted on the relationship between street-level greenness and housing prices using GVI calculated through street-view images (Ye et al., 2019b; Zhang & Dong, 2018; Fu et al., 2019). Ye et al. (2019b) show that visible street greenery and street accessibility yield significant positive coefficients for housing prices, using data of 1,395 private neighborhoods in Shanghai. Through comparing two pairs of neighborhoods with highly similar characteristics, yet different average prices and street-level greenness, the research team concludes that street-level greenness, among implicit attributes, is of significance for the hedonic model and positively associated with housing price (Ye et al., 2019b). Zhang and Dong (2018) reaches a similar conclusion in a study of the housing market in Beijing and finds that a one-unit increment of street-level greenness may improve housing value by 10 % (RMB 342,930, approximately USD 48,990) on average (Zhang & Dong, 2018). Fu et al. (2019) documents that a 1% increase in GVI leads to an enhanced willingness to pay by residents in Beijing and Shanghai by about 39,377 RMB and 21,689 RMB, respectively. Kang et al. (2020b) shows that street view images capture environmental factors that may affect house price appreciation rates.

While there is some literature studying the effect of urban greenery on housing prices, none of the research to date has assessed the impacts of urban greenery on commercial buildings. Within commercial markets there is evidence of a correlation between green building practices, as measured by Breeam, LEED or Energy Star labels, and positive transaction prices (Fuerst & McAllister, 2009, 2011; Eichholtz et al., 2010, 2013; Kok & Jennen, 2012; Deng & Wu, 2014; Chegut et al., 2014; Turan et al., 2020). A better understanding of this relationship would serve as a crucial supplement to urban landscape design, investments in urban greenery and improving local property tax bases.

3. A geospatial and relational dataset

3.1. Study area

To investigate the impact of urban greenness on commercial property transaction prices, we study office building transactions in Manhattan, New York City over the 2010 to 2017 period. We use commercial building transaction data provided by Real Capital Analytics (RCA, 2019) and office lease contract data from Compstak to provide fundamental building, neighborhood and contract features for our hedonic transaction and rental pricing models (CompStak, 2019). RCA's building transaction data includes financing details, prior transaction history, and owner and seller type identification. Compstak provides lease contract characteristics, tenant profiles, and market variables from verified professionals in commercial brokerage and appraisal firms. We cull prices, contract features, location and transaction time data for individual property transactions from the RCA dataset. We then pair this data with Building Class features for each building that transacted from the Compstak dataset to control for the overall quality of the buildings in the sample dataset. We also calculate the distance between building samples and the closest parks and subway stations from MapPLUTO (Property Land Use Tax lot Output) (New York City Department of City Planning, 2020). We create two binomial variables denoting buildings that are located within a given distance to parks or subway stations, which yield known economic impacts on commercial property values (Debrezion et al., 2007; Yang & Diez-Roux, 2012). In addition, we also incorporate average sidewalk widths within 250 meters of each building using NYC's sidewalk data (New York City Department of City Planning, 2020). In addition to these datasets, we include three variables that document buildings' award status, which have significant economic impacts on commercial property transaction prices: awarded architects, awarded firms, and awarded architects and firms. In total, we have a complete transaction dataset of 1,404 observations for the 2010 to 2017 period.

3.2. Google street view images

We then pair our transaction dataset to our GVI measures. For each transaction observation, we match street- level greenness to a 50-meter radius GVI. To measure GVI, we collect GSV images at a set of equal interval sampling points generated along the street networks in Manhattan. Fig. 1 depicts for each sampling point, four GSV images with North, South, East and West panoramic photographs of the urban landscape. In total, 90,382 sampling points are generated along the streets in Manhattan. Each sampling point has four up-to-date GSV images downloaded through the Google Street View Application Programming Interface (API). Given that street view images collected in winter may not represent the real greenness of the street and bring strong side effect for the further analysis, we filter the downloaded street view images according to their months. Only GSV images that were taken between April and September were kept for calculation of the street-level greenness.

Depicted in Fig. 2, for each transacted building, we create multiple buffer zones at different radii – 30, 50, 80, and 100 m - to filter collected GSV images. While the 30-meter buffer collects just a few GSV points in proximity to the sample building, it does not offer an expansive view of the immediate street-level greenery. In contrast, the 100-meter buffer collects GSV points from other urban blocks that would not reflect the visual experience of the transacted building's occupants. Manhattan

Fig. 1. Example of Google Street View images. *Notes*: Fig. 1 demonstrates street-level images from four directions collected at a Google Street View sampling coordinate point.

