Valuing Design and Designing Value: The Financial Impact of Daylight and Views in Office Building Real Estate

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Abstract

Architecture and finance both contribute to the conception and production of the built environment. Their agendas for buildings are sometimes in agreement and other times at odds. In this dissertation, I examine the intersection of architecture and finance by quantitatively assessing the economic value of design. Specifically, I measure the premium of two visual attributes—daylight and views—in office spaces in the borough of Manhattan in New York. Combining computational building performance analysis with empirical commercial rent data, I evaluate offices simultaneously as designed spaces and as property. First, I simulate spatially-distributed daylight and views in 5,154 offices. In the case of views, the hybrid performance-finance approach informs a new method for view modeling in an urban context. Second, using a hedonic pricing regression, I measure the premium for daylight and views in office rent prices. The results show that spaces with high levels of daylight have a 5 to 6% premium over spaces with low daylight; and spaces with high access to views have a 6% premium over spaces with low access to views. The combined value of spaces with both high daylight and view access, similarly, is 6%, indicating that the impact of daylight and views together is significant but is not additive.

The identified premiums reflect how much more tenants are willing to pay for these attributes, holding all other building, neighborhood, and lease contract characteristics constant. At a moment when the affordability and sustainability of the urban built environment are in question, identifying the financial value of spatial characteristics can inform the production and regulation of properties. Architectural design and the flow of real estate capital are among a multitude of factors that collectively impact the creation of buildings. Combining methods of building performance analysis and financial modeling, this dissertation presents a new lens through which to understand how spatial design relates to economic forces governing our built world.

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I am profoundly grateful for the people who have supported and anchored me during my time at MIT—over the past four years as a Ph.D. student and preceding two years in the Master's program. The wisdom, kindness, and generosity of my mentors, classmates, friends, and family resonate deeply.

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I dedicate this dissertation to my parents Mete and Nilgün, and brother Ekin Turan. Their unconditional love and support have carried me through the world, far before and far after this work was conceived. I am grateful to my parent for their wisdom and encouragement in all situations, and to Ekin for teaching me to challenge assumptions.

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Related Publications

The following publications were written in the context of this dissertation:

Turan, I., Chegut, A., Fink, D., & Reinhart, C. (2020). The Value of Daylight in Office Spaces. *Building and Environment*, 168:106503.

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Turan, I., & Reinhart, C. (2019). A New Framework for Evaluating Indoor Visual Connectivity in Open Plan Workspaces. *Prometheus 03: Building, Cities, and Performance*, 03:54–57.

Turan, I., Chegut, A., & Reinhart, C. F. (2017). Connecting Environmental Performance Analysis to Cash Flow Modeling for Financial Valuation of Buildings in Early Design. In *Proceedings of the 15th IBPSA Building Simulation Conference*, pages 773–782, San Francisco, CA. IBPSA.

Part I: Introduction

Indeed, structures such as the Empire State Building or Board of Trade are magnificent not because they were designed by great architects, but because their designers worked intelligently within a formula with its own beautiful economy.

Carol Willis, *Form Follows Finance*

1. Motivation and Problem Statement

Architecture and finance have a complicated, entwined relationship. Both shape the design and construction of buildings, particularly in market economies. The financial world drives the built world and the contemporary built environment is a physical manifestation of real estate supply and demand. Yet, the indelible influence that finance has on building design is buried under other environmental, social, and contextual considerations. Inversely, the value of good design is commonly over-simplified in financial considerations of a building project. As architect Brett Steele writes, "Many routinely overlook architecture's main property: that it simply *is* property" (2014). Indeed, design and finance are entangled in a messy knot, seemingly independent of one another yet impossible to untie.

In this dissertation, I quantitatively examine the relationship between building design attributes and financial value. I specifically evaluate two architectural qualities that directly impact building occupants: daylight and views. Both govern the visual experience of users in a building. At the same time, they are generally understood to be desirable features in real estate. Measuring the financial value of these particular building attributes provides a new way through which to frame the building's relationship to its social and spatial context. It enables new opportunities for design to engage with the world around it.

1.1 Occupant Experience, Health, and Well-Being

Visual perception contextualizes a person in space and connects them to the surrounding environment. At the same time, it inspires awe, awakens alertness, and enables social connections. Through these means and more, visual perception plays a key role in building occupant comfort and well-being. Given that people spend up to 21 hours per day inside (Environmental Protection Agency, 1989), the quality of indoor environments—of which visual factors are a part—are increasingly important. Daylight and views, as components of the indoor environmental spatial experience, impact occupants' well-being and health. Access to a window benefits occupants, both physiologically and psychologically.

A wide body of literature shows that, particularly in workplaces, natural light and views lead to greater productivity, decreased stress, and higher employee satisfaction (Al Horr et al., 2016; Aries et al., 2010; Frontczak and Wargocki, 2011; Galasiu and Veitch, 2006). As working adults across cultures spend the majority of their time indoors (Khajehzadeh and Vale, 2017; Leech et al., 2002; Odeh and Hussein, 2016; Schweizer et al., 2007; Yang et al., 2011), it is critical that we optimize the conditions of work spaces for those inside.

Historically, access to a window has been considered not an amenity but a necessity and a basic right. In the United Kingdom, the doctrine of ancient lights, dating back to 1663 and still in effect today, guards the access to light through an existing window (Kerr, 1865). In the United States, litigation and regulation in a number of states protect building occupants' right to light (Pfeiffer, 1982; Davis, 1989). In cities around the world, zoning policies enacted in the 20th Century that aim to protect both private and public rights to light have shaped the current urban form (Davis, 1989). Notably in the context of this dissertation, in New York City, the zoning regulations of 1916 and 1961 aimed to minimize shading and ensure that daylight reaches pedestrians on the street by stipulating rules about the exterior form of buildings (Willis, 1995).

Complementing zoning regulations, most green building rating systems, including the Leadership in Energy and Environmental Design (LEED) certification and the WELL Building Standard reward good daylight and view access (U.S. Green Building Council, 2013; International WELL Building Institute, 2017). The occupant benefits of daylight and views make these visual attributes fundamental components of building sustainability.[1]

If the urban zoning regulations and sustainability certifications are any indication, as a society we prioritize daylight and views in buildings. Does the social value of daylight and views translate into economic value? Prior to this work, there has not been any previous work that measures the value of daylight in offices spaces. In the case of views, previous work shows that it does. The preference for desirable views can increase the value of a property anywhere from three to over 50% depending on property type and location (Jim and Chen, 2009; Kaysen, 2017; Damigos and Anyfantis, 2011; Baranzini and Schaerer, 2011). There is no precedent work, however, that has measured the real estate value of views in New York City using market-wide real estate data. Furthermore, the methods by which views are quantified vary vastly, making it hard to apply the identified premiums across different geographic contexts.

1.2 Urban Growth, Environmental Impact, and Sustainability

Worldwide, cities are expanding and so are their physical infrastructures. The growing built environment contributes to anthropogenic greenhouse gas emissions and is an increasing strain on our natural resources. Buildings and construction account for over 30% of final energy consumption globally (United Nations Environmental Programme, 2016). In order to limit global warming to 1.5°C (as defined by the IPCC's SR1.5), building emissions must

[1] The health and well-being benefits are seconded by the energy saving potential of using natural light to reduce the electric lighting load (U.S. Energy Information Administration (EIA), 2017).

decrease by at least 80% by 2050 (Bazaz et al., 2018). While the average energy use intensity in buildings is steadily decreasing at an annual rate of 1.5%, the total built area is concurrently increasing by 2.3% per year (Abergel et al., 2017). In short, the energy efficiency gains in the building sector are not keeping pace with rapid construction worldwide.

In a world where the building stock is projected to double by 2060, how do we maintain a thriving built environment while lessening its environmental impact? The swelling built environment is a product of economic expansion, and while it is a growing burden on the earth, it is not expected to slow in the near future. We need, therefore, to take steps to make the building stock more sustainable at all levels; both to make the buildings more resource efficient and more livable. This is where the real estate market can inform design. While the market has historically been at odds with the environment, there are opportunities within the existing system to steer buildings towards a more sustainable future.

1.3 Leveraging Economic Preferences

What design features are of value to building occupants? Examining the economic choices that buyer and renter make, we can identify the aspects of a building that are valued. Sometimes these features are in line with the environmental sustainability of a building, and other times they are at odds. In the case where sustainability features are not valued, there is a need for building codes and regulations. In the delicate dance between design freedom and building codes, recognizing the value of environmental features in economic terms can guide effective policy development. At the same time, understanding people's preferences in buildings will inform decision-makers about how to build better, both to design more livable spaces and make more efficiently operating buildings, now and in the future.

Thoughtful design can make buildings more sustainable and can foster the people inside. How do we best motivate (or require) that all buildings receive careful design attention? For public buildings in the United States, this is done through policy, such as the General Service Administration's requirement for new federal buildings to achieve at least LEED Gold certification and meet minimum energy demand targets (U.S. General Services Administration, 2018).[2] For buildings in the private sector, enforcement is often through building codes, though this varies widely by city and state. While regulations and incentives are critical to the adoption of environmental standards, there is also space for consumers to demand better performing buildings. Understanding preferences of those on the demand-side of real estate can propel change in three ways: first, it reveals what sustainable strategies may be naturally adopted by the market; second, it gives project teams agency to push for design strategies that may otherwise be value engineered out; and third, understanding what sustainability measures are not naturally preferred can prompt regulation and incentives to ensure that they are implemented nevertheless. This dissertation examines the connection between real estate

[2] One can argue whether LEED certification counts as thoughtful design. Given the design and technological possibilities in buildings today, the certification requirements are hardly aspirational. However, at the most basic level, it requires environmental performance that is above the baseline conventional building.

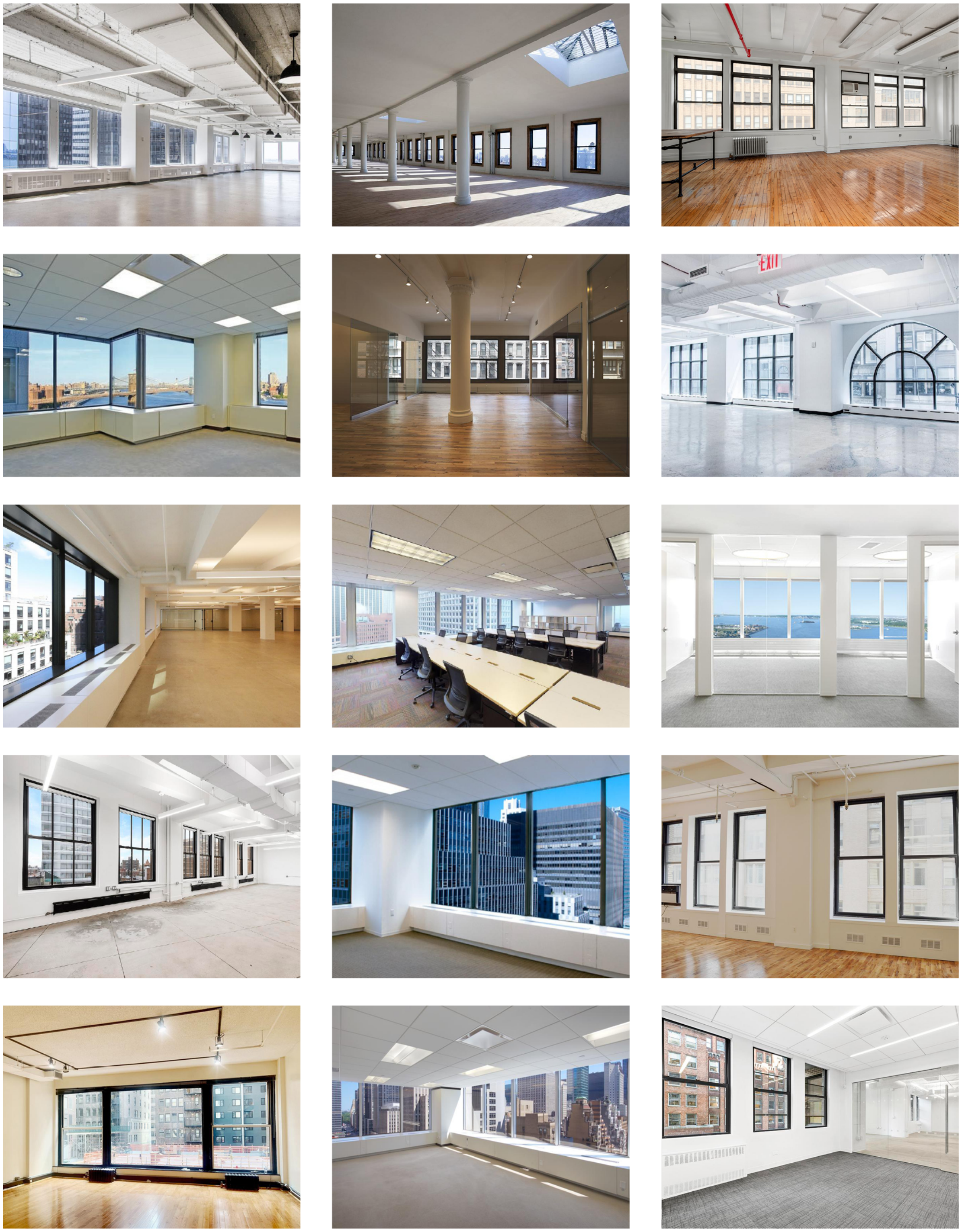


Figure 1.1: Examples of Manhattan office properties listed online in July 2020. All photos are pulled from active broker listings on *42Floors*, an online commercial real estate listings database (Knotel, 2020). The photos represent the type of imagery that tenants see when considering a space. The properties in the photos are not part of the dataset used in this work, but represent comparable spaces listed at the time of writing.

economics and design to reveal some of the veiled forces driving the production of the built environment.

1.4 Research Scope

The objective of this work is to explore the intersection of architectural design and financial value of real estate properties by combining methods from both realms, and critically exploring how they do and do not impact one another. In particular, I examine the economic premium of two visual design attributes, daylight and view. Using office spaces in the borough of Manhattan in New York City as the case study, I first evaluate the daylight and view performance in the offices; and second, I measure the economic value associated with each attribute. Figure 1.1 depicts examples of office property listings comparable to those evaluated in this work.

Framing the work in this dissertation, I seeks to answer the following research questions:

1. What is the distribution of daylight and view levels within office spaces throughout the dense urban context of Manhattan? (Chapters 3 and 5)
2. How can views throughout an interior space be quantitatively measured in an urban context? (Chapter 5)
3. What is the value of daylight and views in the commercial office spaces in Manhattan? (Chapters 4 and 6)

Design performance in the scope of this work is defined to be the quantitative analysis of architectural elements of a building—in this case, daylight and views. For the former, there are established computational methods that are widely-used in architectural practice. I employ these methods, commonly used at the building scale, to develop a workflow for evaluating spatially-distributed daylight at the urban scale. The second visual quality in question, the view, does not have an accepted simulation-based analysis method. I propose a new simulation approach and metric to computationally model views, specifically to evaluate them in a large number of spaces in the urban context.

The objective of simulating daylight and view performance in the city-wide data-set is two-fold: first, to evaluate how daylight and views are distributed throughout office spaces in the dense urban context of Manhattan; and second, to create a dataset of performance values to be used in the hedonic pricing model to measure the value of daylight and views. The office spaces in the data are all within Manhattan. While Manhattan is one of five boroughs in New York City, its population and density rivals that of other large U.S. cities.[3] Therefore, in the context of this work, the data is considered to be at the urban scale.

[3] Manhattan has a resident population of 1.6 million, however during the daytime the island's population increases to 3.1 million. 52% of Manhattan's daytime population consists of commuting worker; the remainder is made up of local residents, visitors, hospital patients and commuting students (Moss and Qing, 2012).

To evaluate the economic premium of daylight and views, I employ a hedonic pricing model, a method widely-used to estimate real estate price indices (Geltner et al., 2013). In hedonic pricing theory, consumers place value on individual attributes of a property. The market price of a property is the sum of all its attributes. A hedonic model can include architectural and building characteristics, location, time of transaction, and leasing/sales terms. By including all variables together, the hedonic regression measures the impact each variable has on the rental price, ceteris paribus (i.e. all other factors being equal).

The variables of interest in this study, examined through the hedonic model, are daylight and views. Up to this point, daylight and views have been incorporated into hedonic analysis in a simplified way (in the case of views) or not at all (in the case of daylight). In this dissertation, I create a detailed dataset of daylight and view performance using computational modeling

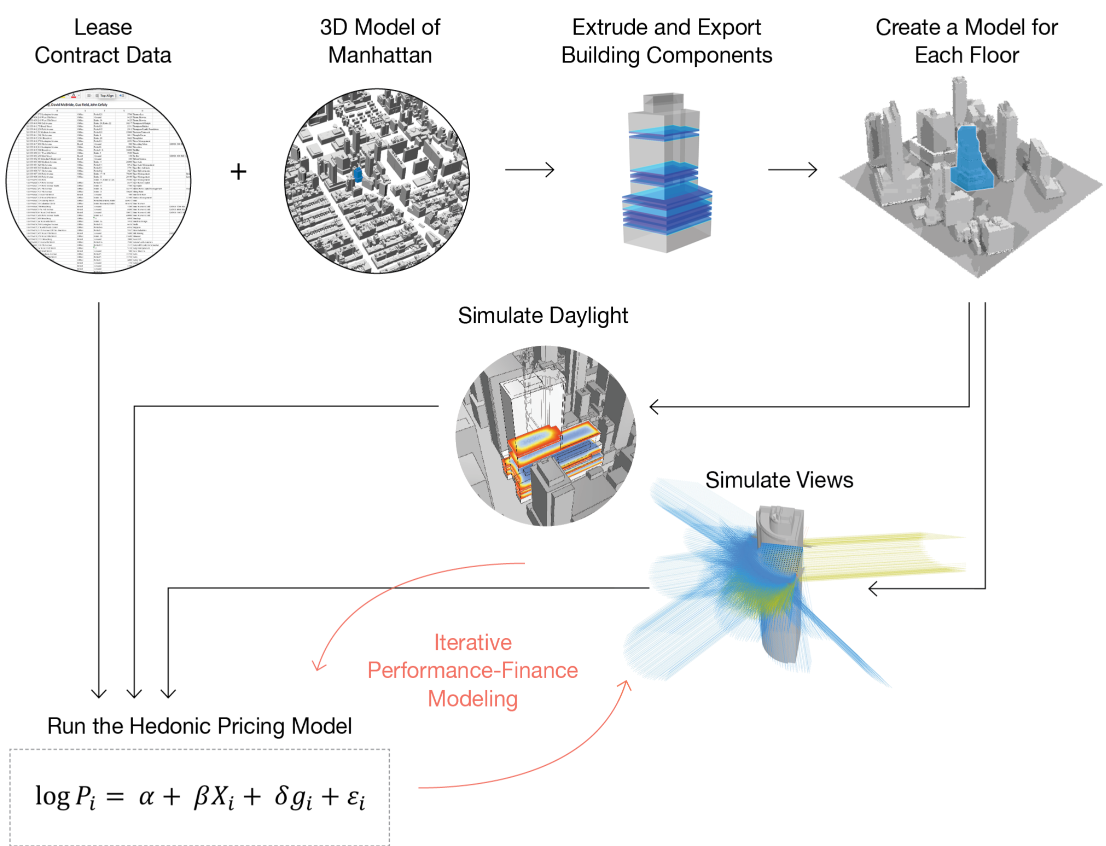


Figure 1.2: Dissertation analysis workflow. Quantitative and geospatial data are the foundation of the daylight and views simulations, as well as the hedonic analysis. The work follows the sequence indicated by the black arrows. Concurrently, the red arrows represent the iterative nature of the performance and finance analysis. Contrary to being a one-way process, the performance and financial modeling methods iteratively inform one another. The set-up and specification of each method is directly impacted by the opportunities and constraints of other. This is especially true for the view simulations, for which an established modeling method does not exist—this is is explored in Chapters 5 and 6. The daylight simulations are presented in Chapter 3; view simulations are presented in Chapter 5; Chapters 4 and 6 each present a version of the hedonic pricing model.

methods to be used in the hedonic analysis. The performance data generated reflects the intricacy and dynamism of daylight and views across a floorplate, and is more developed than metrics use in previous work. Figure 1.2 illustrates the process I follow to generate the daylight and view performance data, and carry out the hedonic pricing analysis. While a seemingly linear workflow, combining the performance simulations with the hedonic analysis is an iterative process, in which the methods are continually informing one another to evaluate the buildings through a new framework.