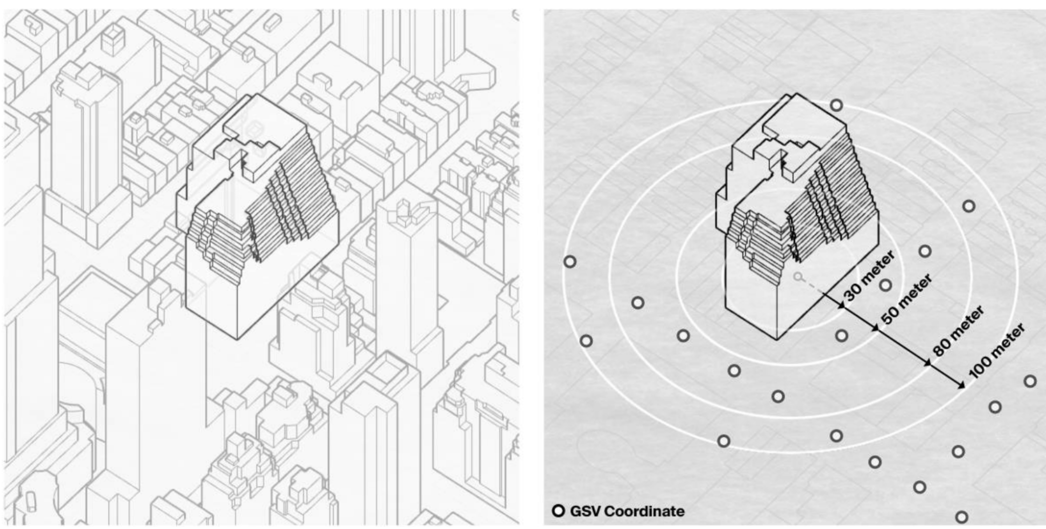

Fig. 2. Example of Google Street View images collected near a building sample. *Notes*: Fig. 2 demonstrates the buffer areas with different radii in relation to a randomly selected transacted building in Manhattan, New York City. The left figure visualizes the selected building in relation to its physical environment. The right figure demonstrates four buffer zones around the selected building sample. The dots included in the right figure represent the GSV sampling coordinates, from which we extract street-level images.

block size is on average 274 by 80 m, which means a 50-meter buffer, with the centroid of the building footprint as the center of circle, is an appropriate identifier of the immediate street-level greenery of the transacted building. Fig. 3 depicts the 50-meter buffer and shows the street space at a building's door front while excluding the street on the other side of the block. If a building has two entrances on both sides of the block, the 50-meter buffer zone collects GSV points only from the front and the back, but not from nearby blocks.

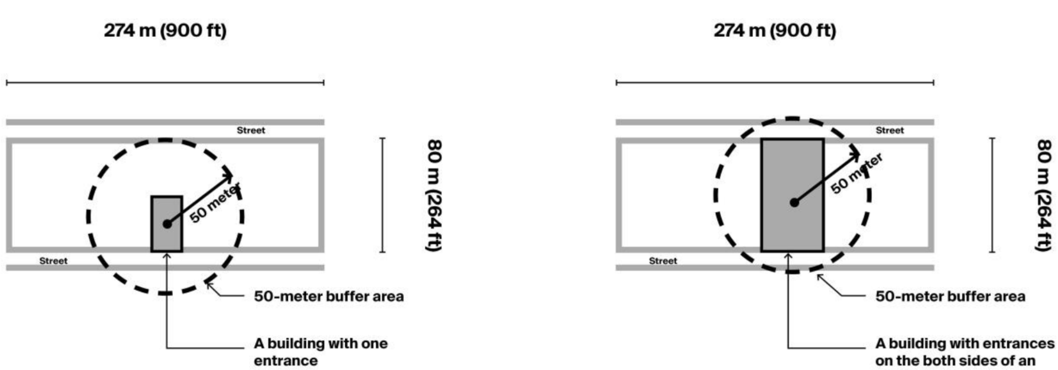

Fig. 3. 50-meter buffer zone around a building sample as the filter for GSV images. *Notes*: Fig. 3 demonstrates two scenarios of collecting GSV points through a 50-meter buffer area around a building sample in a Manhattan block. The left diagram indicates the buffer area around a building that faces only one side of the block, while the right diagram indicates the buffer area around a building that has two entrances facing both sides of the block.

3.3. Building transaction-level descriptive statistics

Table 1 documents the dependent and independent variables included in the transaction price analysis, and compares buildings' average transaction characteristics across GVI quartiles and the transactions of the full sample. Transactions with Medium (Column 3) and High GVI (Column 4) yielded average transaction prices that are 147.86 million and 148.33 million, respectively. Both are higher than that of the full sample, which is 133.95 million. Transactions with High GVI yielded the highest average transaction price at 148.33 million. Transactions with Very Low GVI (Column 1) and Low GVI (Column 2) have comparatively low prices at 119.78 million and 119.49 million, respectively.

We also find that High GVI transactions occur in buildings that are relatively young and low in floor height, at 77 years of age and 15 stories tall, respectively. Transactions of Low GVI occur most often in Class B and Class C buildings at 57% and 24% t, respectively. All other GVI levels have transactions of Class A buildings at above 30% , and with that High GVI has the highest percentage of Class A transactions at 35% . Interestingly, buildings with High GVI have the lowest average distance to parks of 142.85 meters, and the highest distance to subway stations at 207.65 meters. This is in contrast to Very Low GVI transacted buildings that have the highest park distance and the lowest subway station distance, at 183.70 meters and 153.18 meters, respectively. The distances to the closest subway stations increase as the GVI increases from very low to high.

Transactions with Very Low GVI, Low GVI, and Medium GVI are mostly in Downtown, Midtown East, Midtown South, and Midtown West. Transactions with Low GVI have a high concentration in Midtown West at 41% . A noticeably higher portion of transactions with High GVIs are in the Upper East Side. Transactions with different GVI levels are relatively evenly distributed between 2011 and 2016, but significantly less in 2010 and 2017.

Our transaction sample indicates real estate private companies are the dominant buyers. These companies usually constitute over 30% of buyers, except for buildings with Medium GVI (29%). Private companies are also the largest sellers for the buildings with different levels of GVI. The proportion of private sellers remains relatively consistent with that of the full sample at 25% . As for lending types, our sample shows that buildings with different GVIs have a similar combination of lenders in four categories, namely CMBS, International Bank, National Bank, and Regional/Local Bank. Yet, the distribution of lenders remains rather consistent across different levels of GVI.

Table 2 shows the dependent and independent variables included in the rental contract analysis, and compares buildings' average effective rent characteristics across GVI quartiles and the rent price of the full sample. Effective rent increases as the GVI increases from Very Low GVI to High GVI. Leases with High GVI yielded the highest average effective rent at 613.34 USD per square meter.

We also find that the age of building samples decreases as GVI increases, with t High GVI leases having the lowest average building age, at 52.7 years. Leases of Very Low, Low, and Medium GVIs occur most often in Class A and Class B, while transactions of High GVI have a significant concentration in Class A.

Similar to that for the RCA transaction price dataset, the distances to the closest subway stations are positively correlated with the GVI levels, while the distances to the closest parks are negatively correlated with the GVI levels.

Leases with Very Low GVI occur mostly in Downtown (36%) and Midtown East (27%). Half of the leases with Low GVI occur in Midtown West, while the highest concentrations of leases with Medium GVI are Midtown West and Midtown East, at 46% and 36% , respectively. High GVI has the most leases in Midtown East (55%) and the second largest concentration in Midtown West (25%).

Leases with different GVI levels occur relatively evenly between 2011 and 2016, but significantly less in 2017. For lease terms, most

Table 1
Building Sample Characteristics Street-level Greenery - Transaction Price Data.

Variable	Very Low GVI (Quartile = 1)		Low GVI (Quartile = 2)		Medium GVI (Quartile = 3)		High GVI (Quartile = 4)		Full Sample	
	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Street-Level Greenness										
Green View Index (Percentage)	0.21	(0.06)	0.40	(0.06)	0.64	(0.10)	1.78	(1.10)	0.76	(0.82)
Building Prices										
PSM	8,051.06	(6,042.50)	8,275.41	(6,487.08)	8,569.88	(6,521.32)	9,242.28	(6,405.71)	8,542.94	(6,376.92)
logPSM	8.81	(0.57)	8.84	(0.56)	8.88	(0.57)	8.95	(0.59)	8.87	(0.57)
Price (Millions)	119.78	(176.14)	119.49	(198.41)	147.86	(240.45)	148.33	(268.78)	133.95	(224.17)
logPrice	17.71	(1.42)	17.69	(1.4)	17.66	(1.61)	17.58	(1.63)	17.66	(1.52)
Urban Infrastructure										
parkdistance	183.7	(110.58)	181.99	(111.16)	169.22	(116.26)	142.85	(98.74)	169.36	(110.46)
metrodistance	153.18	(119.13)	154.47	(112.95)	166.85	(121.02)	207.65	(157.70)	170.64	(130.76)
within250park	0.77	(0.42)	0.79	(0.41)	0.73	(0.44)	0.84	(0.37)	0.78	(0.41)
within250metro	0.88	(0.33)	0.88	(0.32)	0.81	(0.39)	0.67	(0.47)	0.81	(0.39)
sidewalkwidth	4.07	(0.73)	4.28	(0.85)	4.16	(0.8)	4.13	(0.98)	4.16	(0.85)
Building Awards										
Awarded Architects	0.01	(0.07)	0.01	(0.09)	0.00	(0.05)	0.02	(0.15)	0.01	(0.10)
Awarded Firms	0.01	(0.09)	0.00	(0.05)	0.01	(0.11)	0.00	(0.05)	0.01	(0.08)
Awarded Architects & Firms	0.01	(0.09)	0.00	(0.05)	0.02	(0.14)	0.03	(0.17)	0.01	(0.12)
Building Characteristics										
Age	82.02	(31.06)	86.22	(28.44)	78.01	(32.17)	77.02	(32.98)	80.78	(31.41)
Number Floors	17.66	(12.1)	16.36	(12.94)	16.35	(12.31)	15.58	(13.49)	16.49	(12.73)
SqM nb	22,760.94	(34,090.33)	17,848.28	(23,456.03)	22,501.95	(32,549.80)	22,412.59	(40,472.37)	21,413.06	(33,302.72)
Class A	0.31	(0.46)	0.19	(0.39)	0.34	(0.47)	0.35	(0.48)	0.3	(0.46)
Class B	0.49	(0.50)	0.57	(0.5)	0.42	(0.49)	0.50	(0.50)	0.49	(0.50)
Class C	0.20	(0.40)	0.24	(0.43)	0.24	(0.43)	0.15	(0.36)	0.21	(0.41)
Renovated	0.18	(0.38)	0.10	(0.29)	0.12	(0.32)	0.11	(0.31)	0.12	(0.33)
	359		344		355		356		1414	

Notes: Table 1 highlights the mean and variation of building characteristics for the transaction sample over quartiles of GVI and the full sample. Each transacted building reflects neighborhood, temporal and other contract characteristics that we have categorized for our model. However, transacted building market locations by submarkets, time period of transaction, buyer and seller types as well as lending characteristics are not shown, but are available upon request.

Table 2
Building Sample Characteristics Street-level Greenery - Rent Data.