Guided by the thesis' three research questions, this work makes three main contributions to the building science and real estate finance domains. First, the daylight and view simulations are the first of their kind conducted at the urban scale for New York City. The results provide a distribution of daylight and view performance for floors throughout a dense urban environment. Second, the proposed view analysis workflow and metric provide a new method for evaluating spatially-distributed views in an urban environment. Third, this is the first study of its kind to measure the price premium for daylight and views in commercial office spaces. The results paint a picture of how visual design elements and economics intersect in commercial office spaces.

1.5 Dissertation Outline

This dissertation is comprised of seven chapters divided into four parts: *Introduction*, *Daylight*, *Views*, and *Impact, Outlook and Conclusion*. The organization of the parts, in particular of *Daylight* and *Views*, reflects the sequence in which the research was conducted. The work presented in the *Views* chapters is built upon, and relies on assumptions made in, the work established in the *Daylight* chapters.

Part 1: Introduction presents the problem statement, motivation, and background for the research questions considered in the dissertation.

- Chapter 2 presents a critical literature review contextualizing the work of this dissertation. In particular, it touches upon current state-of-art methods used for measuring and evaluating daylight, views, and value in buildings. It highlights where there are limitations and gaps that are addressed in this dissertation.

Part 2: Daylight evaluates daylight and its impact on office rent prices throughout Manhattan.

- Chapter 3 presents the results of the urban scale daylight simulations. The chapter describes how the computational modeling method, normally employed at the building scale, is scaled up to be applied across thousands of office spaces. The chapter presents the results of the simulations, revealing how daylight is distributed throughout office spaces throughout Manhattan.
- Chapter 4 presents the results of the hedonic pricing analysis measuring the value of daylight on rental lease transactions in Manhattan office spaces. It describes the sequential build-up of the regression specification to include the building characteristics,

lease contract terms, location fixed effects, and time fixed effect. The chapter ends with a discussion of the results and their implications.

Part 3: Views first proposes a novel analysis methodology to quantify views in an urban context; second, using the view analysis results, it presents views' impact on office rent prices throughout Manhattan.

- Chapter 5 introduces a novel computational method for simulating views in the urban context and presents the results its application to the Manhattan office sample. It describes the conceptual approach to views, the modeling workflow, and results of the urban scale analysis.
- Chapter 6 presents the results of the hedonic pricing analysis measuring the value of both daylight and view on rental lease transactions in Manhattan office spaces. Building upon the model specification described in Chapter 4, it explores how daylight and views interact and individually contribute to the value of the spaces.

Part 4: Impact, Outlook and Conclusion reflects upon the implications of the work presented in this dissertation and explores future research directions.

- Chapter 7 summarizes the intellectual contributions of the dissertation, and discusses impacts of the work, potential applications, and closing thoughts.

Note about pronouns used in the forthcoming chapters: This dissertation is the culmination of collaborative work published in multiple co-authored papers that use first person plural pronouns (Turan et al., 2020, 2019; Turan and Reinhart, 2019; Turan et al., 2017). For simplicity, I retain the same convention in Chapters 3 through 6. Where it is used, "we" represents the author of the dissertation while acknowledging the collective efforts of all contributors.

2. Background

In this chapter, I present a review of the literature that pertains to the environmental impacts of daylight and views on occupants, methods for simulating views, as well as the real estate value of building features measured through hedonic analysis. Additional literature, specific to individual portions of the dissertation work, are reviewed and cited in the forthcoming chapters.

2.1 Impact of Daylight and Views on Occupants

Working adults across cultures spend the majority of their time indoors (Khajehzadeh and Vale, 2017; Leech et al., 2002; Odeh and Hussein, 2016; Schweizer et al., 2007; Yang et al., 2011). In the United States, people spend up to 21 hours a day inside (Environmental Protection Agency, 1989). Therefore, the conditions of indoor spaces—environmental factors such as acoustics, air quality, and daylight—have a significant impact on inhabitant well-being. A wide body of literature shows that, insofar as environmental conditions affect human health, access to natural daylight and views benefits people, both physiologically and psychologically. Particularly in workplaces, natural light, when properly controlled, leads to greater workplace productivity, decreased stress, and higher employee satisfaction (Al Horr et al., 2016; Aries et al., 2010; Frontczak and Wargocki, 2011; Galasiu and Veitch, 2006; Jamrozik et al., 2019; Colenberg et al., 2020). Similarly, the views that an occupant sees from within building impact their health, happiness, and understanding of the surrounding environment. Across building types, from offices and schools to hospitals and residential dwellings, views affect occupants in a multitude of ways: they improve workplace satisfaction, productivity, focus, memory, employee retention, life satisfaction, stress modulation, and patient recovery time in hospitals (Aries et al., 2010; Chang and Chen, 2005; Farley and Veitch, 2001; Gladwell et al., 2012; Kim and Wineman, 2005; Li and Sullivan, 2016; Ko et al., 2020).

As part of the occupant's multi-sensory experience in a building, visual factors also influence non-visual engagement, affecting the occupant's thermal perception and comfort in a space (Ko et al., 2020). Alongside the bodily and psychological effects, visual perception shapes a person's experience moving through a building and their sense of place, both within a building and in the greater surrounding context. In short, daylight and views govern our spatial experience in buildings in complicated and dynamic ways that are both visual and non-visual. They are valued for their impact on occupants within a building. In this dissertation, I explore how this social value reflects as financial value.

2.2 Views in the Urban Environment

Within architecture, there has been a long fascination with views and vision's role in our conception of space (Holm, 1992). Given the complexity of the visual experience, arguably, it is impossible to analytically dissect how we see. Perception is more complicated than simply the objects in view, and therefore, evades modeling and simulation (Pepperell, 2012). Yet, there are ways to evaluate *elements* of the view, and more broadly, our visual experience in the built environment. In the book *The Image of the City*, Kevin Lynch remarks that our visual understanding of the urban environment is multi-sensory and complex: "Structuring and identifying the environment is a vital ability among all mobile animals. Many kinds of cues are used: the visual sensations of color, shape, motion, or polarization of light, as well as other senses such as smell, sound, touch, kinesthesia, sense of gravity, and perhaps of electric or magnetic fields" (1960). Following precedent work in this area, in this dissertation (Chapter 5), I propose a view analysis approach—not to measure a view's quality but rather to measure its visual components and composition. Human visual perception is based on relational observations, and thus is not just about *what* is seen (whether it be buildings, sky, landmarks, or open space), but also *where* and *how* each of the elements relate to one another (Arnheim, 1974). Considering relational observation as a core principle of visual perception, I introduce a method that captures and characterizes the composition of the occupant's view.

Much of the development of computational view analysis in architecture is built upon work done within the disciplines of landscape management and urban planning. Tandy first proposed the idea of a isovist or viewshed, a 2D field of space visible at eye height, for landscape surveying (Tandy, 1967). This concept was adopted by Benedikt to create the isovist field, or viewshed, measuring the volume of space visible in architectural form, as depicted in Figure 2.1 (Benedikt, 1979). The idea has been further expanded in space syntax research to assess mutual connections between two points through a visibility graph, and in three dimensions as a 3D visibility graph (Turner et al., 2001; Varoudis and Psarra, 2014). At the urban scale, Morello and Ratti proposed a method to count urban visual elements (paths, nodes, districts, edges, landmarks) that are visible through a 3D isovist in order to understand the city's form as a system (Morello and Ratti, 2009). At the building scale, various proposed architectural view analysis methods have adopted the isovist and 3D visibility graph concepts. The Ladybug Grasshopper plug-in uses this method to determine if pre-specified visual features are viewable from designated positions (Sadeghipour Roudsari, 2016). Similarly, Doraiswamy et al. used raytracing to analyse lines of sight that are unobstructed, varied, and those that see either landmarks or landscape in Manhattan (Doraiswamy et al., 2015). Others, such as Li and Samuelson, propose an image-based approach using 3d imagery of the urban context

(Li and Samuelson, 2020). In practice, computational view analysis methods are used both to inform building design and to enable comparison between buildings. Numerous design practices (such as the few cited) have devised their own methods of evaluating views, often developed for a particular location or project site (Doraiswamy et al., 2015; Studio Gang, 2016; Sasaki Associates, 2019).

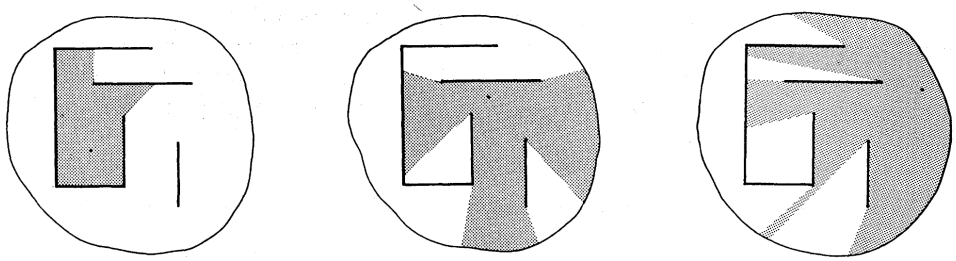


Figure 2.1: Examples of 2D isovists by Benedikt (Benedikt, 1979). Benedikt defines the isovist to be "the set of all points visible from a given vantage point in space and with respect to an environment." The grey hatch represents the area that can be seen from the observer's position (indicated by the black dot).

Isovist analysis is a geometric evaluation that identifies what is within a line-of-sight from particular locations. Looking beyond what *can* be seen, work has been done to evaluate the quality of *is* seen. Human surveys have been used to develop qualitative scales of visual preference. Steinitz, a pioneer of geographic information systems (GIS) technology, proposed a visual preference model that ranked elements of a scenic landscape to inform landscape management policies (Steinitz, 1990). Using photographs of various vistas, he surveyed visitors to Acadia National Park to rank views in visual preference categories including mystery, water view, distant view, and land form.

Addressing specifically visual experiences in the urban environment, Kevin Lynch cataloged formal elements of the physical environment: "The contents of the city image so far studied, which are referable to physical forms, can conveniently be classified into five types of elements: paths, edges, districts, nodes, and landmarks" (Lynch, 1960). In *The View from the Road* the formal symbols are recorded not at a static point but moving through space and time to express the visual experience of a person moving—specifically, driving—through the city (Appleyard et al., 1963). Figure 2.2 illustrates the visual elements encountered by the observer as they move along the route, creating montage of views from the perspective of the viewer. Lynch's evaluation approach relies primarily on graphic analysis the views encountered.

Addressing views from inside buildings, various design standards and guidelines have proposed unique methods of evaluation. The Leadership in Energy and Environmental Design (LEED) certification system's Quality Views credit requires views to flora, fauna, sky, movement or objects at least 25-feet away from the facade (U.S. Green Building Council, 2013). The WELL Building Standard that focuses on human health and wellness in buildings recommends that the majority of regularly occupied zones in a building are within 25-ft (7.5-m) of a window or atrium but does address the view seen through the window (International WELL Building Institute, 2017). The recently-adopted European Union standard *EN-17037 Day-*

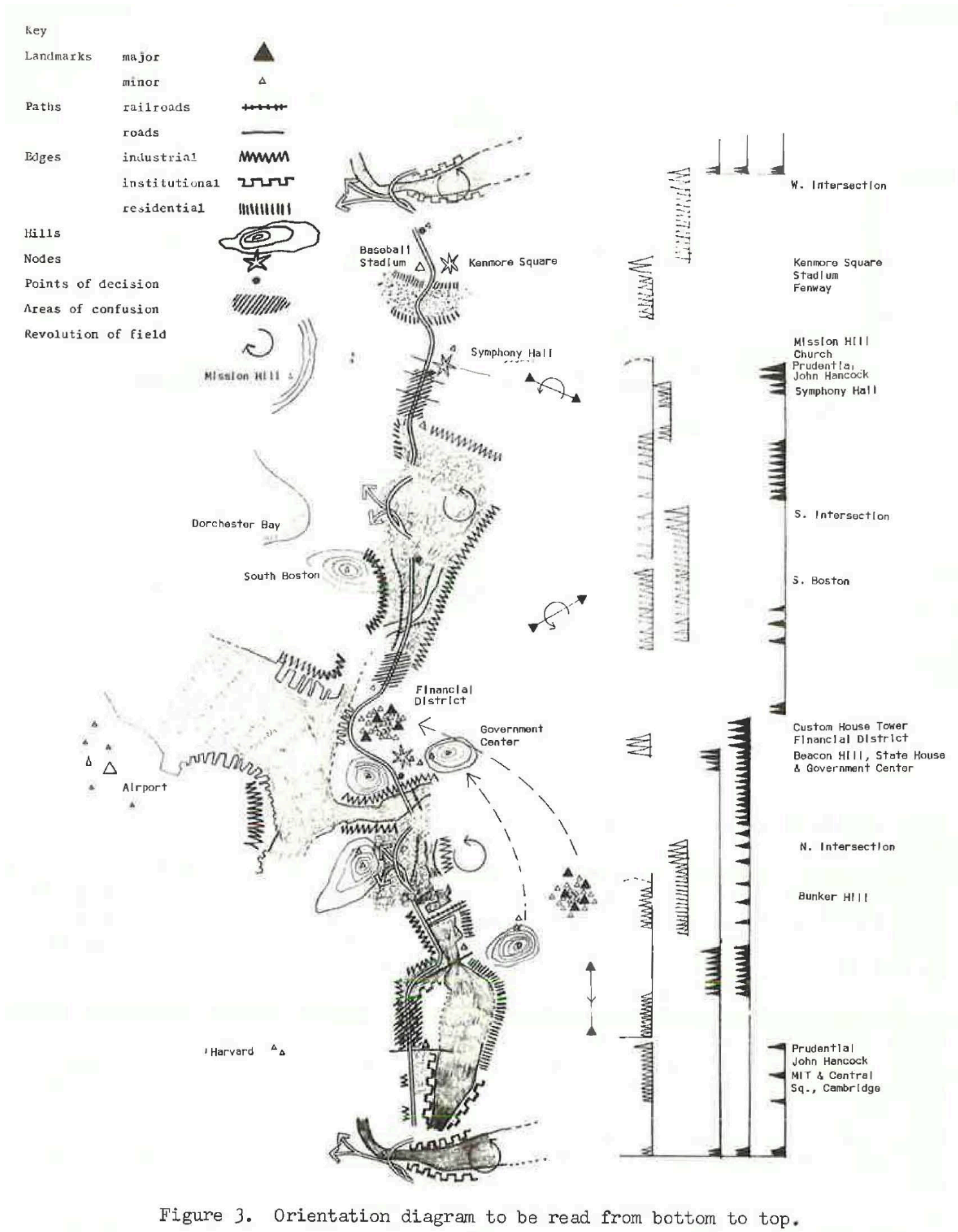


Figure 2.2: Visual orientation diagram from *The View from the Road* by Appleyard, Lynch and Myer (Appleyard et al., 1963). The diagram illustrates the formal components that the observer sees as they drive the inner belt expressway in Boston, thus serving as a record of the spatial experience over time.

light in Buildings suggests a minimum horizontal angle-of-view, depth-of-field, and layering of multiple view objects (European Committee for Standardization Technical Committee CEN/TC 169, 2018). The vagueness of the criteria in all three standards reflects the difficulty of establishing explicit view quality parameters that can be both exacting and widely-applied. With this background, in Chapter 5, I propose a method that combines computational techniques with the urban taxonomy of views to evaluate views within an urban context.

2.3 Measuring Real Estate Value

Previous research has found that sustainable buildings command a financial premium over conventional properties in both rental and sales transactions in cities around the world. This trend is true in residential and commercial markets, though notably more pronounced in the latter (Deng and Wu, 2014). Studies on commercial properties in the United States, United Kingdom, Switzerland, and the Netherlands have identified a 13 to 30% premium on sales transaction prices and a cash flow increase of 6.5 to 21.5% in rental properties (Chegut et al., 2014; Eichholtz et al., 2010a, 2013; Fuerst and McAllister, 2011; Kok and Jennen, 2012; Miller et al., 2008). These studies have primarily evaluated the sustainability of buildings based on green building certification systems, such as LEED. Less work has been done to evaluate the economic incentive of individual design measures that contribute to the overall sustainability of buildings. Studies that do evaluate individual sustainability measures have considered energy efficiency, walkability and transportation access (Kok and Jennen, 2012; Pivo and Fisher, 2011; Fuerst et al., 2013).

The value of daylight and views is less explored. Desirable views can increase the value of a property anywhere from three to over 50% depending on property type and location (Baranzini and Schaerer, 2011; Damigos and Anyfantis, 2011; Jim and Chen, 2009; Kaysen, 2017). However, the method by which views are assessed and quantified in these studies varies vastly. In some cases, it is based on whether certain features (such as a mountain or water) are visible, and in others, it is based on a GIS spatial projections. In all cases, the view is assessed from discrete points on the facade of a building. In no studies, to our knowledge, is the view assessed throughout the interior space.

Far less work has been done to evaluate the value of daylight. Fleming et al. evaluated the real estate value of direct sunlight exposure for residential properties in New Zealand (Fleming et al., 2018). They measured the amount of direct sunlight reaching the roof of each building. Up to this point, the value of daylight and views in *offices* had not been measured through market-wide empirical data analysis. In Chapters 4 and 6, I present the results of both the daylight and view value modeling. This work is, to our knowledge, the first to have quantified the impact of daylight and views on rent prices in the commercial office market, particularly in Manhattan.

Part II: Daylight

The shape grew naturally from the purely technical and economic considerations of how to give normal lighting to every spot of usable space.

Sigfried Giedion, *Space, Time and Architecture: The Growth of a New Tradition*

3. Daylight: Design Performance

In this chapter, we measure the daylight levels in offices throughout Manhattan. Daylight modeling simulates how natural light permeates through an indoor space, taking into account the surrounding context and physical characteristics of the interior. In dense urban environments, the penetration of daylight into a building depends largely on the shape of the floor plate, façade elements, neighboring buildings, size of the street blocks, and width of urban canyons (Nasrollahi and Shokri, 2016).

Rather than interpolating the light distribution in each space, as is commonly done, we simulate the hourly illuminance values at each point in the analysis grid on every floor. The purpose of this detailed approach is both to account for direct and diffuse light, and to ensure precision and confidence in the results at each point. By simulating daylight in over five thousand offices, we create picture of the daylight performance in offices across the city. We present the distribution of daylight levels, illustrating that the there is significant variation in the amount of light entering the office spaces. This is the first city-wide simulation of spatially-distributed daylight performance in offices in Manhattan.

3.1 Methodology

We simulate daylight entering each office floor throughout Manhattan individually. While running simulations with this resolution is simple for a single space, it is a computational challenge for a city-wide sample set. Limitations in both computational power and the ray-tracing method require that we develop a new workflow to model each floor individually for all of the spaces throughout the city. The spatial distribution of the sample within Manhattan, and a description of the modeling approach are illustrated in Figure 3.1.