Variable	Very Low GVI (Quartile = 1)		Low GVI (Quartile = 2)		Medium GVI (Quartile = 3)		High GVI (Quartile = 4)		Full Sample	
	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
Street-Level Greenness										
Green View Index (Percentage)	0.20	(0.05)	0.40	(0.06)	0.64	(0.10)	1.78	(1.10)	0.76	(0.82)
Rent Prices										
Effective Rent (USD)	478.46	(152.57)	567.98	(203.66)	560.81	(211.05)	613.34	(232.90)	554.87	(207.78)
Log Effective Rent	3.75	(0.31)	3.91	(0.35)	3.89	(0.36)	3.98	(0.36)	3.88	(0.35)
Urban Infrastructure										
parkdistance	172.5	(93.18)	192.41	(101.83)	178.96	(115.24)	146.2	(95.59)	172.61	(103.19)
metrodistance	122.01	(105.62)	110.97	(72.45)	134.53	(88.44)	141.36	(105.79)	127.17	(94.77)
within250park	0.81	(0.39)	0.77	(0.42)	0.72	(0.45)	0.85	(0.36)	0.79	(0.41)
within250metro	0.89	(0.31)	0.96	(0.2)	0.88	(0.33)	0.83	(0.37)	0.89	(0.31)
sidewalkwidth	4.07	(0.67)	4.39	(0.67)	4.32	(0.74)	4.19	(0.97)	4.24	(0.78)
Building Awards										
Non Awarded	0.97	(0.17)	0.96	(0.19)	0.95	(0.22)	0.94	(0.24)	0.95	(0.21)
Awarded Architects	0.00	(0.00)	0.00	(0.05)	0.01	(0.11)	0.02	(0.13)	0.01	(0.09)
Awarded Firms	0.00	(0.05)	0.01	(0.12)	0.02	(0.16)	0.00	(0.00)	0.01	(0.1)
Awarded Architects and Firms	0.03	(0.17)	0.02	(0.15)	0.01	(0.12)	0.05	(0.21)	0.03	(0.16)
Building Characteristics										
Age	74.19	(28.07)	71.52	(29.61)	67.93	(29.15)	52.7	(27.92)	66.64	(29.87)
Age Squared	6,291.46	(3,456.3)	5,991.56	(3,943.66)	5,463.71	(3,916.41)	3,556.14	(3,366.6)	5,332.74	(3,829.88)
Building<5 years old	0.03	(0.16)	0.01	(0.11)	0.01	(0.07)	0.03	(0.18)	0.02	(0.14)
Renovated	0.77	(0.42)	0.74	(0.44)	0.74	(0.44)	0.55	(0.5)	0.70	(0.46)
Number Floors	31.34	(15.82)	32.6	(20.91)	26.01	(13.8)	32.35	(13.2)	30.57	(16.44)
Class A	0.54	(0.5)	0.51	(0.5)	0.56	(0.5)	0.81	(0.4)	0.6	(0.49)
Class B	0.42	(0.49)	0.47	(0.5)	0.38	(0.48)	0.18	(0.39)	0.36	(0.48)
Class C	0.04	(0.19)	0.02	(0.14)	0.06	(0.24)	0.01	(0.11)	0.03	(0.18)
Log(SqFt)	12.95	(0.94)	12.83	(0.98)	12.71	(1.19)	13.01	(1.05)	12.87	(1.05)
	1862		1853		1859		1829		7403	

Notes: Table 2 highlights the mean and variation of building characteristics for the transaction sample over quartiles of GVI and the full sample. Each transacted building reflects neighborhood, temporal and other contract characteristics that we have categorized for our model. However, transacted building market locations by submarkets, time period of transaction, buyer and seller types, as well as lending characteristics, are not shown but are available upon request.

leases of the full sample have a 6–10 year term and an 11–15 year term, and this trend remains consistent across different GVI levels.

3.4. Street-level greenness valuation

3.4.1. Green view Index calculation

After accessing GSV images, we extract and calculate the greenness from streetscape as an approximation of the physical greenness in the built environment from the street level. To calculate the GVI of each GSV point location, the following equation is used to calculate the proportion of green pixels in four images collected to create a panoramic view.

$$GVI = \frac{1}{4} \times \sum_{i=1}^{n=4} \frac{Pixel_{g\_i}}{Pixel_{a\_i}} \times 100\% \quad (1)$$

where *Pixelg i* refers to the number of pixels that have been identified as green pixels at the *i*th direction, and *Pixelai* indicates the total number of pixels at *i*th direction. All images were processed with Python 3.7. OpenCV library was employed for manipulating pixels of image and GVI calculation. The GVI calculates the ratio of total green pixels from four pictures to the total area of the panoramic pictures, thereby can be used

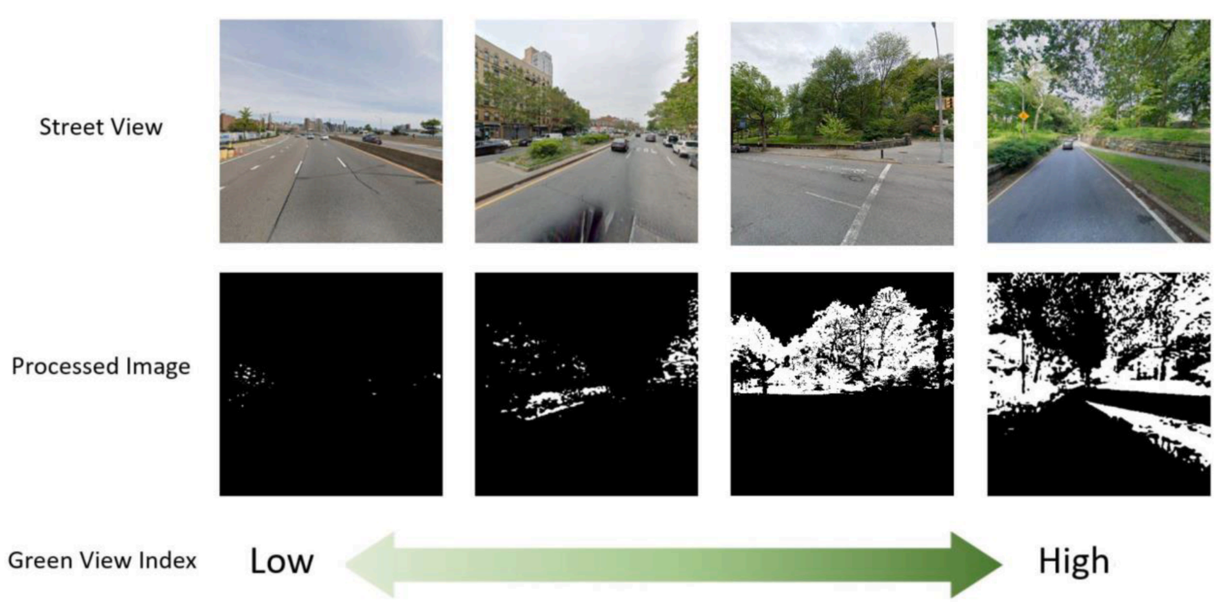

Fig. 4. Example: Google Street View and Black and White Processed Images with Assigned Quartiles 1 to 4.