Previous urban daylight simulation methods have simplified the urban-scale environment in various ways to account for the computational limitations. Compagnon proposed an early method for urban daylight simulation that calculates the irradiance on the facades (2004). This widely-used approach predicts how much sunlight falls on the external faces of the build-

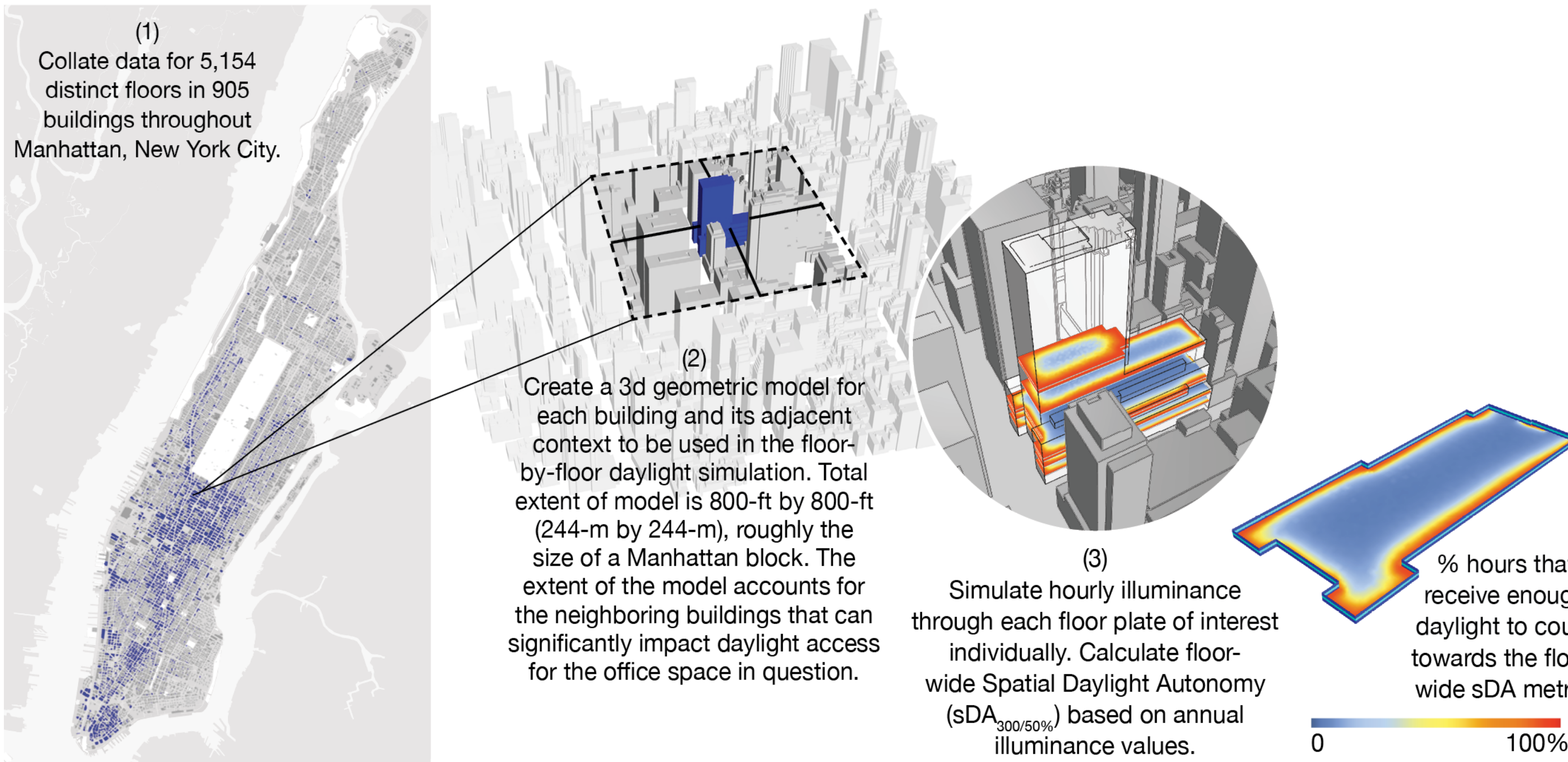


Figure 3.1: City-scale floor-by-floor daylight simulation workflow. Buildings of interest from the NYC DoITT 3D Model are identified using CompStak's rent transaction data—the buildings are marked in blue on the map on the far left. To set up the daylight simulation, From the city-wide 3D model, we isolate each building with its 800-ft-by-800-ft surrounding context (roughly one city block) and create a smaller Radiance model. This model contains each individual floor of the building that corresponds to a lease contract observation in CompStak's data, and the simulation calculates the illuminance throughout the floor plate for each hour of the year. Using the illuminance values, we calculate the spatial daylight autonomy, an annual metric on a scale of 0 to 100% that indicates how much of the floor area receives adequate daylight for a portion of occupied hours.

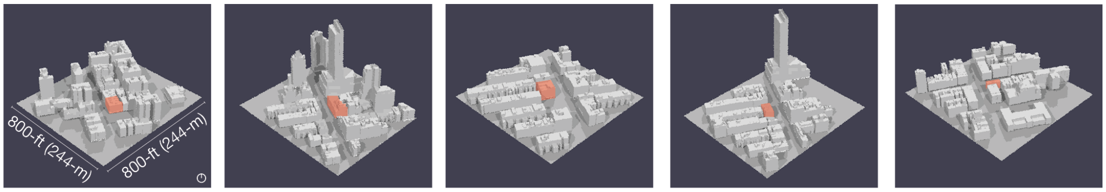


Figure 3.2: Rendered examples of the Radiance scene created for each floor's daylight simulation. Each scene is about 800-ft by 800-ft (244-m by 244-m), roughly the size of a Manhattan block, with the building in the center. Renderings created using Radiance *objView* program.

ings. It does not consider, however, what happens to the light as it moves from outside to inside. Urban Daylight, developed by Dogan et al., expands upon this method by modeling the facade irradiance values and then interpolating how the light will be distributed within the space (2012). While this approach drastically reduces the computation time required to do spatially-distributed daylight simulations, it assumes all daylight entering the building to be diffuse and does not consider direct daylight penetration.

3.1.1 Data

The 3D geometric model used in this analysis comes from New York City's Department of Information Technology and Telecommunications, developed to Level of Detail 1 to 2 (NYC Department of Information Technology & Telecommunications, 2016b). In the Rhino model, we tag the buildings that contain floors we want to simulate. To select the buildings of interest, we merge rental contract data from CompStak based on Building Information Number (BIN) and Borough-Block-Lot (BBL) (CompStak Inc., 2018). Additional data sources used in the hedonic pricing analysis are described in Chapter 4; and Table A1 in the Appendix describes all data sources used throughout all the chapters.

3.1.2 Simulation Modeling Set-Up

Given the computational intensity of simulating spatially-distributed daylight in floors throughout a city, we break down the full Manhattan model into a series of smaller models specific to each building in the sample set. Each model is sized to include the building and its surrounding context. The result is an 800-foot-by-800-foot (244-meter-by-244-meter) square model scene with the building of interest at the center, as depicted in Figure 3.2. The total extent of each model is slightly larger than a standard New York City block, sized to include neighboring buildings that would have a notable effect on the internal daylight distribution (NYC Department of Information Technology & Telecommunications, 2016b). We further subdivide the building model into floor plates of interest and assign a 6-foot-by-6-foot (1.8-meter-by-1.8-meter) grid of sensor points throughout each floor plate at a height of 2.5 feet (0.76 meters) from the floor.

We assume a 30% window-to-wall ratio and 11.4 foot (3.5 meters) floor-to-ceiling height for all spaces. The models do not include internal partitions, furniture, core spaces, or window treatments such as blinds. This is a limitation of the input data and modeling approach.

However, most rented office spaces are fit-out by the tenant once they move in, and often the internal layout is modified during the fit-out. Assuming that the tenant will change the space once they occupy the floor, the model estimates the total possible daylight that the space receives considering the external context and floor plate shape. In other words, the simulations estimate the total *potential* daylight in the space.

3.1.3 Window-to-Wall Ratio Validation

A constant window-to-wall ratio (WWR) of 30% is assumed on all orientations of each building in the sample. This is modeled as a horizontal spandrel window starting 3 feet (0.91 meters) above the floor. We make this assumption because the WWRs values are not documented for the urban level dataset. To validate the WWR assumption, we visually surveyed all buildings in the sample.[1] Using images of each building from Google Earth and Google Maps, we documented the window type and WWR of each orientation of each building. The buildings have an average WWR of 37% for all four orientations, and primary facade WWR of 42%. These values are above the assumed 30% WWR used in the simulations, making the modeled WWR marginally more conservative than the observed WWRs. Based on the observed WWRs, seven window typologies were established for the dataset. A distribution of the observed WWRs and the window typologies are illustrated, respectively, in Figure 3.3 and Figure B.1 in Appendix A.

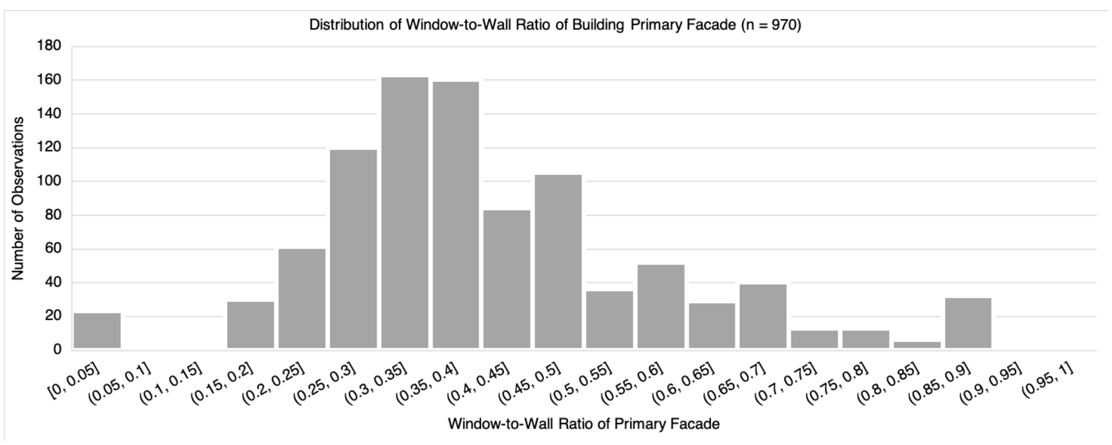


Figure 3.3: Distribution of observed window-to-wall ratio of primary facades of buildings in sample. The histogram depicts the WWR on the primary street-facing facade of each building. The total number of buildings observed: 970.

3.1.4 Simulation Parameters

To model daylight autonomy, we first simulate illuminance (the total amount of direct and diffuse light) falling onto a given surface at one point in time. This is calculated throughout every floor plate in our sample for all 8,760 hours of the year. We model daylight using the

[1] This work was carried out by MIT graduate student Ana Alice McIntosh. We thank her for her contribution.

climate-based backward ray-tracing programs Radiance (version 5.0), DAYSIM (version 4.0), and DIVA (version 4.0), taking into account both the sun and sky conditions at the particular location (Mardaljevic, 2006; Ward, 2016; Solemma, 2018; Reinhart, 2012). Using these results, we calculate the floor's spatial daylight autonomy (sDA), a metric that measures the percentage of the floor area that receives a sufficient amount of ambient natural light. Qualitatively, sDA is a measure that describes the extent to which a space is naturally illuminated. The threshold for sufficiency, as defined by the Illuminating Engineering Society of North America (IESNA), is 300 lux for 50% for all occupied hours ($sDA_{300/50\%}$). We assume the occupied hours to be standard office work hours from 8am to 6pm, Monday through Friday. The $sDA_{300/50\%}$ threshold is referenced in both the LEED and WELL building certification systems (IES Daylight Metrics Committee, 2012; U.S. Green Building Council, 2013; International WELL Building Institute, 2017), and considered a best practice throughout the industry.

For each office floor in question we run the following Radiance programs to obtain the hourly illuminance level at each sensor point within analysis grid: radfiles2daysim, gen_dc, ds_illum, and ds_el_lighting (Ward, 2016; Reinhart, 2012). The Radiance simulation parameters used are: ambient bounce (ab) 5, ambient division (ad) 512, ambient super samples (as) 20, ambient resolution (ar) 300, ambient accuracy (aa) 0.1, limit reflections (lr) 6, specular threshold (st) 0.1500, specular jitter (sj) 1.0000, limit weight (lw) 0.001953125, source jitter (dj) 0.0000, source substructuring (ds) 0.200, direct relays (dr) 2, direct pretest density (dp) 512, direct thresholding (dt) 0. We specify the simulation parameters such that they maintain a degree of precision while being applied in a reasonable timeframe to over 5,000 different spaces in the data sample.

To determine the appropriate simulation parameters, we tested 16 configurations of ambient bounce and ambient division, comparing the results with a reference model used ab 5 and ad 1024. We evaluated the divergence of the results of the reference model and tracked the simulation time for each configuation. The results of the analysis are presented in Figure 3.4. Based on the parameter testing, we decrease the ad from 1024 to 512 to cut the simulation time by half while keeping the simulation results within +/- 1% of the reference model.

3.1.5 Geometric and Material Assumptions

We assume the following material reflectance values for various building components: walls – 50%, floor – 20%, ceiling – 70%, exterior facades – 30%, ground – 20%, windows – 96% reflectance with 88% transmittance. We specify a transmittance value corresponding to that of a single pane window to measure the total potential light entering the space. As described earlier in this section, in the simulations, our objective is to measure the upper bound of daylight access. This value may be less depending on the specific glazing properties, shading elements, and interior design elements.

We use the sDA metric as an indicator of total daylight potential in a space, with the aim of comparing properties within a dense urban context. We recognize that, although we employ the sDA metric as it is defined by IESNA, we do not follow certain widely-used IES LM-

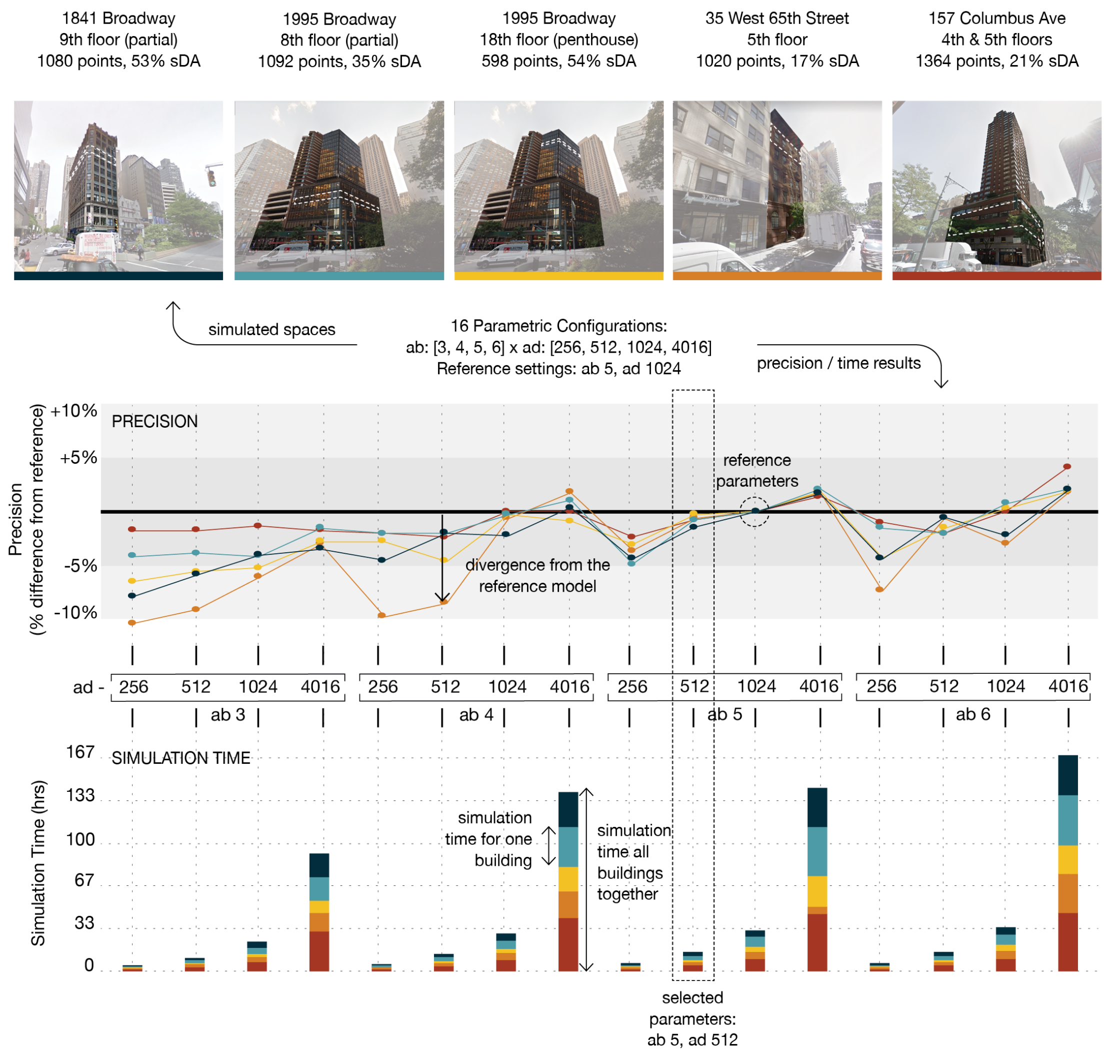


Figure 3.4: Daylight simulation parameter testing. We simulate daylight in five sample office spaces using 16 configurations of ambient bounce (ab) and ambient division (ad). Using ab 5 / ad 1024 as a reference model, we compare the simulation time and precision of each configuration to determine which parameters enable high precision within a reasonable simulation timeframe. Based on the parameter testing, we decrease the ad from 1024 to 512 to cut the simulation time by half while keeping the results within +/- 1% of the reference model.

83-12 and LEED criteria—namely, using a 2-foot-by-2-foot grid spacing and consideration of dynamic shading systems (IES Daylight Metrics Committee, 2012; U.S. Green Building Council, 2013). In this work, we employ a 6-foot-by-6-foot (1.8-meter-by-1.8-meter) grid, as we are not simulating to measure LEED compliance. We chose the grid spacing to match the resolution of the geometric model and interior floor layouts, and to enable the urban-scale computation of many spaces at once.[2] Moreover, we do not consider the core inside floor plates, assume open floor plans, and simplify the building facade properties. Particularly disregarding the core inside a floor may cause an underestimation of sDA results. Our primary objective in the simulations, however, is to assess the impacts of floor plate shape and surrounding context on daylight accessibility in a dense urban setting. To this end, the specified modeling parameters provide an adequate estimate.

In this work, our aim is to measure how much *potential* daylight might enter an office, considering mainly the shape of the building, height of the floor, and the neighboring context. To this end, we believe that sDA is a valid and reliable metric despite its limitations. We acknowledge that sDA is not a holistic indicator of daylight quality and comfort in a space. It measures minimum illuminance levels throughout the day, ensuring primarily that spaces are not underlit. It does not consider daylight quality, overlighting, or visual discomfort. Our objective in this work, however, is not to capture the full qualitative visual experience within an office. This depends significantly on the architecture, facade system, internal layout, and material properties of the space. In this work, sDA serves as a simplified measure of comparing daylight access in office spaces across a city. We suggest that quality and comfort are considered in a subsequent study to further investigate daylight conditions throughout the urban environment.

3.2 Results

A city-wide database of measured daylight performance on each floor of a building does not exist. To carry out this research, we created our own data of floor-by-floor daylight values. We simulate daylight distribution in 5,154 office spaces, located in 905 buildings throughout Manhattan in New York City, as mapped in Figure 3.1. To our knowledge, this is the first data set of floor-by-floor daylight autonomy values in buildings across a city.

In the LEED certification system, the requirements to earn the daylight the credits is 55% $sDA_{300/50\%}$ for the first tier, and 75% $sDA_{300/50\%}$ for the second tier (U.S. Green Building Council, 2013). We adopt these thresholds to organize the distributions of the daylight simulation results into three levels: low ($sDA_{300/50\%} < 55\%$), high ($55\% \leq sDA_{300/50\%} < 75\%$), and very high ($sDA_{300/50\%} > 75\%$). Figure 3.5 depicts the distribution of daylight results across the

[2] The 6-foot-by-6-foot grid is larger than the 2-foot-by-2-foot grid prescribed by the LEED guidelines. The larger grid resolution, however, has limited effect on the results. We have tested our model set-up against a 2-foot-by-2-foot grid and find that the 6-foot-by-6-foot tends to inflate the sDA results marginally. The impact is most notable in low daylight spaces where the sDA results are increased by maximum 2%; in high daylight spaces the impact on sDA values is less than 1%. Given the resolution of our simulations, the maximum 2% variation falls within the margin of error for the sDA results.

sample. The average $sDA_{300/50\%}$ throughout the floors is 43%, with a standard deviation of 23%. The median $sDA_{300/50\%}$ is 39%. Sixteen percent of the floors have high daylight autonomy (i.e., $sDA_{300/50\%}$ between 55% and 75%) and 12% have very high daylight availability ($sDA_{300/50\%}$ over 75%). The median and mean sDA result are both less than the minimum 55% $sDA_{300/50\%}$ recommended by LEED. In total, 74% of the floors throughout this Manhattan sample have daylight autonomy levels below the LEED threshold.[3]

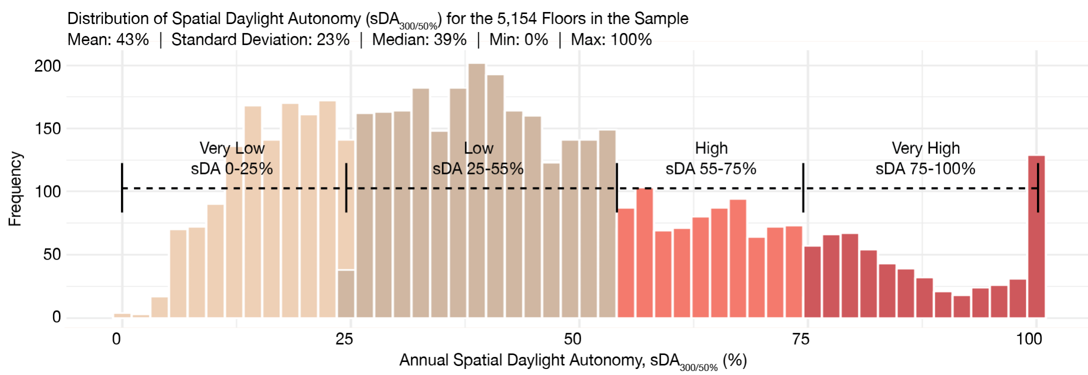


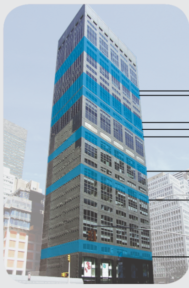
Figure 3.5: Distribution of daylight simulation results for the 5,154 spaces modeled. The color coding indicates the sDA thresholds of 25%, 55% and 75% to illustrate how daylight performance varies within the sample. 74% of the spaces have very low to low daylight levels (0-55% sDA), and 26% of the spaces have high to very high daylight levels (55-100% sDA).

Figure 3.6 depicts the spatial daylight autonomy results for floors within four buildings in the sample. Within each building, daylight autonomy increases as one moves from low to high floors. Figure 3.7 similarly depicts the daylight and rent performance values for observations in 30 buildings in the sample. As visually illustrated in these examples, there is a positive relationship between floor height and daylight performance: At higher elevations there are fewer surrounding buildings to shade the facade, allowing more sunlight to reach the windows. The correlation between daylight and floor number suggests that one of these variables may serve as a proxy for the other. The hedonic model, described in Chapter 4, methodologically identifies the statistically significant impact of each variable on rent price independently. We describe the method of separating daylight and floor number impacts using an interaction term in Section 4.2.

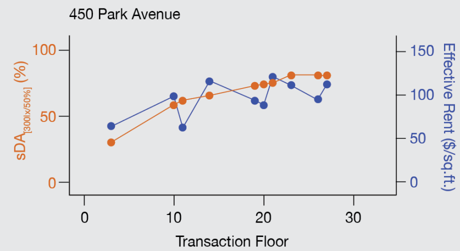
As shown in the charts in Figure 3.6, the daylight level may increase with floor number, but the rent values do not always follow suit. The impact of both daylight and floor number on rent price is not clearly discernible from the sub-sample set alone. At the individual building level, it is not possible to identify a significant impact of daylight on rent values. This is where the hedonic model comes in. The hedonic linear regression disentangles the impact of each factor on the dependent variable.

[3] Figure 3.5 depicts a spike in observations at 100% $sDA_{300/50\%}$. This is a result of the sDA metric calculation approach. Some spaces receive much more than 300 lux for most hours of the day, while others just surpass the 300 lux limit. Despite the variation in daylight performance, they are all considered to have 100% $sDA_{300/50\%}$, and thus there is an accumulation of observations at the maximum level.

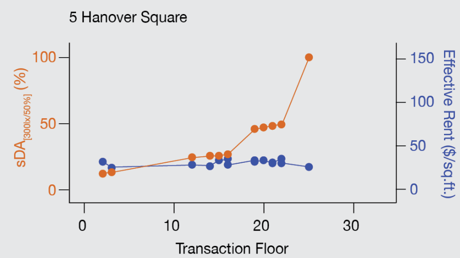
Rent and Spatial Daylight Autonomy by Floor in Select Buildings
(rent contracts enacted between 2011 and 2013)



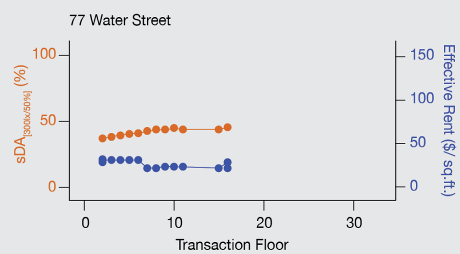
Floor	Effective Rent ($/sq.ft.)	sDA (0-100%)
27	$110.48	80%
26	$93.10	81%
21	$120.00	75%
20	$87.30	74%
19	$92.50	73%
14	$115.00	65%
10	$97.22	58%
3	$62.07	29%



Floor	Effective Rent ($/sq.ft.)	sDA (0-100%)
25	$24.14	100%
22	$28.57	49%
20	$31.39	46%
19	$30.60	45%
16	$32.89	26%
12	$26.28	23%
3	$23.90	12%
2	$30.49	11%



Floor	Effective Rent ($/sq.ft.)	sDA (0-100%)
16	$27.14	45%
15	$20.24	43%
11	$21.41	43%
9	$22.25	43%
7	$20.15	42%
5	$29.31	40%
3	$29.31	38%
2	$26.26	36%



Floor	Effective Rent ($/sq.ft.)	sDA (0-100%)
28	$31.43	81%
26	$34.60	82%
23	$31.43	77%
18	$32.30	67%
15	$36.50	63%
15	$32.00	63%
10	$27.20	37%
8	$28.26	26%

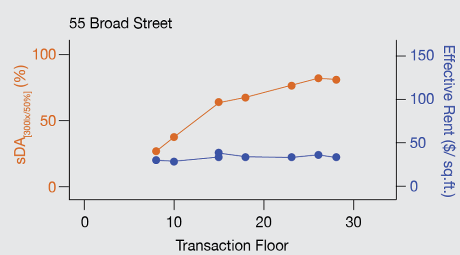


Figure 3.6: Spatial daylight autonomy and rent prices on sample floors in select buildings. The floors on which we simulated daylight are highlighted in blue on the building images. The tables and charts list the transacted rent price and daylight results for each floor. It includes only rent contracts signed between 2011 and 2013. In the case of 55 Broad Street, there are two rent prices listed for floor 15 because the floor is shared between two tenants who have independent rent contracts. The charts on the left visually show that daylight performance (sDA) and rent ($/sq.ft.) do not always track with one another. In the case of 450 Park Avenue, they both rise moving up the building; but in other three buildings, there is not the same clear visual correlation.

Figure 3.7: Spatial daylight autonomy and rent price by floor number for observations in 30 sample buildings. Observations depicted are for transactions enacted between 2011 and 2013.

3.3 Summary of Contributions

This chapter presents the results of city-wide daylight simulations in 5,154 office spaces. Daylight modeling at the urban scale is conventionally based on the solar rays hitting the facade of a building. In this work, both direct and diffuse daylight penetration throughout each floorplate is modeled. This is carried out by dividing the 3D model of Manhattan into smaller block-size Radiance scenes.

The results indicate that 74% of office floors in Manhattan have spatial daylight autonomy levels below the LEED recommended standard of 55% $sDA_{300/50\%}$. The average $sDA_{300/50\%}$ throughout the floors is 43%, with a standard deviation of 23%. The median $sDA_{300/50\%}$ is 39%. Sixteen percent of the floors have high daylight autonomy (i.e., $sDA_{300/50\%}$ between 55% and 75%) and 12% have very high daylight availability ($sDA_{300/50\%}$ over 75%).

This is the first sample, to our knowledge, of spatial daylight autonomy levels for office spaces throughout Manhattan. The results are used in the following chapter to measure the value of daylight in Manhattan office spaces.

4. Daylight: Real Estate Value

To analyze the relationship between daylight performance and effective rent observed in lease contracts, we employ a hedonic pricing model (Rosen, 1974). Hedonic pricing theory measures the value of differentiated products, considering the utility derived for the tenant by building, contractual, temporal, and neighborhood characteristics (Chegut et al., 2014, 2015; Fuerst and Wetering, 2015; Eichholtz et al., 2010b; Feige et al., 2013). The hedonic framework assumes that individual building components and lease terms each add to the overall rent price of a property(Rosen, 1974). A hedonic characteristic's marginal value depends on the tenant's preference or willingness to pay for it. Equation 4.1 presents the functional form of the vectorized hedonic model specification:

$$logY_i = \alpha + \varphi D_i + \beta B_i + \gamma L_i + \delta N_i + \omega T_i + \varepsilon_i, \tag{4.1}$$

where the dependent variable Y is the net effective rent per square foot for rental contract observation i. D is the variable of interest, the categorical daylight autonomy level ($sDA_{300/50\%}$ 0–55%, 55–75%, 75–100%) for rental contract observation i. B is a vector of exogenous hedonic building characteristics (such as age, class, LEED certification, etc.) of the building in which the rental contract observation i is located. L is a vector of the lease contract terms (such as lease duration, transaction floor number, landlord concessions, etc.) for rental contract observation i. N is a vector of exogenous location fixed effects by Manhattan neighborhood, defined by 24 submarkets (such as Chelsea, Financial District, Grand Central, and Times Square). T is a vector of time fixed effects by quarter and year that the lease is executed, between 2010 and 2016. φ, β, γ, δ, and ω are the estimated parameter vectors, representing the functional relationship between each independent variable and the dependent variable. ε is the error term, a vector of independent, identically distributed regression disturbances. A full description of the variables is presented in Table C1 in the Appendix.

4.1 Data

In total, we analyze the spaces associated with 6,267 lease contracts signed between 2010 and 2016, located on 5,154 floors throughout Manhattan.[1] We compile property and building data for the sample from multiple sources: a city-wide three-dimensional Level of Detail 1 to 2 model from New York City's Department of Information Technology and Telecommunications; property information from the city's Department of Planning; rental contract data from CompStak; sustainable building certifications from Green Building Information Gateway; and telecommunications data from Geotel (CompStak Inc., 2018; NYC Department of Information Technology & Telecommunications, 2016b; NYC Department of City Planning Information Technology Division, 2018b; U.S. Green Building Council, 2018; GeoTel, 2018). Table A1 in the Appendix describes all data sources used.[2]

Table 4.1 provides the descriptive statistics (mean and standard deviation) of the lease contract data for the sample set as a whole, and separately for each sub-sample of daylight low, high and very high daylight values. Table C1 in the Appendix provides a description of each variable included in the data.

The variable of interest is spatial daylight autonomy, $sDA_{300/50\%}$. $sDA_{300/50\%}$ is the proportion (between 0 and 100%) of floor area that receives a minimum amount of daylight during the day. See Section 3.1.4 for a full definition of the metric. We separate the results into three categories: *low daylight* (0–55% $sDA_{300/50\%}$), *high daylight* (55–75% $sDA_{300/50\%}$), and *very high daylight* (75–100% $sDA_{300/50\%}$). Henceforth, we refer to these categories using the terms low daylight, high daylight, and very high daylight; or alternatively, low sDA, high sDA, and very high sDA. The ranges are based on the LEED recommended 55% and 75% thresholds for good daylight autonomy in commercial office spaces (U.S. Green Building Council, 2013). We adopt these thresholds because they are widely applied and understood within the building sector and guide the daylighting design of contemporary buildings. In total, 72% of contracts in our sample are in spaces with 0 to 55% $sDA_{300/50\%}$, putting them in the low daylight category. The average $sDA_{300/50\%}$ for these spaces is 31.4%. Only 28% of contracts have high daylight to very high daylight, and for these spaces the average $sDA_{300/50\%}$ is 64.2% and 87.4%, respectively.

To measure value, we use the net effective rent in U.S. Dollars. CompStak defines net effective rent as the "actual amount of rent paid (subtract[ing] lease concessions from starting

[1] The total number of contracted spaces differs from the floor count because of particular terms in the contracts. Some of the floors in the sample are associated with multiple contracts, either because there are multiple tenants sharing one floor or the space changed hands within the 2010 to 2016 period. Inversely, some contracts encompass more than one floor, as the tenant leased multiple floors together.

[2] Data from the NYC DOITT, NYC Department of Planning, and GBIG are public and open access through their respective online portals (NYC Department of Information Technology & Telecommunications, 2016b; NYC Department of City Planning Information Technology Division, 2018b; U.S. Green Building Council, 2018). CompStak and Geotel data sets are proprietary (CompStak Inc., 2018; GeoTel, 2018). The data are based on market research and, therefore by nature, are privately held.

rent)" (CompStak Inc., 2018).[3] We use the logarithmic transformation of the dependent variable in the regression, as it enables a clear interpretation of the resulting coefficients and it adjusts for slight skewness of the rent price distribution. The average net effective rent is $49.94, with a standard deviation of $20.55 per square foot (or in metric units, $537.55, with standard deviation of $221.20 per square meter). In Table 4.1, in addition to presenting descriptive statistics for the full sample, we present the summary statistics for sub-samples by daylight level. Low daylight contracts have an average net effective rent of $47.32 per square foot ($509.35 per square meter) with comparable variation to the whole sample. High daylight and very high daylight achieve average net effective rents of $56.05 and $57.90 per square foot ($603.32 and $623.23 per square meter), respectively, with comparable variation. Notably, these values are approximately $8.00 to $10.00 more per square foot than the average rent for the low daylight sub-sample. While this difference is not a statistically-derived value premium, it suggests that there may be an added value for high daylight.

For controls, we add the building class associated with each contract, the building's age, renovation status, LEED certification, and whether the building has fiber-optic telecommunications. When we differentiate between low, high, and very daylight we find that contracts with high and very daylight cluster in class A more than those with low daylight, 63% and 66% versus 50% of low daylit spaces. The building age is on average 70 years, 62 years, and 64 years for low, high, and very high daylit spaces, respectively. LEED certification occurs 13%, 13%, and 5% for the low, high, and very high daylit samples, respectively. Lastly, fiber optic infrastructure is nearly standard with at least 94% of spaces across all groups being in a fiber lit building (i.e., in a building connected to a high-speed fiber optic cable).

Alongside the building properties, we control for lease contract characteristics. Again, when differentiating between low, high, and very high daylight, we see that lease contract terms vary. Transaction floors for high and very high daylit spaces cluster between floors 16-30, and lease durations are more frequently 6 to 10 years. Across all three groups rent free periods are generally for six months or less, and landlord concessions are generally in cash through tenant improvements. The transaction size is notably smaller for the high and very high sub-samples; however, the spread of transaction size is very wide across all samples. Overall, the transaction size data is strongly positively skewed, with a few outlier observations above 900,000 sq.ft.[4] Finally, subletting, partial floor leasing, multiple floor leasing, tenant brokerage and landlord brokerage is comparable across all of the samples.

Lastly, we include location and time fixed effects. The location fixed effects are represented by 24 submarkets (i.e. neighborhoods) in Manhattan. Time fixed effects are represented by the time of the lease transaction (year and quarter) from 2010 to 2016. Figures 4.1 and 4.2

[3] The expense reimbursement structure depends on the type of lease, thus the expenses included in net effective rent varies across the observations. The leases types represented in the data are full service, gross, modified gross, double net (NN), triple net (NNN), net, and net of electric. A full breakdown of the lease types is included in Appendix D.

[4] The transaction size is the total square footage rented in the lease. In many cases, the leases are for multiple floors and the transaction size represents the total area across all of the floors.

Table 4.1: Summary statistics for variables included in the daylight hedonic model. Mean and standard deviation presented for all observations, and separately for the low (0-55% sDA), high (55-75%), and very high (75-100%) daylit spaces.