for an approximation of the visibility of street-level greenery. As street view images are stored in three color channels R (red), G (green), B (blue), pixels with high green channel values may refer to the targeted green pixels. To identify green pixels, the following equation is employed using the method proposed by Li et al. (2015):

$$G_{pixel\_i} = \begin{cases} 0, if (G_i - B_i) \times (G_i - R_i) < t \\ 1, if (G_i - B_i) \times (G_i - R_i) > t \end{cases} \tag{2}$$

Where *Gpixel i* indicates whether the *i*th pixel is a green pixel, *Ri*; *Gi*, *Bi* denote the R, G, B channel values of the *i*th pixel; *t* is a threshold that classifies pixels as a green pixel or a non-green pixel. Fig. 4 shows four examples of Google Street View images with Very Low, Low, Medium, and High GVI values, respectively. After processing and extracting green pixels, the average ratio of green pixels in four street view images at a specific location is used for measuring the street-level greenery. Fig. 4 depicts the quality of the GVI to measure street-level greenery quantitatively. It should be noted that the threshold which may affect the identification of green pixels is selected based on human perception and experience. To reduce uncertainty, we randomly selected images from our collection and manually compare the processed images with the raw street view images to make sure pixels that represent trees are identified accurately.

3.4.2. Hedonic regression model

In this study, we employ the hedonic pricing method to analyze and understand commercial real estate pricing dynamics. The hedonic pricing method captures the impact on asset pricing of a property's building, neighborhood and market factors. Using a cross-sectional dataset of hedonic characteristics, we estimate the incremental value of street-level greenness inputted into the hedonic valuation model specified below:

$$LogP_i = \alpha + \beta X_i + \delta GVI_i + \varepsilon_i \tag{3}$$

Where the dependent variable is the logarithm of the transaction price (and the logarithm of the net effective rent per square meter), *P*, for commercial office transactions (and leases) *i*. *X* is a vector of hedonic characteristics including transaction, contract, building and neighborhood amenity features for building transactions *i*-, and lease contract terms, exogenous location-fixed effects by submartkets, and timefixed effects by quarter and year executed between 2010 and 2018 for rental contract *i*. *GVI* is a vector of quartile identifications, where 1 is denoted if the transaction of building *i* falls into the categories of Very Low, Low, Medium, and High GVI values. We evaluate the value of higher GVIs in relation to the Very Low GVI value. A change in GVI levels may generate a positive or negative change in transaction price or lease rent. For both operations of the data, α is a constant while β and δ are estimated parameters and *E* is assumed to be an independently, identically distributed error term.

4. Results

Employing Eq. (3) we estimate the impact of street-level greenness upon the logarithm of building transaction prices and the logarithm of effective rents. Columns (1) and (2) of Table 3 document the results of the operationalized transaction price model, which explains 88% of the variation of the logarithm of transaction prices. Columns (3) and (4) document the results of the operationalized effective rents model, which explains 50 to 51% of the variation in the logarithm effective rent per square meter.

In column (1) we operationalize Eq. (3) with GVI quartiles, where Low (the second quartile), Medium (the third quartile), and High (the fourth quartile) GVIs, are priced relative to Very Low (the first quartile). We find that the Low, Medium, and High GVI buildings transact for 8.2 to 10.2% more than Low GVI buildings, ceteris paribus.

In column (2), we include two binomial variables denoting buildings that are within a 250 m radii from a park or a subway station, respectively. We also incorporate the average sidewalk width. In addition, we add the architect or architectural firm's award designation. These results document an economically positive and statistically significant impact on commercial real estate prices, in line with the literature on awarded designers and commercial real estate (Hough & Kratz, 1983; Vandell &

Table 3
Building Transaction Prices and Rents Results for Green View Index by Quartiles.

DATA	(1) Price	(2) Price	(3) Rent	(4) Rent
VARIABLES	GVI Quartiles	With Urban Infrastructure and Awards	GVI Quartiles	With Urban Infrastructure and Awards
Street-Level Greenness				
GVI Low	0.105**	0.105**	0.085***	0.078***
	[0.042]	[0.042]	[0.008]	[0.008]
GVI Medium	0.100**	0.100**	0.051***	0.041***
	[0.040]	[0.040]	[0.009]	[0.009]
GVI High	0.097**	0.089**	0.066***	0.056***
	[0.042]	[0.042]	[0.009]	[0.009]
Urban Infrastructure				
Park within 250 *eters*		0.085**		0.047***
(1 = YES)		[0.040]		[0.008]
Subway within 250 *meters*		0.032		−0.027***
(1 = YES)		[0.040]		[0.010]
Sidewalk Width		0.001		0.015***
(Area Average)		[0.018]		[0.004]
Architectural Award Designation				
Awarded Architects		0.159		0.429***
		[0.190]		[0.056]
Awarded Firms		0.385***		0.068*
		[0.121]		[0.035]
Awarded Architects And Firms		0.434***		0.031
		[0.066]		[0.020]
Building Characteristics				
Age	−0.005***	−0.004**	−0.009***	−0.009***
	[0.002]	[0.002]	[0.001]	[0.001]
Age Squared	0.000**	0.000**	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Number Floors	−0.002	−0.002	−0.000	−0.000
	[0.002]	[0.002]	[0.000]	[0.000]
Renovated	0.232***	0.241***	−0.008	−0.005
	[0.045]	[0.045]	[0.008]	[0.008]
Class B	−0.224***	−0.218***	−0.176***	−0.172***
Relative Class A to	[0.042]	[0.042]	[0.009]	[0.009]
Class C	−0.313***	−0.304***	−0.295***	−0.279***
Relative Class A	[0.054]	[0.055]	[0.019]	[0.020]
Log(SqM)	0.806***	0.799***	0.016***	0.015***
	[0.014]	[0.014]	[0.004]	[0.004]
Transaction Characteristics	YES	YES	NO	NO
Lease Characteristics	NO	NO	YES	YES
NYC Submarket FE	YES	YES	YES	YES
Transaction Time FE	YES	YES	YES	YES
Constant	10.473***	10.411***	6.239***	6.166***
	[0.157]	[0.171]	[0.048]	[0.054]
Observations	1,414	1,414	7,403	7,403
R-squared	0.886	0.887	0.501	0.515
F Adj R-Squared	0.880	0.880	0.500	0.510