		All Observations		Low (sDA 0-55%)		High (sDA 55-75%)		Very High (sDA 75-100%)	
Dependent Variables		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Net Effective Rent ($ per sq.ft.)		49.944	(20.551)	47.324	(18.416)	56.059	(25.532)	57.901	(21.632)
Log Net Effective Rent		3.839	(0.376)	3.792	(0.358)	3.941	(0.402)	3.990	(0.377)
Variable of Interest									
Spatial Daylight	Low (0-55%)	0.724	(0.447)	-	-	-	-	-	-
Autonomy	High (55-75%)	0.161	(0.367)	-	-	-	-	-	-
($sDA_{300/50\%}$)	Very High (75-100%)	0.115	(0.319)	-	-	-	-	-	-
Building Characteristics for Each Contract									
	A	0.545	(0.498)	0.507	(0.500)	0.633	(0.482)	0.661	(0.474)
Building Class	B	0.383	(0.486)	0.411	(0.492)	0.325	(0.469)	0.290	(0.454)
	C	0.072	(0.258)	0.082	(0.275)	0.042	(0.200)	0.049	(0.215)
——									
Building Age at Lease Signing (years)		67.766	(29.284)	69.763	(29.752)	61.813	(27.985)	63.514	(26.399)
Renovated building (1 = yes)		0.500	(0.500)	0.499	(0.500)	0.506	(0.500)	0.497	(0.500)
LEED Certified (1 = yes)		0.121	(0.326)	0.130	(0.336)	0.133	(0.340)	0.050	(0.218)
Fiber Lit Building (1 = yes)		0.950	(0.219)	0.943	(0.232)	0.962	(0.191)	0.974	(0.160)
Lease Contract Terms									
	0-15	0.620	(0.485)	0.760	(0.427)	0.327	(0.469)	0.147	(0.355)
Transaction Floor	16-30	0.276	(0.447)	0.179	(0.383)	0.511	(0.500)	0.562	(0.496)
Number	31-45	0.091	(0.287)	0.054	(0.226)	0.148	(0.355)	0.244	(0.430)
	46 and over	0.013	(0.113)	0.007	(0.086)	0.014	(0.117)	0.046	(0.209)
——									
	5 or less	0.393	(0.488)	0.387	(0.487)	0.391	(0.488)	0.435	(0.496)
	6-10	0.423	(0.494)	0.391	(0.488)	0.512	(0.500)	0.501	(0.500)
Lease Duration (years)	11-15	0.135	(0.342)	0.160	(0.367)	0.081	(0.274)	0.057	(0.232)

Table 4.1 – *Continued from previous page*

		All Observations		Low (sDA 0-55%)		High (sDA 55-75%)		Very High (sDA 75-100%)	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	16-20	0.036	(0.186)	0.046	(0.209)	0.014	(0.117)	0.007	(0.083)
	21-25	0.007	(0.084)	0.010	(0.099)	0.000	(0.000)	0.000	(0.000)
	26 or more	0.005	(0.070)	0.006	(0.080)	0.002	(0.045)	0.000	(0.000)
——									
Free Rent Period (months)	No free rent	0.184	(0.387)	0.187	(0.390)	0.174	(0.379)	0.174	(0.379)
	6 months or less free	0.546	(0.498)	0.512	(0.500)	0.610	(0.488)	0.669	(0.471)
	7-12 months free	0.228	(0.419)	0.246	(0.431)	0.204	(0.403)	0.144	(0.352)
	13-18 months free	0.035	(0.184)	0.045	(0.207)	0.010	(0.099)	0.010	(0.098)
	19-24 months free	0.005	(0.068)	0.006	(0.075)	0.001	(0.031)	0.003	(0.053)
	Over 24 months free	0.003	(0.054)	0.004	(0.061)	0.001	(0.031)	0.000	(0.000)
——									
Landlord Concession (Work Type)	As-Is	0.016	(0.127)	0.017	(0.131)	0.009	(0.094)	0.021	(0.143)
	Built to Suit	0.001	(0.025)	0.001	(0.026)	0.000	(0.000)	0.001	(0.037)
	New Building Installation	0.044	(0.206)	0.040	(0.196)	0.052	(0.221)	0.061	(0.240)
	Not Specified	0.140	(0.347)	0.131	(0.338)	0.155	(0.362)	0.174	(0.379)
	Other	0.001	(0.025)	0.000	(0.021)	0.002	(0.045)	0.000	(0.000)
	Paint & Carpet	0.002	(0.042)	0.002	(0.039)	0.002	(0.045)	0.003	(0.053)
	Pre-Built	0.023	(0.149)	0.018	(0.133)	0.033	(0.178)	0.039	(0.193)
	Tenant Improvements	0.770	(0.421)	0.788	(0.408)	0.741	(0.438)	0.696	(0.460)
	Turnkey	0.003	(0.058)	0.002	(0.047)	0.007	(0.083)	0.006	(0.074)
——									
Transaction Size (sq.ft.)		34,335	(83,088)	42,617	(95,060)	15,911	(31,693)	7,914	(10,706)
Sublease (1 = yes)		0.118	(0.323)	0.128	(0.334)	0.101	(0.302)	0.079	(0.270)
Partial Floor Flag (1 = yes)		0.523	(0.500)	0.524	(0.499)	0.551	(0.498)	0.479	(0.500)
Multiple Floors in Lease (1 = yes)		0.237	(0.426)	0.269	(0.443)	0.174	(0.379)	0.129	(0.336)
Tenant Broker (1 = yes)		0.628	(0.483)	0.643	(0.479)	0.595	(0.491)	0.578	(0.494)
Landlord Broker (1 = yes)		0.682	(0.466)	0.686	(0.464)	0.685	(0.465)	0.653	(0.476)
Number of Observations		6,267		4,539		1,008		720	

plot the net effective rent values by submarket and least transaction year-quarter.

4.2 Results

Hedonic pricing theory assumes that the price of a property—in this case, net effective rent of an office space—is the value that a tenant is willing to exchange for a bundle of spatial characteristics they wish to lease. Thus, the net effective rent represents the weighted sum of the building characteristics, lease contract conditions, relative spatial market supply and demand as well as macroeconomic market conditions for each of the properties as valued by the tenants.

Table 4.2 documents the results of the hedonic rent model as specified in Equation 4.1. The five columns in Table 4.2 present the incremental development of the regression model. In each column, a new set of variables is added in the following order: location fixed effects, time fixed effects, building characteristics, lease contract terms, and interaction effects. By building the regression incrementally, we observe how the independent variables impact the dependent variable, interact with one another, and affect the overall model fit. To operationalize the model, we estimate via ordinary least squares with robust standard errors. We find that this form of the ordinary least squares model provides the best linear unbiased estimator of coefficients with heteroskedasticity-consistent robust standard errors (White, 1980). For robustness, we estimated multiple specifications to assess the functional form of daylighting, the dependent variable, and the independent variables. Results are robust to these specifications, however the functional form of the model presented in the paper is selected for its ease of economic and statistical interpretation in application.[5] Additionally, we employed a Double Selection Lasso technique, and found no change to our specification based on various penalization indicators. This procedure suggests that the model should include all co-variates to explain the variation of net effective rents and the variable of interest sDA (Chernozhukov et al., 2015).

The results of the model explain up to 59.6% of the variation in net effective rent prices, in line with previous studies that use the same data (Liu et al., 2016; Chegut and Langen, 2019). The low daylight (0-55% $sDA_{300/50\%}$) level serves as the base category. We find that spaces with high daylight (55-75% $sDA_{300/50\%}$) have a 5.2% premium over spaces with low daylight, while spaces with very high daylight command a 6.3% premium over spaces with low daylight.[6] This means that, for example, if the low daylight space transacts for \$50 per square foot

[5] The low daylight (0–55%) is the base level in the regression. To validate the robustness of the model, we tested the $sDA_{300/50\%}$ as a continuous variable. The results of this test are consistent with the model's final function form. We choose to employ the categorical form of the variable in the final model for two reasons. First, the levels are consistent with the LEED daylight thresholds, 55% and 75%, which are accepted industry-wide as indicators of a well-lit daytime space. Second, occupants' perception of daylight levels can vary based on natural and electrical lighting conditions, as well as spatial conditions (Sadeghi et al., 2018), thus we choose to consider the daylight autonomy levels in steps that are clearly distinguishable rather than in single point increments.

[6] For ease of interpretation of the results, the regression coefficients are converted into percentage changes in net effective rent (Y) by taking the exponent of both sides of Equation 4.1 and applying the approximation

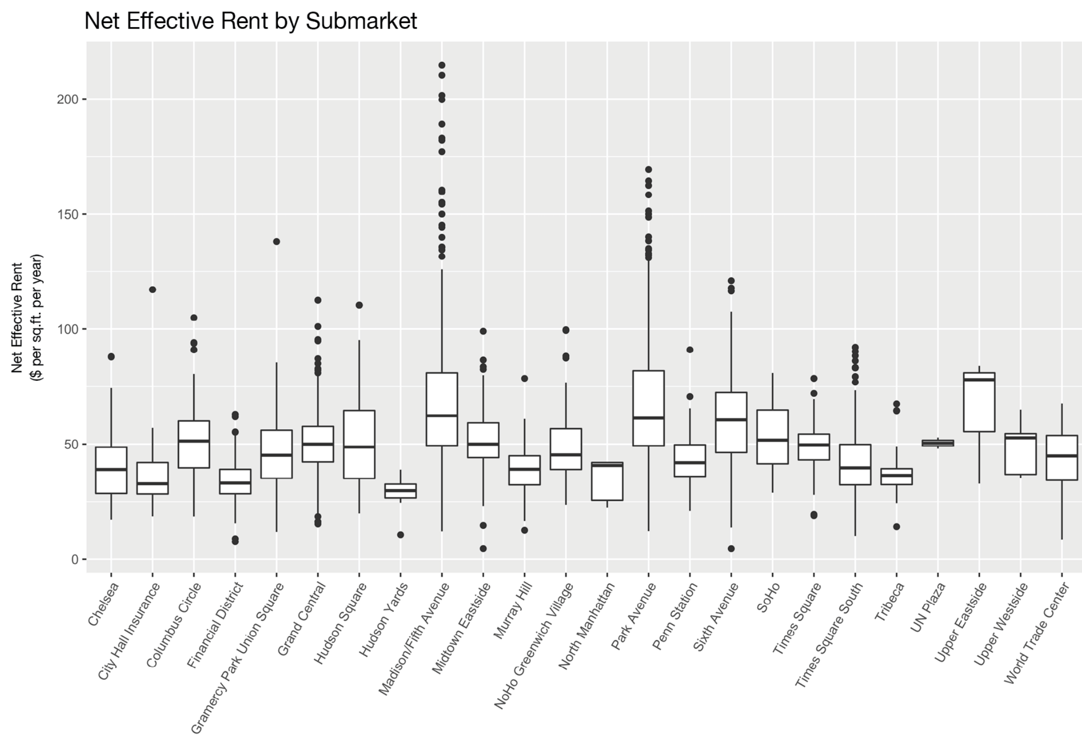


Figure 4.1: Plot of net effective rent by submarket (i.e. neighborhood) for the full sample. The submarket is to control for market conditions (location fixed effects) in the hedonic regression.

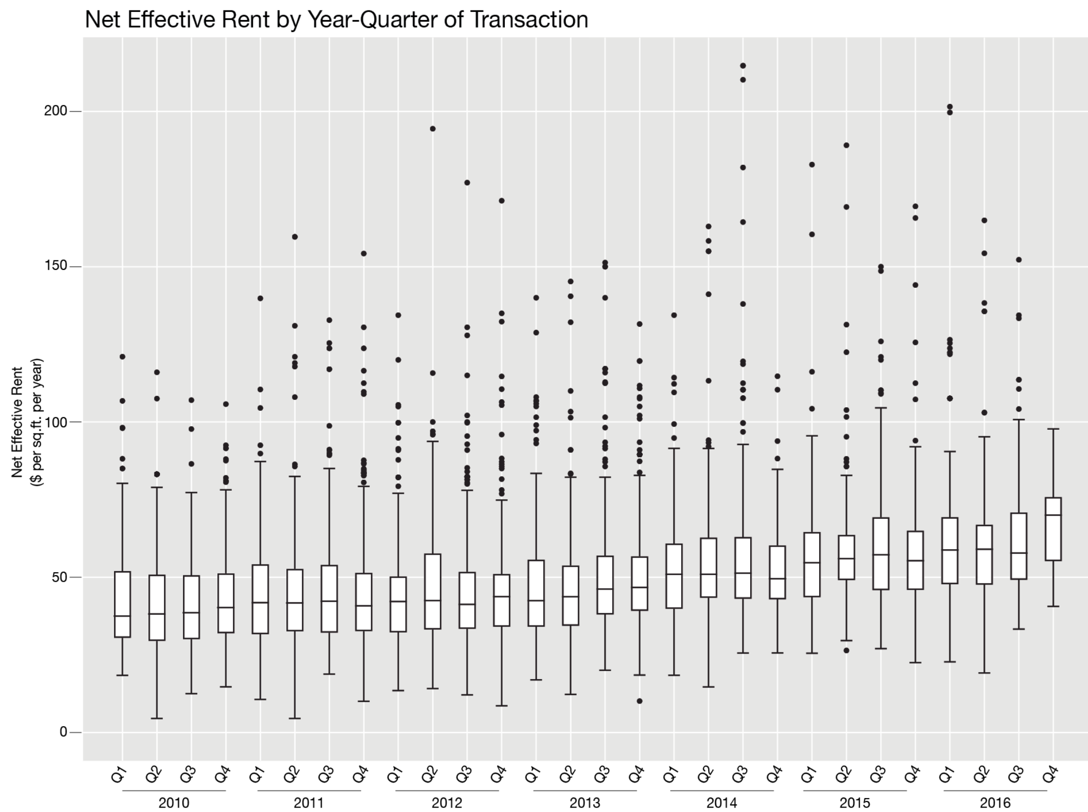


Figure 4.2: Plot of net effective rent by lease transaction year and quarter for the full sample. The lease transaction year and quarter is used to control for macroeconomic conditions (time fixed effects) in the hedonic regression.

Table 4.2: Hedonic pricing regression: daylight autonomy results
(Dependent Variable: Logarithm of Effective Rent per Square Foot ($/sq.ft.))

Variables	(1)	(2)	(3)	(4)	(5)
Variable of Interest: Spatial Daylight Autonomy (Base Level: Low Daylight (sDA 0-55%)					
High Daylight	**0.108^{***}**	**0.101^{***}**	**0.089^{***}**	**0.037^{***}**	**0.052^{***}**
(sDA 55-75%)	[0.011]	[0.010]	[0.009]	[0.010]	[0.014]
Very High Daylight	**0.122^{***}**	**0.103^{***}**	**0.104^{***}**	**0.021^{*}**	**0.063^{**}**
(sDA 75-100%)	[0.013]	[0.011]	[0.011]	[0.012]	[0.027]
Building Class (Base Level: Class A)					
Class B Building			-0.146^{***}	-0.111^{***}	-0.114^{***}
			[0.010]	[0.010]	[0.010]
Class C Building			-0.236^{***}	-0.196^{***}	-0.200^{***}
			[0.016]	[0.016]	[0.017]
Building Age at Lease Signing (years)			-0.010^{***}	-0.010^{***}	-0.010^{***}
			[0.001]	[0.001]	[0.001]
Building Age, Squared			0.000^{***}	0.000^{***}	0.000^{***}
			[0.000]	[0.000]	[0.000]
Renovated Building (1 = Yes)			0.041^{***}	0.039^{***}	0.040^{***}
			[0.007]	[0.007]	[0.007]
LEED Certified (1 = Yes)			0.008	0.005	0.004
			[0.011]	[0.010]	[0.010]
Fiber-Lit Building (1 = Yes)			0.042^{***}	0.020	0.022
			[0.016]	[0.016]	[0.016]
Lease Term Duration (Base Level: 6-10 years)					
Lease term 5 years or less				-0.046^{***}	-0.047^{***}
				[0.008]	[0.008]
Lease term 11-15 years				0.061^{***}	0.061^{***}
				[0.011]	[0.010]
Lease term 16-20 years				0.099^{***}	0.097^{***}
				[0.018]	[0.018]
Lease term 21-25 years				0.207^{***}	0.204^{***}
				[0.043]	[0.043]
Lease term 26 years or more				0.055	0.057
				[0.050]	[0.051]
Free Rent Period (Base Level: 0-6 months)					
No free rent				0.023^{**}	0.023^{**}
				[0.009]	[0.009]
7-12 months free				-0.033^{***}	-0.033^{***}
				[0.009]	[0.009]
13-18 months free				-0.052^{**}	-0.054^{**}
				[0.021]	[0.021]
19-24 months free				-0.118^{**}	-0.130^{**}
				[0.053]	[0.055]
Over 24 months free				-0.066^{**}	-0.065^{**}
				[0.027]	[0.027]
Transaction Size (sq.ft.)				0.000^{***}	0.000^{***}
				[0.000]	[0.000]

Table 4.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)
Sublease (1 = Yes)				-0.170***	-0.171***
				[0.011]	[0.011]
Partial Floor Flag (1 = Yes)				0.040***	0.038***
				[0.008]	[0.008]
Multiple Floors in Lease (1 = Yes)				0.008	0.007
				[0.010]	[0.010]
Tenant Broker (1 = Yes)				0.010	0.010
				[0.008]	[0.008]
Landlord Broker (1 = Yes)				0.035***	0.035***
				[0.009]	[0.009]
Landlord Concessions / Work Done (Base Level: Tenant Improvements)					
As-Is				0.041	0.041
				[0.029]	[0.029]
Built to Suit				-0.046	-0.044
				[0.071]	[0.069]
New Building Installation				0.064***	0.065***
				[0.012]	[0.012]
Not Specified				0.031***	0.032***
				[0.009]	[0.009]
Other				0.012	0.012
				[0.052]	[0.056]
Paint & Carpet				0.057	0.058
				[0.059]	[0.059]
Pre-Built				0.097***	0.099***
				[0.021]	[0.021]
Turnkey				0.141***	0.141***
				[0.040]	[0.040]
Transaction Floor Number (Base Level: Floors 0-15)					
Transaction Floor Number 16-30				0.115***	0.121***
				[0.009]	[0.010]
Transaction Floor Number 31-45				0.210***	0.225***
				[0.014]	[0.021]
Transaction Floor Number 46+				0.256***	0.321***
				[0.049]	[0.069]
Interaction Effect: sDA Level x Transaction Floor Number					
High sDA x Trans. Floor 16-30					-0.030
					[0.020]
High sDA x Trans. Floor 31-45					-0.027
					[0.033]
High sDA x Trans. Floor 46+					0.073
					[0.093]
Very High sDA x Trans. Floor 16-30					-0.042
					[0.031]
Very High sDA x Trans. Floor 31-45					-0.070*
					[0.038]
Very High sDA x Trans. Floor 46+					-0.233**
					[0.113]

Table 4.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)	(5)
Location Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	–	Yes	Yes	Yes	Yes
Constant	3.838***	3.648***	3.993***	3.936***	3.928***
	[0.010]	[0.024]	[0.034]	[0.034]	[0.034]
Observations	6,267	6,267	6,267	6,267	6,267
R-squared	0.315	0.448	0.536	0.600	0.602
F Adj R2	0.312	0.444	0.531	0.595	0.596

Notes: The five specifications presented: (1) includes location fixed effects; (2) adds time fixed effects; (3) adds the building characteristics; (4) adds contract lease terms; and (5) adds the interaction effect between sDA and floor number. Robust standard errors in brackets and statistical significance is denoted at the following levels *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

($538.20 per square meter), the space with high daylight will transact for an added 5.2% or $52.60 per square foot ($566.19 per square meter), ceteris paribus. The premium expressed in the regression results approximates the difference in the average net effective rent values across the sDA categories, as observed in the Table 4.1 summary statistics.

In column (1), the model includes the variable of interest sDA and location fixed effects in the form of a submarket (i.e. neighborhood) categorical variable.[7] For this specification, the model explains 31.2% of the variation in the net effective rent. Grand Central is the base submarket because it has the largest sample of observations. The majority of submarkets have negative coefficients relative to Grand Central with eight exceptions: Gramercy Park Union Square, Hudson Square, Madison / Fifth Avenue, NoHo Greenwich Village, Park Avenue, Sixth Avenue, SoHo, and Upper Eastside. As depicted in the full expression of the model in Appendix Table F1 (column 1), these neighborhoods receive a relative value premium of 4.0%, 8.5%, 25.7%, 7.7%, 25.1%, 9.0%, 16.0% and 40.3% more per square foot, respectively. The variable of interest sDA appears to be correlated with other factors at this stage, where relative to contracts with low sDA levels, high and very high contracts receive 10.8% and 12.2% more per square foot in effective rent.

In column (2), we add controls for macroeconomic conditions through a quarterly time categorical variable. For this specification, the model explains 44.4% of the variation of effective rent per square foot. The results indicate that effective rents positively increase quarter-over-quarter, and that relative to the first quarter of 2010, rents in the fourth quarter of 2016 are 48.8% higher for the Manhattan office property market. The variable of interest sDA con-

$e^x \sim 1 + x$. Thus, for example, the fitted coefficient of 0.052 for high daylight actually has a fractional effect on Y of $e^{0.052} = 1.053$. The approximation results in a marginal variation in the percentages that is less than the standard error for most coefficients.

[7] For ease of reading, the location and time fixed effects are not included in Table 4.2. These variables are included in the full expression of the model in column (1) of Table F1 in the Appendix.

tinues to have statistical significance and comparable scale in coefficient size, where relative to contracts with low sDA levels, high and very high sDA contracts receive 10.1% and 10.3% more per square foot in effective rent.

In column (3), we add controls for building characteristics: building class, building age, LEED certification, and fiber optic connectivity of the building. For this specification, the model explains 53.1% of the variation of effective rent per square foot. Relative to Class A buildings, Class B and C buildings receive effective rent per square foot discounts of -14.6% and -23.6%, respectively. Building age depicts comparable depreciation, where for every year that the building ages, the physical depreciation of the asset decreases the effective rent per square foot by -1.0%. For spaces in renovated buildings, net effective rents per square foot are higher by 4.1%. Similarly, for spaces with fiber-optic connectivity, there is an effective rent premium of 4.2%. LEED certified buildings, however, show no statistical significance and do not receive an effective rent premium in Manhattan. This is in line with previous research that shows that the marginal value of LEED certification decreases as the population of certified buildings increases in an area (Chegut et al., 2014). Finally, the variable of interest sDA continues to have statistical significance and marginally decreases in coefficient size, where relative to contracts with low sDA levels, high and very high contracts receive 8.9% and 10.4% more per square foot in effective rent.