Notes: Table 3 documents regression results of street-level greenness upon the logarithm of building transaction prices (Column 1 and 2) and the logarithm of effective rents (Column 3 and 4). Location, time, transaction deal features, and lease deal information are not shown as independent variables and are in line with the literature, but are available upon request. Robust standard errors are in brackets and statistical significance is denoted within the table where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Lane, 1989; Millhouse, 2005; Fuerst et al., 2009; Nase et al., 2016; Kang, 2019; Rong et al., 2020). We find that the Low, Medium and High GVI transaction values remain positive and statistically significant, relative to Very Low, ceteris, paribus.

In column (2) we operationalize Eq. (3) with the same GVI quartiles as shown in column (1), but using the rent dataset from Compstak. We find that the Low, Medium, and High GVIs remain positive and statistically significant to commercial real estate rents.

In column (4), we find that the Low, Medium and High GVIs remain positive and statistically significant to commercial real estate rents. We also find the proximity to parks yields economically positive and statistically significant impacts on commercial real estate rents, in line with literature on proximity to urban green spaces (Crompton, 2001; Crompton et al., 2001; Morancho, 2003; Ye et al., 2019b; Arvanitidis et al., 2009; Crompton & Nicholls, 2019; Fu et al., 2019; Hamidi et al., 2020). We find the coefficients of the GVIs, the proximity to parks and subway stations, and the surrounding sidewalk width are stable and consistent with results from previous columns.

4.1. Robustness checks

Local investment in street-level greenery made by a community could be highly correlated with the local residential tax base. To control variation in local investment we measure the impact of GVI upon commercial buildings across income levels within NYC. Table 4 documents the results of income variation by two household income levels in Manhattan, New York City for transaction prices and rents. For the transaction price dataset, Income Level 1 has an average household income of $170,110 USD per year, while Income Level 2 has an average household income of $287,424 USD per year. For the rent dataset, Income Level 1 has an average household income of $160,043 USD per year, while Income Level 2 has an average household income of $256,210 USD per year.

Table 4 results for Income Level One are reported in Columns 1 and 3. Column 1 documents positive and significant impacts of Medium and High GVIs on commercial real estate prices, at 10.8% and 15.6% , respectively. In column 3, we report rental impacts and find a 5.9% to 6.8% statistically, economically and positive rent premium for offices with low to high street-level greenness.

Results for Income Level Two are reported in Columns 2 and 4. Column 2 reports positive and significant transaction price premiums for Low and Medium GVIs, at 16.5% and 15.3% , respectively. High GVI yields a statistically insignificant impact on prices. In Column 4, rents in higher income areas results show that Low GVI yields a 6.3% statistically, economically and positive rent premium for offices, while Medium and High GVI do not retain their relative statistical or economic significance. The other coefficients within the model stay constant and are available upon request.

For further analysis upon investment in streetscape and real estate prices, we look at the impact of Business Improvement Districts (BIDs). BIDs invest in their communities in various ways and in NYC spend an unreported amount on in upgrading and maintaining the streetscape. The results of this analysis are reported in the Appendix.

In further robustness checks we explore clustering and spatial modeling. First, we cluster observations into years and assess whether they may be correlated within each year, but would be independent between years. The existing operationalized model's results are robust and are available upon request. Second, we further assessed heteroskedasticity and autocorrelation in the model by a Breusch Pagan heteroscedasticity and Durbin Watson d-statistic tests on our final operationalized specifications. To assess heteroskedasticity in the transaction price model, the Chi with 56 parameters is 103.11 and the p-value is 0.0001, indicating the presence of unknown form heteroscedasticity. For the rent price model, the Chi with 56 parameters is 604.67 and the p-value is 0.0001, indicating the presence of unknown form of heteroscedasticity. As a result, we run robust standard errors to correct for unknown form of heteroscedasticity. Further, we assess the temporal autocorrelation of the operationalized models:; the Durbin-Watson d-statistic is 1.53 for the transaction price model and 1.18 for the rent price model. These results suggest the presence of positive autocorrelation, to correct for both unknown forms of heteroscedasticity and autocorrelation, we use robust standard errors in our reported results.

Finally, street-level greenery may be highly spatially correlated and overestimate the price impact of street level greenery on transaction prices. To further investigate spatial autocorrelation, we assessed the Moran's I of the GVI point estimates, which documented statistically significant and a positive spatial autocorrelation. Further, to assess the

Table 4

Building Transaction Prices and Rents Results for Green View Index Quartiles and Household Income Levels.