In column (4), we add controls for leasing contract features: lease term, free-rent period, transaction size, sublease clause, partial or multiple floor, brokerage, landlord concessions, and transaction floor number. For this specification, the model explains 59.5% of the variation in net effective rent per square foot. Relative to a lease term of 6–10 years, shorter leases (less than 5 years) have a -4.6% discount. Longer leases (over 10 years) are more valuable up to a point; leases that are 21 to 25 years long have the maximum value, 20.7% higher than the base period, but beyond 25 years there is no significant added value. As rent-free periods increase, there is a decrease in effective rents per square foot, where contracts with 19–24 months free have the highest discounts of -11.8% less per square foot than 0–6 month leases on average. The transaction size of the lease has a statistically significant 0.0% impact on the net effective rent, indicating that the size of the lease does not influence the rent price. This does not agree with previous results that indicate a positive relationship between transaction size and rent price (Chegut et al., 2014). While the coefficient for transaction size in this work shows a strong statistical significance, this is an area for further study to evaluate the relationship between transaction size and rent price.[8] Contracts with subleasing clauses are discounted by -17.0%. Partial floor contracts receive 4.0% more per square foot. Contracts with multiple floors do not have a statistical significance impact on value.[9] Tenant concessions also play

[8]The transaction size is the total area (sq.ft.) leased by the tenant. Many of the contracts in the sample include multiple floors. Given the wide range of total transaction areas, the distribution of transaction size across the sample is strongly positively skewed. To account for this, we tested both transaction size and log transaction size in the specification. The log transformation of the variable, however, was not statistically significant.

[9]In a separate specification that did not include transaction size, the multiple floor variable expressed statistically significant value. The collinearity between these two variables warrents further investigation in future work.

a key role in lease negotiations; results indicate that turnkey contracts yield the largest premium of 14.1%. Most notably, transaction floor number has strong statistical significance and marginally increases at floors higher in the building. Compared to contracts on floors 0–15, contracts on floors 16–30, 31–45, and 46 and above receive 11.5%, 21.0%, and 25.6% more per square foot in effective rent, respectively. The variable of interest sDA maintains significance though it decreases to 3.7% for high daylight and 2.1% for very high daylight. The addition of the lease terms, particularly transaction floor number, decreases the value associated with daylight levels. This is expected as daylight and floor number are closely tied. We address the relationship between the two variables in the next and final specification.

In column (5), we evaluate the interaction effect between floor number and the variable of interest sDA. The floors that are higher in a building transact for higher rent prices, as indicated in the results in column (4). This may be attributed to qualitative factors, such as greater prestige, better views, more acoustic separation from the street, and perhaps, increased daylight. As illustrated in Figure 3.6, however, the relationship of daylight and floor number to rent value varies from one contract to another. Given the collinearity, it is important to determine whether floor number is serving as a proxy for sDA. To address this, we interact the floor number categories and the sDA categories to identify whether the sDA value premium is, in fact, associated with floor height or sDA (Brambor et al., 2006). The purpose of the interaction term is to identify how these two variables act together. By identifying the interaction effect, we determine how both sDA and floor number impact rent prices independently and in concert with one another.

To consider the condition of having both high daylight *and* high floor number, we add the coefficients of both variables, plus the interaction term in line with the literature on interpreting conditional marginal effects (Brambor et al., 2006). The interaction effect is statistically significant only for very high sDA on floors 31–45 and floors 46 and above, with coefficients of -7.0% and -23.3%, respectively. The negative coefficient on the interaction terms indicates that the value of being on a high floor and having very high daylight is tempered. As none of the interaction terms for high sDA are statistically significant, the conditional value of a contract with high daylight at any floor level is simply the addition of the 5.0% sDA coefficient and the transaction floor coefficient. In the case of contracts with very high sDA, if they are in either floors 31–45 or 46 and above, there is a discount of either -7.0% or -23.3%, respectively. Thus, a contract with very high daylight on floor 46 or above has a conditional value of 6.3% for daylight performance plus 32.1% for transaction floor plus -23.3% for the interaction effect, resulting in a conditional added value of 15.1% on the log net effective rent.

The interaction term measures the conditional value of daylight at specific floor heights. The results in the previous paragraph highlight that value that is associated with the conditional case of an office having *very high daylight on a high floor*. Because of the model specification, the interaction effect associated with very high daylight on a low floor is omitted and cannot be observed. Thus, to test the case of *very high daylight on a low floor*, we run a secondary specification of the hedonic model, changing the transaction floor base case to be floors 31 and over. The results of this analysis show that there is a deep discount of -23.4% associated with being on low floors (floors 0-15), along with a 9% value premium for the interaction between low floor and very high daylight. In other words, a *low floor with high daylight* has a 9% daylight premium (over the base case of a *high floor with low daylight*) but at the same time has a -23.4% discount because it is a low floor. The statistical and economic discounts of being on lower floors overshadows the value that better daylight brings to the floor. This test shows that there is a value proposition associated with better daylight access on all floors, both high and low, however the discount of being a low floor outweighs the daylight premium.

4.3 Discussion

A century ago, the health benefits of daylight led to new urban zoning codes to ensure that pedestrians at street level would not be cast in perpetual shadow from the growing high-rise buildings (Willis, 1995). The enactment of New York's 1916 Zoning Resolution signaled a societal recognition that daylight is not an amenity but a public right. The 5 to 6% financial premium for daylight in office rent prices identified in this work indicates that people value natural light not just outside but also inside buildings. Daylight's positive economic internalities and externalities (spanning from workplace productivity and office morale to occupant happiness and well-being) impact all facets of the built environment, including real estate, building codes, urban planning, and design. Most directly, the results can inform the pricing of properties in the real estate market, affecting both building owners and tenants. The financial premium may also be used to inform new building codes, as it did a century ago. Lastly, recognizing the market value of daylight can guide policies to ensure that all building inhabitants have equal access to adequate natural light regardless of economic means.

Daylight is a core consideration in architectural design. Buildings are oriented according to the sun's path, and facades are detailed in response to seasonal and daily conditions. In architectural practice, there are plenty of resources to design for better daylit spaces, from widely-used simulation tools to specialized lighting consultants. Thus, the quality and quantity of daylight in a space may be anticipated and shaped far before a new building is ever realized. When a project is being developed, daylight is sometimes a design driver and other times it is not. It is for the latter cases that the results of this work are most relevant. In a situation where it is not prioritized, daylight-enhancing or daylight-controlling facade elements are more likely to be eliminated to potentially limit construction costs.[10] Understanding the importance of daylight design, not just in social and environmental but also in economics terms, can be the key to retaining daylight-optimizing design elements in a project. If a developer or investor knows daylight's value, then they can include it in the financial models to inform the budget of a project. Recognizing daylight's potential to increase the operating income can justify initial construction costs associated with creating better daylit spaces.

A large part of a property's value is associated with architectural characteristics that are not

[10]There is no study, to our knowledge, on the construction costs specifically of daylight-enhancing design elements. However, previous work on the cost of green building by Chegut et al. found a marginal increase in cost to build, and more notably, a significant increase in design fees. Additionally, the work revealed that green construction projects take longer to complete (Chegut et al., 2019).

always quantifiable. When a potential tenant views an office space, more often than not, they are not basing their decision on measured daylight levels. To our knowledge, it is not standard practice to take illuminance measurements in a space, either by a broker or a potential tenant. Thus, tenants most likely assess the daylight quality based on their own experience in the space rather than any quantified indicator. This is a testament to the importance of spatial quality and individual occupant experience. The architectural elements that make a pleasant indoor space (such as layout, materials, daylight, and views) are often not considered in financial valuation. While it may not be standard to include spatial qualities in cash flow modeling, the tools to quantify such elements—either measured or modeled—are widely applied in design. Therefore, there exists an opportunity to incorporate building performance metrics, such as daylight levels, into financial valuation models at all stages of a building's development. Once these features are understood in financial terms, they can be prioritized in the design and development process by all stakeholders, from architects to developers and building owners.

The hedonic model used in this work explains just under 60% of the rent price of office spaces in Manhattan, in line with previous studies (Liu et al., 2016; Chegut and Langen, 2019). Roughly 40% of the price, therefore, is still undetermined. This is not surprising as so much of real estate value depends on qualitative features of a space. Just as a tenant likely judges daylight through experience, architectural quality cannot be easily quantified in a real estate listing. Thus, it is important that we continue to develop new ways of characterizing spatial features so that their value can be recognized. One characteristic that is currently missing from the model is views. We predict that there exists a relationship between daylight and views, though in the current model, we do not distinguish between the two. Where there is a good view, there is often also high levels of daylight because both require a degree of spatial openness at the facade. Thus, it is likely that the variable of interest sDA may be serving a proxy for views to a certain extent. However, this is not always the case and it is possible to also have daylight without preferential views and vice versa. This relationship is addressed in the forthcoming chapters: Chapter 5 presents a method for quantitatively evaluating views and Chapter 6 presents a hedonic analysis with daylight and views considered together.

While the results of this work directly applies to commercial offices in New York City, we expect them to be relevant for cities around the world. Previous work that compares commercial real estate in major cities globally finds that there are commonalities in the value trends associated with specific hedonic factors, such as size and building height (Chegut et al., 2015). The particular premium may differ but we expect there to be a consistent positive relationship between daylight and rent price.

4.4 Summary of Contributions

Natural daylight has long been appreciated for its positive impacts on human health, energy efficiency, and spatial quality in buildings. While the benefits of daylight are widely acknowledged, until now, it has not been confirmed that the value is reflected in economic decision-making. We pair urban daylight simulation with real estate hedonic modeling to determine the value of daylight in the rental price of office spaces in Manhattan. We find that tenants pay 5 to 6% more for spaces with high daylight access over those with low daylight access. In other words, if a low daylight space transacts for $50 per square foot ($538.20 per square meter), the same space with high daylight will transact for an added 5.2% or $52.60 per square foot ($566.19 per square meter). This premium for daylight in the market is independent of all other factors, including LEED certification and floor number. The results indicate that, in a dense urban environment with differentiation in daylight levels, tenants value high daylight, as indicated by their willingness to pay for well daylit spaces.

Given its integral role in the shaping of space, daylight has always been a critical factor in architectural design. It is not, however, often awarded the same attention on a financial balance sheet. This work shows that daylight can have an appreciable impact on the operating income of a building, and thus should be considered in all stages of project financing and investment. The added value in rent prices can offset potential costs associated with designing and constructing for daylight optimization. Moreover, understanding the financial value of daylight can inform building and planning policies to equalize rent prices and ensure that daylight is available to all.

The 5 to 6% premium identified in this work is based on the existing commercial office market in Manhattan. While the study is specific to New York City, previous literature shows that the results are likely reflected in major office markets around the world. By understanding the current value of daylight in a particular market, stakeholders in the building sector are incited to recognize the importance of designing and constructing with daylight in mind. The following chapters will expand on this work: Chapter 5 presents a method for evaluating views independently of daylight; and Chapter 6 presents the results of the hedonic regression considering daylight and views in parallel.

Part III: Views

Looking at cities can give a special pleasure, however common-
place the sight may be.

Kevin Lynch, *The Image of the City*

5. Views: Design Performance

The elements of a desirable view are context dependent and subjective. A good view in a dense urban setting is different from a good view in a rural environment. Examples of some views from Manhattan office windows are depicted in the photos in Chapter 1, Figure 1.1. Despite the variability, most views share visual components, albeit in different proportions: sky, landscape, ground, and objects of interest. In combination, these elements provide a connection to the natural world; establish a sense of place in the surrounding context; and create intrigue and delight. Alongside the objects being seen, geometric spatial properties such as view angle and depth-of-field contribute to the conceptualization of a view. Lastly, a view changes as one moves within a room. Therefore we propose an architectural analysis of views that accounts for an occupant in different positions in space.

In architectural analysis, views are often grouped together with lighting, and specifically, daylight qualities. The light conditions impact how we see a view. The properties of spatial daylight such as intensity, temporal dynamics, contrast, and spectrum can suggest whether the conditions are right for view gazing (Andersen, 2015). Yet, while there is an deeply intertwined relationship between the two phenomena, they are distinct visual qualities. It is possible to have good daylight with a bad view and bad daylight with a good view. Therefore, using daylight as a proxy for views has limited range.

5.1 Methodology

We propose a method for view analysis inside inside office spaces in an urban context. The method is developed to be employed in parallel with spatial daylight autonomy simulations carried out in Chapter 3 to evaluate the rent value of daylight and views together. The approach responds to three objectives: first, it is computationally lightweight such that it can be applied to a large sample of spaces throughout a city—in this case, 5,154 unique office spaces; second, it can be applied alongside daylighting analysis without significant overlap in the results (i.e. the analysis measures elements of the view that are independent of the daylight potential); and third, it characterizes the view distributed spatially throughout a floorplate rather than at distinct points on a building's facade.

Similar to proposed view analysis methods, we use raytracing to evaluate three-dimensional spatial views (Doraiswamy et al., 2015; Sadeghipour Roudsari, 2016; Studio Gang, 2016; Sasaki Associates, 2019). Precedent methods identify a few view targets, or particular elements in the surrounding context that are desirable (or not) to be seen. Rather than selecting individual elements in the landscape, we aim to count all objects in the surrounding field of view. The quality of a view is a product of the entire composition within one's frame of view rather select landmarks. Kevin Lynch describes this coalescence of visual elements as the core of the urban image: "Nothing is experienced by itself, but always in relation to its surroundings, the sequences of events leading up to it, the memory of past experiences" (Lynch, 1960). Similar to Lynch's taxonomy of urban form, we categorize objects in the urban context based on type: sky, iconic landmarks, neighboring buildings, landscape, water, and ground. Figure 5.1 illustrates conceptually how rays are traced from one point within a floor-wide analysis area:

- For each node within the office floorplate, rays are traced. Some rays intersect with the indoor space and some go through the window opening to the outside surroundings.
- Each object in the urban model is tagged with a type (sky, landmark, surrounding buildings, water, or ground). For each ray cast, the intersecting object and its distance is recorded.

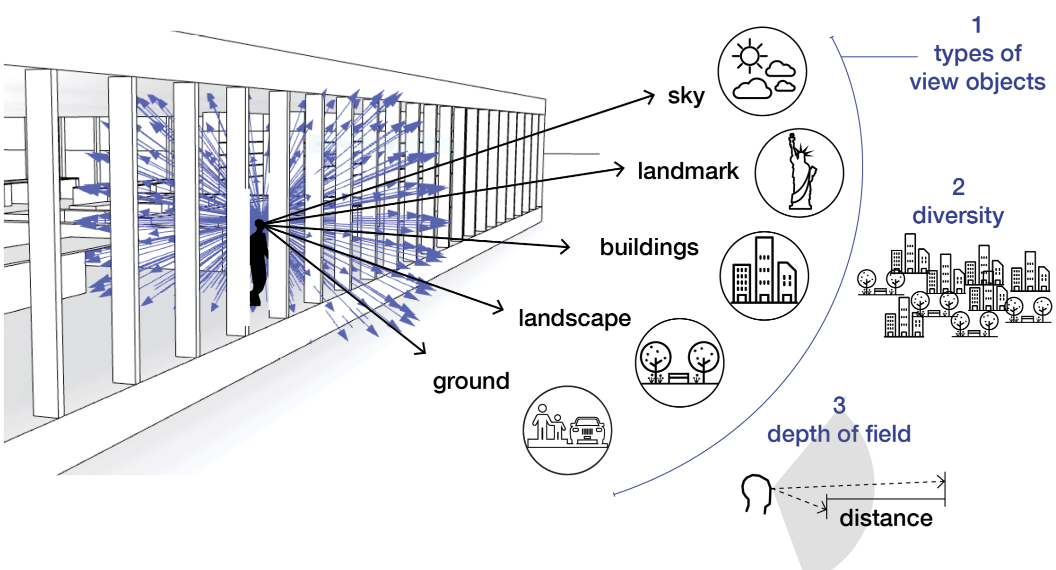


Figure 5.1: Elements of the observer's view captured by the view analysis method: exterior object types (sky, landmark, buildings, landscape, ground); the diversity of objects seen; the depth-of-field, i.e. range between the closest and farthest object seen (excluding the sky). *Graphic by the author; icons (ground, landscape, building, landmark, sky) by the Noun Project contributors: Madeleine Bennett, Alvaro Cabrera, Made x Made, ani, and Peter van Driel.*

5.1.1 Model Set-Up and Assumptions

The proposed framework utilizes the Rhinoceros 3D modelling environment and its visual scripting plug-in Grasshopper, Radiance, and DIVA-for-Rhino (Robert McNeel & Associates, 2016b,a; Solemma, 2018; Ward, 2016). Building the 3D context model in Rhinoceros, we label all 3D objects by layer to identify each type of view element. As in the daylight simulations, a 6-foot-by-6-foot (1.8-meter-by-1.8-meter) analysis grid is created on each office floorplate using DIVA-for-Rhino.[1] All objects in the Rhino model are exported as .obj files using Grasshopper. Then, through a Python script and Radiance programs *obj2rad* and *oconv*, the exported .obj files are processed to create the Radiance scene. To carry out the raytracing, we use the Radiance program *rtrace*. A Python script initiates the Radiance simulation and post-processes the output to return the view results.

An array of 6,111 rays are cast from the position of a observer's eye within a 120-degree cone of vision at an eye height of 5-feet (1.5-meters), as diagrammed in Figure 5.2. We assume that one's perception of a view within a space is often not based on the field-of-vision from one specific position and direction in space. Rather, we consider that occupants' might consider the view at multiple positions in a space and the changing views that they experience as they move through a space. Therefore, all orientations are weighted equally.

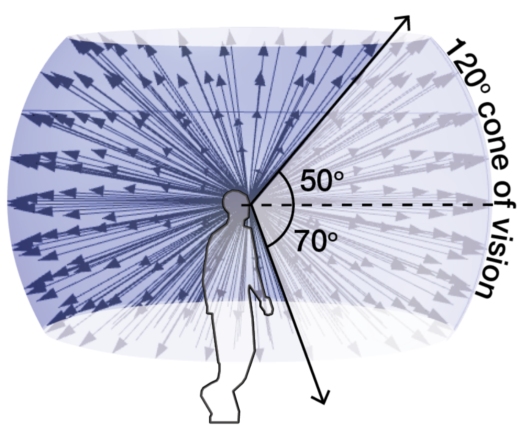


Figure 5.2: Conceptual diagram of rays cast from position of occupant eye within the 120-degree cone of vision, 180-degrees around the origin point (i.e. the occupant's head).

The ray-tracing method used in the view analysis is the same as that used in the daylight modeling described in Chapter 3. We use the same dataset of office spaces, the same 3D model of Manhattan, and make many of the same modeling assumptions as for the daylight work, as

[1] The process is executed utilizing Rhinoceros, Grasshopper, SQL, C#, and JSON. We match the CompStak data with each building's three-dimensional representation using the Building Identification Number (BIN) as provided by the NYC DOITT's 3-D Model of NYC. Based on the BIN matching, we create a JSON library of building properties attached to each BIN-identified geometric object. Then, we identify buildings that contain floors with rental contract data. The geometric meshes representing those buildings are cleaned and split by the assumed floor-to-ceiling height using Rhinoceros 3D and Grasshopper, and we extrude geometric objects representing walls, glazing, and ceilings on the floors of interest.

described in Section 3.1.2. While similar in many respects, there are two key differences in the set-up of the view and daylight analyses:

1. The Radiance scene used in the view simulations includes the *entire* Manhattan massing model. In the daylight simulations, it was possible to limit the Radiance scene to a one-block (800-foot-by-800-foot) area around the building in question, as depicted in Figure 3.2, because the immediate surrounding context is what most significantly impacts the daylight penetration into a space. In the view simulation, however, the analysis includes all of the urban environment as a view is not governed by what is closest to the space. On the contrary, the further one can see into the distance, the better the view is.