	(1)	(2)	(3)	(4)
INCOME LEVEL	1	2	1	2
DATA	Price	Price	Rent	Rent
VARIABLES	GVI Quartiles	With Urban Infrastructure and Awards	GVI Quartiles	With Urban Infrastructure and Awards
Street-Level Greenness				
Low GVI	0.086	0.165**	0.059***	0.063***
	[0.054]	[0.070]	[0.010]	[0.015]
Medium GVI	0.108**	0.153**	0.022**	0.022
	[0.050]	[0.071]	[0.011]	[0.015]
High GVI	0.156***	0.020	0.068***	−0.003
	[0.052]	[0.072]	[0.010]	[0.017]
Urban Infrastructure	YES	YES	YES	YES
Architectural Award Designation	YES	YES	YES	YES
Building Characteristics	YES	YES	YES	YES
Lease Characteristics	NO	NO	YES	YES
Transaction Characteristics	YES	YES	NO	NO
NYC Submarket FE	YES	YES	YES	YES
Transaction Time FE	YES	YES	YES	YES
Constant	10.238***	10.165***	6.103***	6.212***
	[0.232]	[0.315]	[0.081]	[0.095]
Observations	913	501	4,723	2,680
R-squared	0.901	0.880	0.560	0.558
F Adj R-Squared	0.890	0.870	0.550	0.550

Notes: Table 4 documents regression results of street-level greenness upon the logarithm of building transaction prices (Column 1 and 2) and the logarithm of effective rents using lower income subsample data (Column 3 and 4). Urban infrastructure, architectural award designations, location, time, transaction deal features, and lease deal information are not shown as independent variables but are available upon request. Robust standard errors are in brackets and statistical significance is denoted within the table where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

confounding impact of spatial autocorrelation on the prices, we estimate both a spatial error and spatial lag model for transaction prices. The results are reported in Table 3 are robust and more conservative in economic magnitude than the spatial models, which indicates further that there is a positive, statistically and economically significant impact of street-level greenery on transaction prices. Future research can be extended to explore spatial models in the context of leasing and over-crowded matrices.

5. Discussion

We examine the impact of the street-level greenness upon building valuation. Different from most literature that focuses on land use or functional programs pertinent to greenery, we measure urban greenness by measuring the amount of green pixels present in the collected GSV images through an automated color extraction method (Li et al., 2015). Recent research on image collection and recognition created original urban greenery data that support other research (Li et al., 2015; Seiferling et al., 2017; Li & Ratti, 2018). By controlling for the time of the year (from April to October) and the numeric value of green colors in computer vision, this image recognition method provides an enhanced measurement of urban greenness from the street-level. The approach presents an objective assessment by excluding subjective responses from participants or surveyors participating in surveys or field audits. However, the measurement does not provide instructive guidance to professionals in urban planning and design fields as it does not include information of plant types, areas, program spaces, or plantations of other colors, but can as research in this field develops further.

Based on our estimation strategy, we document a positive, economically and statistically significant impact for street-level greenness, as measured by GVI, upon commercial building transaction prices and rents. P-values of GVIs are <0.05 or 0.01, we cannot accept the null hypothesis. In turn, results suggest a positive price premium between 8.9% and 10.5% for transactions and a rent premium between 5.6% and 7.8% for leases for Low, Medium, and High GVIs, relative to Very Low GVIs. The research results suggest that for the 736 buildings with a GVI above 0.29% of street-level greenness acquire an average $11.73 mln more per transaction and rent for an average $ 2.59 per square meter more per lease, ceteris paribus, than those buildings with Very Low GVI. Furthermore, our results are robust to urban infrastructure, architectural design, household income levels, Business Improvement Districts (BIDs) investment variation, various GVI functional forms and several spatial identification strategies of our model. Our findings robustly contribute to the nascent academic literature on the economic performance of street-level greenery and extend the margin of understanding to now include commercial buildings.

The link, until now, between street-level greenery and commercial real estate has been silent. Cities are comprised of both residential and commercial buildings. Thus far, the street-level greenery literature has focused on impacts to residential values. This focus is understandable due to the sheer size and value of the residential real estate market, which the 2018 US Census estimates at 89 million owner occupied units and Zillow values at about $31.8 trln. Per unit,however, , commercial buildings have a larger role to play as it shelters the collective workforce's productivity. The Commercial Buildings Energy Consumption Survey (CBECS) estimates 5.6 mln commercial building units and the National Association of Real Estate Investment Trusts (NAREIT) estimates the total US commercial real estate stock is worth about $16 trln. This suggests that the per unit value of commercial real estate is higher and changes to each building are immense. Furthermore, the amount of planning and development that goes into each structure, has a high economic benefit to urban occupants as well as economic benefits to cities and building owners. In this way, these results help to not only align urban residents, but incentivize institutional investment stakeholders and urban planners in the improvement of street-level greenery. By documenting the role of greenery in commercial building valuations, our results give a more complete understanding of greenery's impact upon urban environments, and the economic role that urban landscape architecture, planning and development hashave upon cities.

Our research contributes to the current literature by pairing street-level greenness with commercial building pricing in New York City. The commercial office ecosystem is a significant part of the urban fabric. Despite commercial real estate being a $60 trillion dollar industry, there is little evidence in the representation of the impacts of urban greenery. Existing literature has pointed to other environmental and urban design factors correlated with commercial pricing, such as green building certification (Chegut et al., 2014) and daylight accessibility and views (Turan et al., 2020). We aim to pioneer the application of GVI outside the domain of residential experiences and to use urban street-level greenness as an input into commercial building valuation models that have such an important impact on urban infrastructure and development. This paper points specifically to economically positive and statistically robust outcomes of street-level greenness. We anticipate future insights based on this contribution.

The advancement of image recognition technology is making significant impacts on research. Image recognition as a method is increasingly being used in the residential valuation as an input into hedonic valuation models (Zhang & Dong, 2018; Ye et al., 2019b). The research of Shen (2018) deployed a- machine learning algorithm to generate textual data as input for economic valuation in real estate. Another recent research relied on a deep-learningbased algorithm to classify homes by their architectural style using scraped Google Street View images (Lindenthal & Johnson, 2020). Prior research has already documented high levels of concordance between GSV and traditional field survey auditing methods (Yang et al., 2009; Rundle et al., 2011). Contributing to this growing literature, our research presents the earliest commercial real estate valuation paper to use image recognition as an input into commercial real estate valuation models for transaction prices and rents in the United States.

Although further research is needed to enhance our categorical algorithmic understanding of greenery, general applications of street-level greenness is a viable metric that can be used to facilitate decision-making in design, planning and development. As a measure of the visual presence of greenery on the streets, it could be used over time as a standard metric alongside satellite imaging, planning documentation, and on-site surveys. As our models expand to incorporate more features that are of benefit to urban health, productivity, and environmental equity, we can increasingly seek out a more inclusive view of the city that is measurably better for all.

CRediT authorship contribution statement

Juncheng Yang: Conceptualization, Data curation, Formal analysis, Validation, Visualization, Writing - original draft, Writing - review & editing. **Helena Rong:** Conceptualization, Visualization, Data curation, Writing - original draft. **Yuhao Kang:** Software, Investigation, Validation, Writing - original draft. **Fan Zhang:** Software. **Andrea Chegut:** Supervision, Conceptualization, Formal analysis, Funding acquisition, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

We examine the impact of GVI upon geographic co-location within a Business Improvement District (BID) and document the results in Table 5. There are 26 BIDs in Manhattan, and 643 buildings within our dataset are located in these BIDs. These non-profit organizations are

Table 5
Building transaction results for green view index quartiles by business improvement district co-location.

DATA VARIABLES	(1) Price InBID	(2) Price BID Breakdown	(3) Rent InBID	(4) Rent BID Breakdown
Street-Level Greenness				
GVI Low	0.110***	0.054	0.076***	0.064***
	[0.042]	[0.042]	[0.008]	[0.008]
GVI Medium	0.114***	0.088**	0.036***	0.021**
	[0.040]	[0.041]	[0.009]	[0.009]
GVI High	0.104**	0.123***	0.049***	0.055***
	[0.042]	[0.042]	[0.009]	[0.009]
In-BID (1 = YES)				
In-BID	0.063**		−0.052***	
	[0.032]		[0.008]	
BID Neighborhood				
125th Street BID		−0.482***		
		[0.099]		
14th Street BID		−0.173		0.161***
		[0.171]		[0.059]
34th Street BID		0.168***		−0.178***
		[0.058]		[0.012]
47th Street BID		0.144		−0.045
		[0.118]		[0.072]
5th Avenue BID		0.854***		0.262***
		[0.164]		[0.021]
Bryant Park BID		0.216***		0.021
		[0.070]	[0.020]	
Chinatown		−0.135	0.441***	
		[0.088]	[0.161]	
Columbus Amsterdam BID		−2.117***		
		[0.125]		
Columbus Avenue BID		0.272***		
		[0.096]		
Downtown Alliance BID		−0.336***		−0.392***
		[0.055]		[0.010]
		0.122		0.046***
East Mid-Manhattan BID		[0.080]		[0.014]
		0.052		0.014
Flatiron/23rd Street Partnership		[0.050]		[0.013]
		−0.095*		−0.133***
Garment District		[0.050]		[0.011]
		−0.006		−0.005
Grand Central Partnership		[0.057]		[0.009]
		−0.256**		0.010
Hudson Square		[0.127]		[0.033]
		0.224		−0.227***
Hudson Yards/Hell's Kitchen		[0.276]		[0.072]
		−0.333***		−0.219**
Lincoln Square BID		[0.073]		[0.109]
		−0.464**		
Lower East Side BID		[0.207]		
		0.657***		0.364***
Madison Avenue BID		[0.109]		[0.029]
Meatpacking BID		0.543*** [0.130]		0.201*** [0.038]
NoHo BID		−0.150		0.037
SoHo Broadway BID Times Square BID		[0.123] 0.332** [0.151]		[0.041]
		0.323***		−0.092***
		[0.078]		[0.015]
Village Alliance BID		0.473***		0.057
		[0.112]		[0.066]
Urban Infrastructure	YES	YES	YES	YES
Designers' Award	YES	YES	YES	YES
Designation Building Characteristics	YES	YES	YES	YES
Contract Features	YES	YES	YES	YES
NYC Submarket FE	YES	YES	YES	YES
Transaction Time FE	YES	YES	YES	YES
Constant	10.319*** [0.139]	10.148*** [0.149]	6.137*** [0.060]	6.220*** [0.057]
Observations	1,414	1,414	7,403	7,403
R-squared	0.887	0.901	0.516	0.564
F Adj R-Squared	0.880	0.890	0.510	0.560

Robust standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Notes: Table 5 documents regression results of street-level greenness upon the logarithm of building transaction prices (Column 1 and 2) and the logarithm of effective rents (Column 3 and 4) with binomial variables of Business Improvement Districts (BIDs) in Manhattan, New York City. Building characteristics, designers' award designations, location, time, transaction features, and lease information are not shown as independent variables but are available upon request.

funded by special assessments billed to property owners within their boundaries, along with grants, donations, and other revenues. The BIDs that contain high-value land and properties may obtain sufficient funding and invest into streetscape beautification and maintenance, hence enhancing the street-level GVI. Although we do not know the exact amount BIDs invest in street-level greenery, we can examine the general community investment variation upon GVI. To ensure the results are robust to BID investments, we deploy two specifications for both the buildings' prices and rents. The first specification (column 1 and column 3) includes a binomial variable that denotes buildings located within a BID by prices and rents, respectively. The second specification (column 2 and column 4) breaks down BIDs into individual neighborhoods and denotes buildings co-located within BIDs by prices and rents, respectively. Results for the GVI for both transaction and rental prices are in line with results of the full sample in Table 3, results of the full table coefficients remain stable across specifications, where statistical, economic and direction of coefficients are consistent with Table 3, results are available upon request.

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