2. All spaces and places within the urban model are uniquely identified. In the daylight simulations, all buildings and elements of the urban context are treated as undifferentiated massing objects. They serve as shading objects impacting how much sunlight is able to reach the office space in question. Unlike in the daylight simulation, the view analysis requires distinguishing between elements of the urban context. Rather than being treated as nameless massing objects, elements of the urban environment—neighboring buildings, green spaces, iconic landmarks, and water—are individually tagged. The objective of the view analysis is to trace both *how far the view rays extend* from the observer's position and *what is seen*. Thus, in the Rhino model of Manhattan, we created layers for five different unique view objects: (1) iconic landmarks, (2) contextual buildings, (3) green spaces, (4) ground, (5) water and distant views of the greater metropolitan area (which includes the boroughs of Brooklyn, the Bronx, Queens, and Staten Island, as well as New Jersey). A sixth view category, the sky, is represented as the infinite space around the objects in the 3D model. Figure 5.3 depicts each of the view elements as they exist in the in the Rhinoceros model.

The urban and building data tagged in the 3D model comes from the same datasets used in the daylight analysis (described in Section 3.1.2). We add two additional datasets to model, described here and included in Table A1 in the Appendix.

- *Green Spaces and Hydrography:* Through the NYC OpenData online portal (run by the NYC Department of Information Technology and Telecommunications) we add geospatial data designating green spaces and surrounding hydrography (NYC Department of Information Technology & Telecommunications, 2016a; NYC Department of City Planning Information Technology Division, 2018a).

- *Iconic Landmarks:* We define the iconic landmarks to be the group of symbolic buildings and spaces in Manhattan, both new and old, that are widely-recognizable by the general public. We use a list of New York City's most iconic buildings published by *Curbed* (2019).[2] The list includes 22 sites in Manhattan that are widely-known and

[2] The Curbed database contains 30 landmark sites located in the five boroughs of New York City. In the massing model, we tag only the Manhattan landmarks. Landmarks in the other boroughs are far enough from the buildings that they are considered part of the distant views that include all water and land beyond the island.

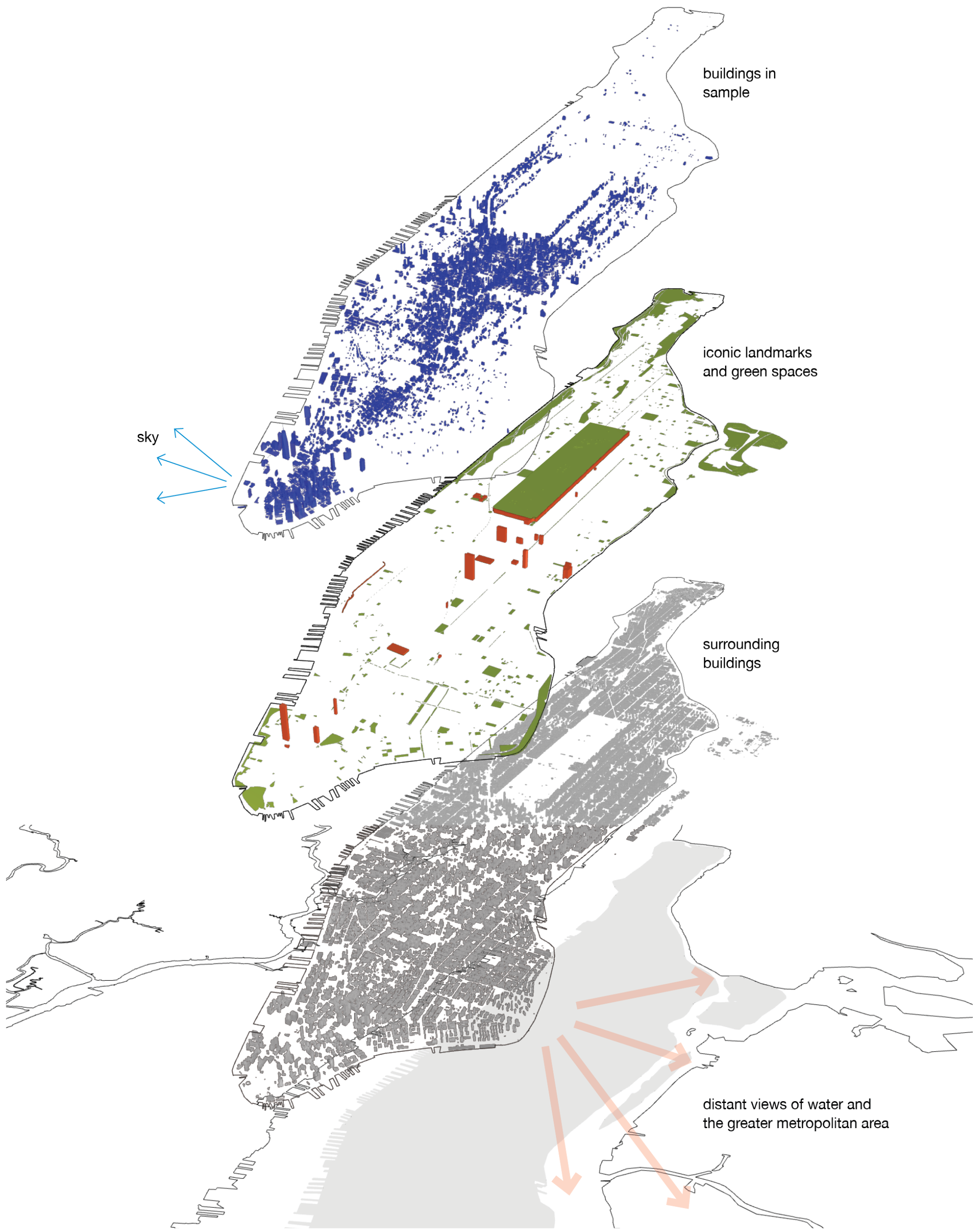


Figure 5.3: View components by layer in the 3D model: sky, greater NYC context, surrounding buildings, green spaces, and iconic landmarks.

loosely considered to be emblematic of New York City: One World Trade Center, the Oculus, the Woolworth Building, 56 Leonard Street, the Cooper Union Foundation Building, the Flatiron Building, the Empire State Building, the United Nations Headquarters, Grand Central Terminal, the Chrysler Building, the New York Public Library main branch, 30 Rockefeller Center, St. Patrick's Cathedral, the Seagram Building, the Lever House, Radio City Music Hall, 432 Park Avenue, the Plaza, Lincoln Center, the Met Breuer, the Metropolitan Museum of Art, the Solomon R. Guggenheim Museum. This list is by no means comprehensive, however it calls out many of the current well-known icons in the City.[3]

5.1.2 Introducing the View Metrics

There is no established metric for quantifying a view. Given the complexity and subjectivity of a visual experience, it is impossible to summarize a view in a single number. We propose a metric that characterizes components of a view, in so far as it can be represented in a simulation. To develop this approach, we draw upon Lynch's taxonomy of visual elements in the urban environment and the spatial daylight autonomy metric developed by the Daylight Metrics Committee of the Illuminating Engineering Society of North America in 2012, used in the daylight analysis component of this thesis and described in Section 3.1.4 (IES Daylight Metrics Committee, 2012; Lynch, 1960).

We create a categorization of view elements seen in an urban context—in particular, Manhattan. In the simulation, 6,111 rays are cast from each node in the 6-foot-by-6-foot (1.8-meter-by-1.8-meter) grid throughout the office floorplate. For each ray, the simulation records the object intersected in the surrounding environment, the distance of the intersection from the origin, and the position of the intersection. This provides the raw data from which we can derive a view metric.

We introduce two metrics to consider the level of view access at the level of both the node and the floor. This approach is derived from sDA metric, which accounts for irregular distributions of light throughout a space. As described in the IES LM-83-12 standard, daylighting in a space is non-uniform, with more light falling near the facade. Moreover, daylight varies temporally throughout the day and year with changing sun, sky, and cloud conditions. Therefore, the sDA metric accounts for the points within the floorplate that receive a minimum amount of daylight rather than averaging illuminance levels across the full floorplate (IES Daylight Metrics Committee, 2012). We approach views with a similar logic: The view in a space does not depend on the view at every point within the space. An open office floorplate may have unremarkable views in most areas and one area with spectacular views. While

[3] New York City's Landmarks Preservation Commission has a database of landmark buildings, interior spaces, outdoor sites, and historic districts that are designated by age (at least 30-years old) and special character, legacy, or provenance. This database contains around 34,000 buildings throughout the city. The Commission's list is primarily based on historic legacy and does not fit our definition of iconic landmarks for the purposes of this study. In the case of the view analysis, we use the *Curbed* list instead to designate a smaller sample of iconic buildings and sites that are widely-recognized by the general public and emblematic of Manhattan.

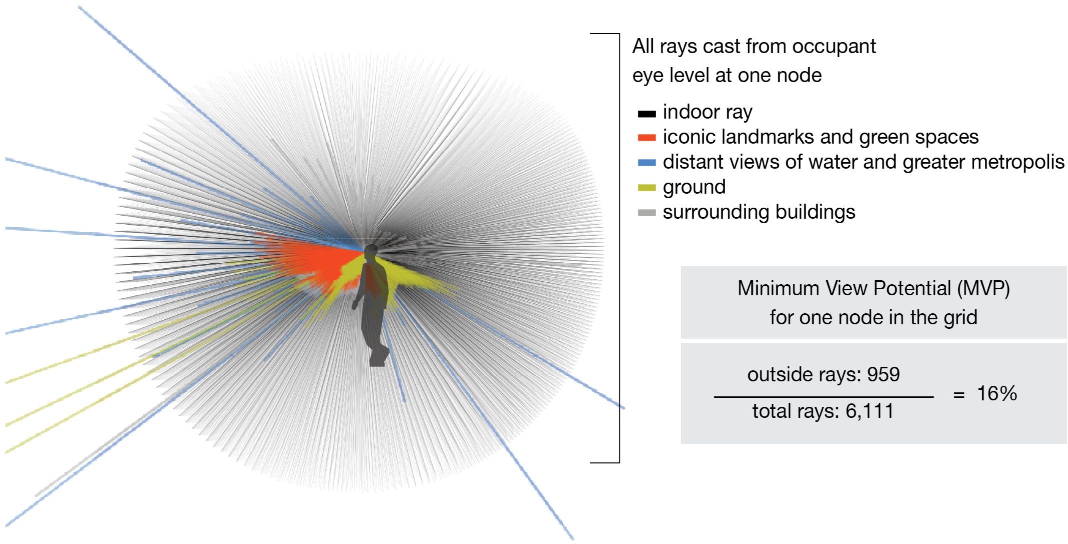


Figure 5.4: View Metric: Minimum View Potential (MVP). Diagram shows how rays are cast from one position, located at 5-feet above floor level (i.e. roughly standing eye level). The black cloud depicts the rays that stay within the interior space. The colored rays are those that reach the outside and hit a view element (excluding rays that reach the sky). The length of the colored rays corresponds to how far they travel before intersecting the view object (scaled down by 1/50). MVP is the proportion of total rays cast that reach outdoor view objects (%)—in the illustrated example, the MVP is 16%.

the visual intrigue is not distributed evenly, overall an occupant may still consider the floor to have high view access. This condition may even be desireable. Previous work shows that occupants prefer a variety in light levels in a space over time (Wang and Boubekri, 2010); we posit that the same may be true for views. The variation of views within the space may even enhance the occupant's rating of the visual experience.

With the aim of characterizing views at both the node and floor levels, we introduce two view metrics:

- *Minimum View Potential* (MVP): The proportion of total rays cast from one origin point that intersect outdoor view elements, expressed as a percentage (0-100%). MVP measures how much of the outside can be seen relative to the full field of view at one point. Figure 5.4 illustrates the ray casting at one point and the MVP calculation.
- *Spatial View Access* (sVA): The fraction of the floor-wide analysis grid that meets a minimum MVP value, expressed as a percentage of the total area (0-100%). Figure 5.5 depicts the view rays across a floorplate and the sVA calculation.

Metric Assumptions and Parameters

MVP is designed to identify the areas in a floorplate with a potential view. It is developed on the assumption that some positions within a floorplate have a preferable view. The outdoor

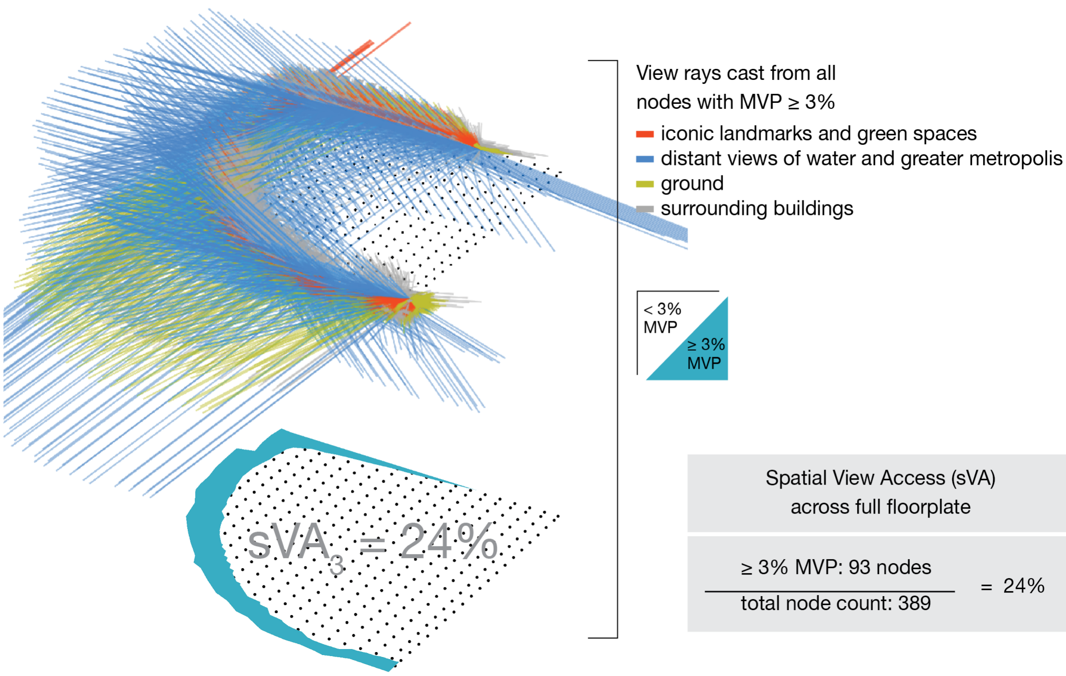


Figure 5.5: View Metric: Spatial View Access (sVA). Diagram depicts view rays cast across a 6-foot-by-6-foot analysis grid on a sample floorplate. Rays are only shown at nodes that have at least 3% MVP, i.e. at least 3% of the rays cast at the node intersect an outside view element. The bottom floorplate outlines the zone that meets this MVP requirement, resulting in a 24% sVA_3.

view elements are considered in the view analysis based on the following criteria:

1. Iconic landmarks, green spaces, and water/distant view rays are included without any exclusion.

2. Neighboring buildings and ground rays that are at least 18-feet (6-meters) away from the origin of the ray. Neighboring buildings and ground rays that terminate closer than 18-feet from the observer are excluded from the MVP calculation. We assume that neighboring building or ground rays that are closer than 18-feet do not add to the quality of a view.[4] The minimum distance is based on the EU standard *EN-17037 Daylight in Buildings*, which suggests that views are at least 18-feet away from a building (European Committee for Standardization Technical Committee CEN/TC 169, 2018).

3. Sky rays are excluded completely from the MVP calculation. These are the rays that extend uninterrupted through the urban context to reach the sky. To some extent, they are a proxy for direct solar access. Therefore, to differentiate the view metric from daylight in the hedonic pricing model, we do not count sky rays in the MVP.[5]

Establishing the Metric Thresholds

The sVA metric is the proportion of points in the analysis grid that meet a minimum MVP threshold. To determine an appropriate MVP and sVA thresholds, we start by making the assumption, based on our knowledge of the New York office spaces, familiarity with the dataset, and anecdotal evidence, that at least 10% of offices in Manhattan have high view access. Considering three possible MVP thresholds—1%, 3%, and 5%—we calculate the resulting sVA distribution. Figure E.1 in the Appendix shows the distribution of sVA for the sample based on six different specifications (note: this work will be described in greater detail in Section 5.2.2). Looking at the distributions, we determine which combination of MVP and sVA provide the closest distribution to the original assumption that at least 10% (i.e. the 90th percentile) of the office spaces have high view access. With 3% MVP, the top 10% of spaces have sVA values of 17% and above. Therefore, 17% should roughly be the cut-off for high view access. To be conservative, we round this down to 10% sVA with a 3% MVP, denoted as 10% sVA_3. Conceptually, this means that for a space to have *high view access*, at least 10% of the floor-wide analysis nodes have a 3% MVP (i.e. 3% of the rays see an outdoor view element).

Given the iterative approach used to develop the view metrics, the simulation results provide further insight into the thresholds. Both MVP and sVA will be further explained in the following Results sections.

[4] In the simulation, the majority of neighboring building and ground rays intersect a view element beyond 18-feet. In the Manhattan-wide view simulations (to be discussed in Section 5.2.2), only 20% of neighboring building rays and less than 1% of ground rays terminate less than 18-feet from the origin point.

[5] If applying the view analysis framework outside the context of this thesis sky rays may be included in the MVP calculation to account for open sky views, which can be essential to a good view. We exclude it in this case because of the close correlation between the sky view and daylight access.

5.2 Results

In this section, we first present the results for view simulations within a single building, and then the results for the entire data sample.

5.2.1 Results for One Building: 17 State Street

To demonstrate the view simulations at the floor level, we present the results for floors within an example office building: 17 State Street. The building is located adjacent to Battery Park at the southern tip of Manhattan. The 43-floor office tower, constructed in 1988, was designed by Emery Roth & Sons and developed by the William Kaufman Organization. Figure 5.6 shows the building in its site in an aerial image and the corresponding 3D model of the building with the 32nd floor view analysis ray results. The building massing, characterized by the sweeping arc in the southwest orientation, maximizes views over the Hudson River. In his *New York Times* review of the building after its completion, architecture critic Paul Goldberger wrote: "This is not a great building, but it is one of the few truly happy intersections of the realities of New York commercial development and serious architectural aspirations" (1988).

Figure 5.7 illustrates how rays are cast from one point within the analysis grid on the 32nd floor of the building. The majority of rays extend to the water, as depicted in blue. The ray direction and length changes based on the location of the node on the floor.

Figure 5.8 depicts how the rays cast change across multiple points the floorplate. Points near the curving southwest facade of the building see more water (blue rays) and green space (orange rays), while those closer to the straight edges of the wedge-shaped massing (the north and east facades) see more of the neighboring buildings (grey rays).

Figure 5.9 depicts how the MVP is calculated for a single point on the 32nd floor. 6,111 rays are cast from the point, 959 rays reach the outside. Thus, the proportion of total rays that reach the outside, a.k.a. the MVP, is 16%. This calculation is carried out for every point within the analysis grid on the floor. As described in Section 5.1.2, we specify that each point must have a minimum 3% MVP be counted towards the floor-wide sVA. If the MVP is less than 3%, then the point is considered to be more inward facing than outward facing.

Figure 5.10 illustrates how the floor-wide ray casting translates into the sVA value based on the spatial distribution of view rays on different floors. The sVA metric is the proportion of the analysis grid that meets the minimum MVP threshold—in this case, it is 3% MVP. On the 7th floor, 24% of the floor area meets the minimum 3% MVP threshold, while on the 32nd floor, 32% of the floor area meets the requirement.

5.2.2 Results for the Entire Manhanttan-Wide Sample

The simulations carried out for the offices in 17 State Street are repeated for 5,154 floors in the sample. In each space, 6,111 rays are cast from every node within the analysis grid on each floor. The output for each ray at each node is post-processed to calculate the MVP for the

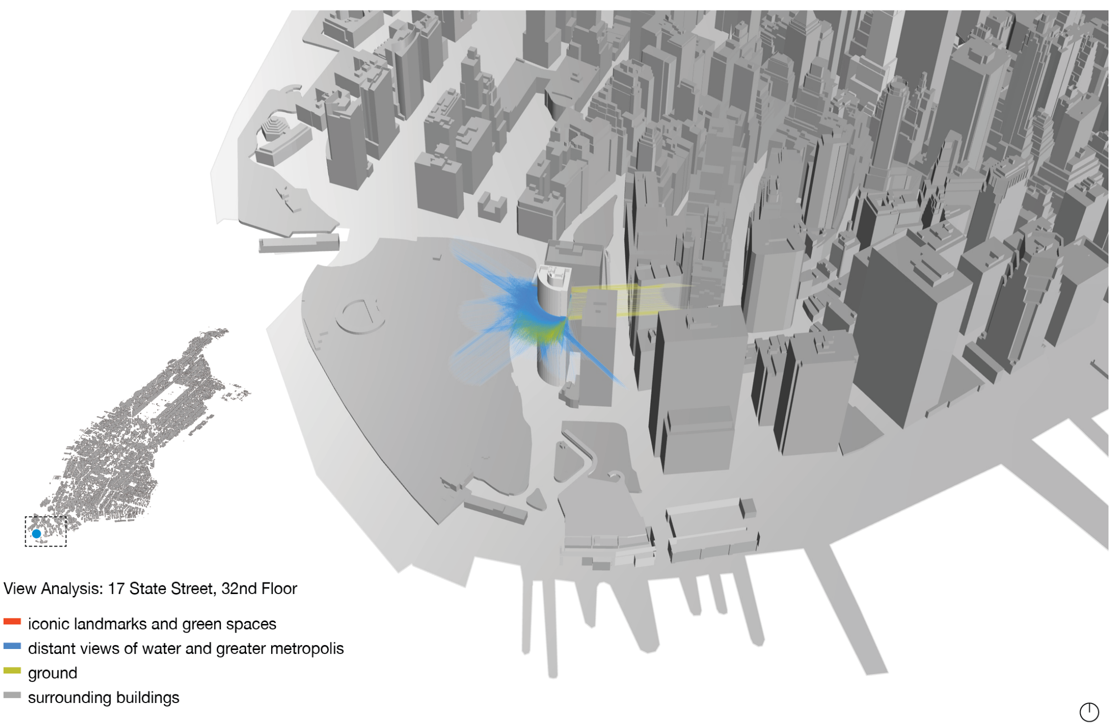


Figure 5.6: 17 State Street, 32nd floor: aerial photo of surrounding urban context and corresponding 3D model. The rays extend in the direction they were cast, and the length reflects how far they travel before intersecting an object (note: rays lengths have been scaled by 1/50). The color indicates the type of view element each ray reaches. Aerial photo via Google Earth (2020).

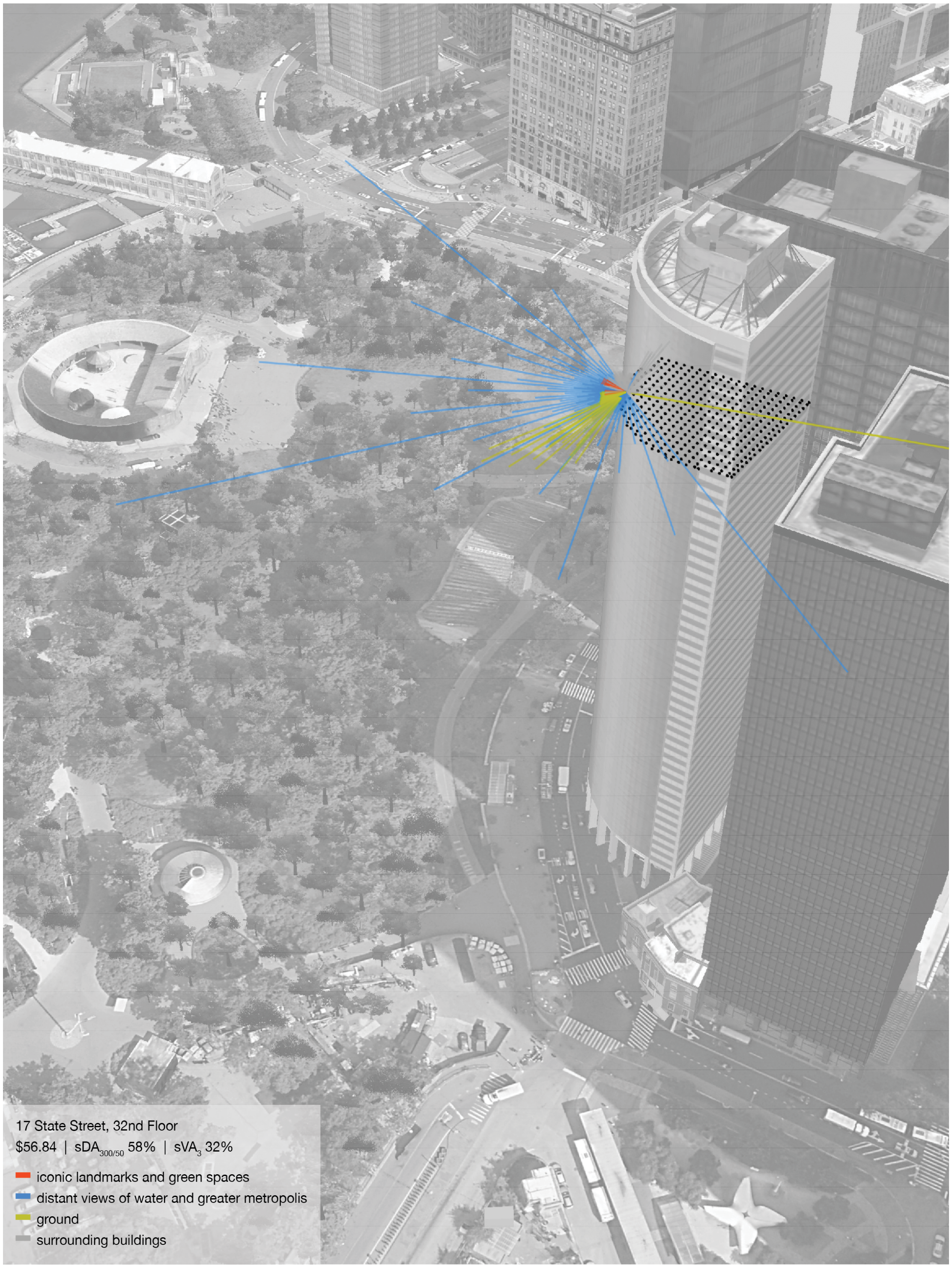


Figure 5.7: 17 State Street, 32nd floor: rays cast from one point in the analysis grid. From each analysis point, the rays extend in the direction they were cast. The length of the ray reflects how far it travels before intersecting an object (note: rays lengths have been scaled by 1/50). The color indicates the type of view element each ray reaches.

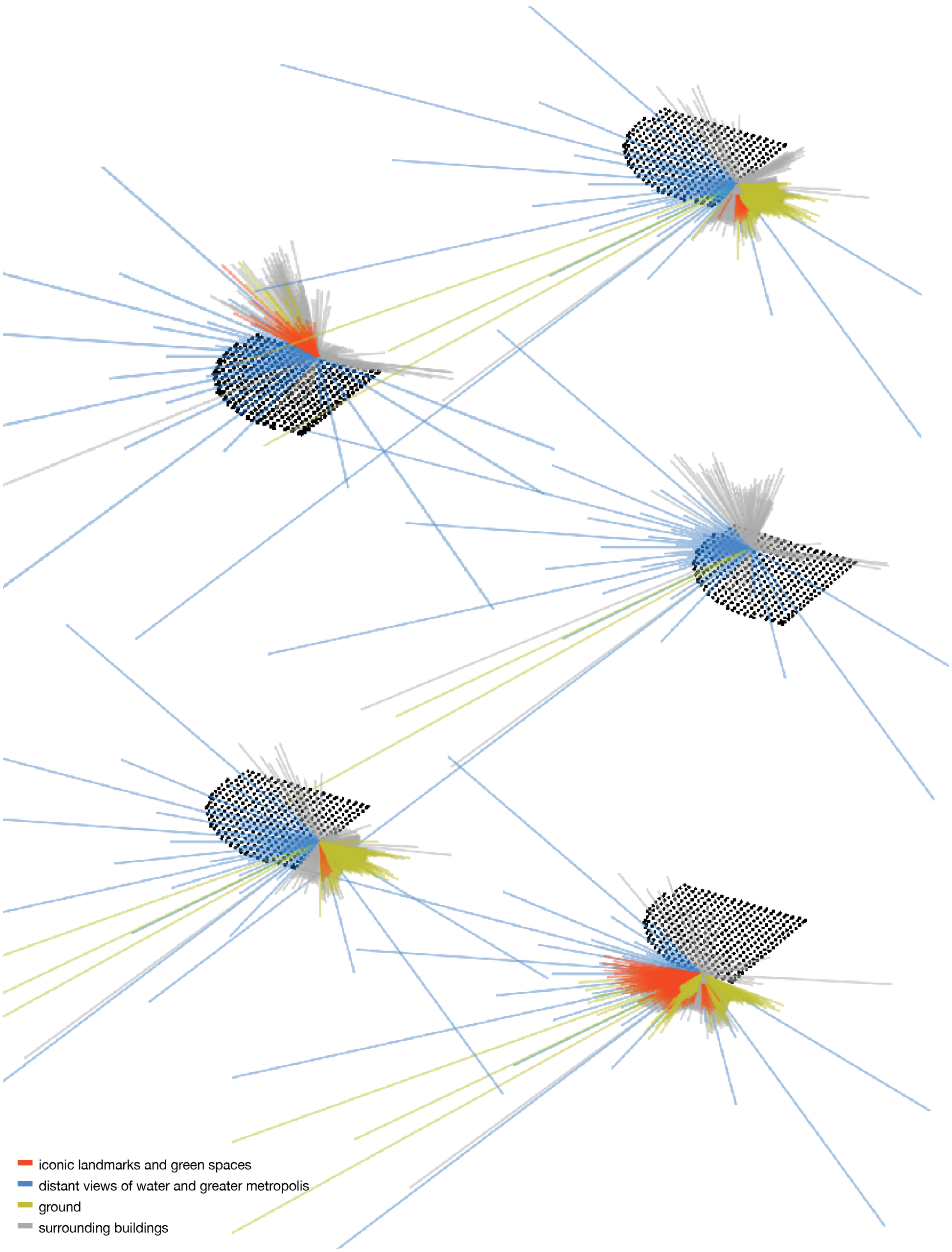


Figure 5.8: 17 State Street, 32nd floor: rays cast from different points in the floor-wide analysis grid. From each analysis point, the rays extend in the direction they were cast. The variation in the rays mapped at each point illustrates how the view changes across a floorplate. The length reflects how far they travel before intersecting an object (note: rays lengths have been scaled by 1/50). The color indicates the type of view element each ray reaches.

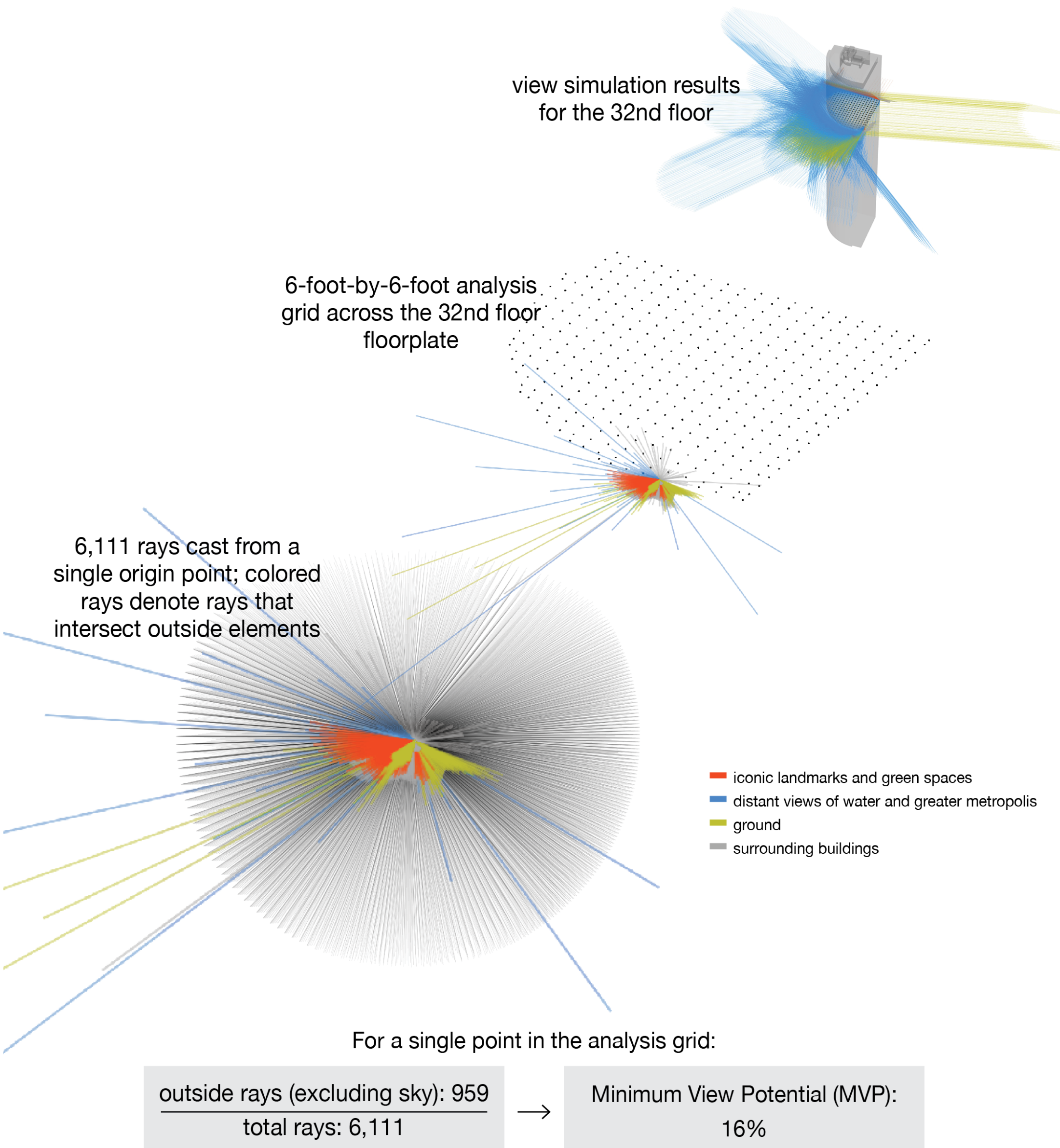


Figure 5.9: 17 State Street, 32nd floor: calculating the minimum view potential at one point. The MVP is the fraction of total rays cast that reach view elements in the outside. In this case, 959 of the 6,111 rays cast reach outside elements, resulting in a 16% MVP. The MVP for each point within the analysis grid is tallied to calculate the floor-wide sVA.

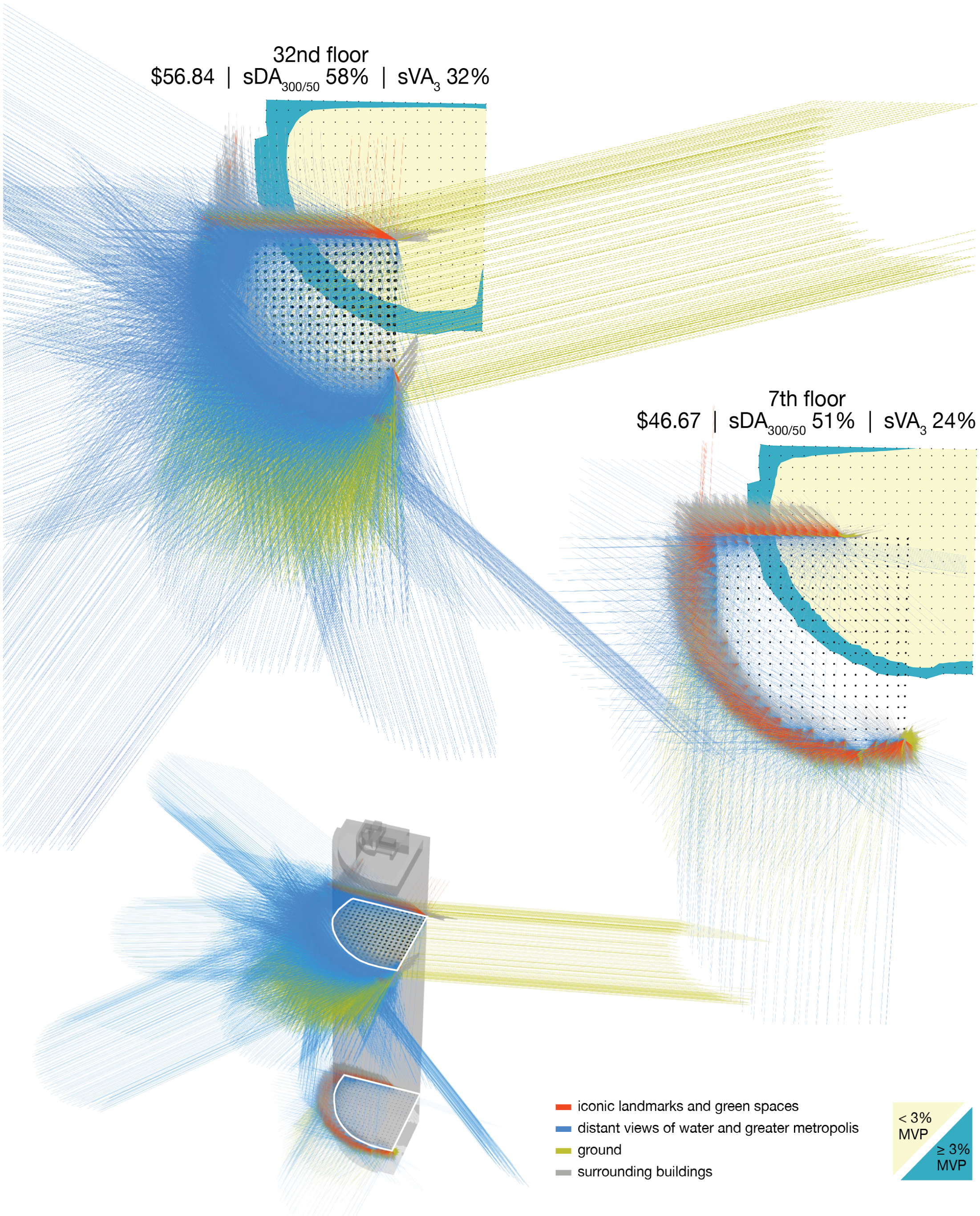


Figure 5.10: 17 State Street: comparison of view simulation results on floors 7 and 32. The color, length, and direction of the rays in the visualization for each floor illustrates how characteristically different views are captured on each floor. On the 32nd floor, distant water views dominate. In contrast, on the 7th floor, the rays intersect objects of interest that are closer to the building—namely, Battery Park open space. The views available at each floor translate into an 8% difference in the floor-wide sVA value: 32% on the 32nd floor and 24% on the 7th floor. The contour plot outlines the area of each floor that meets the 3% MVP requirement that designates high view access.

Table 5.1: View simulation results: descriptive statistics. The number of analysis nodes reflects the size of the floor (as the nodes are distributed in a 6-foot-by-6-foot grid across the floor). The ray counts summarize the rays cast across the whole floor. The spatial view access (sVA_3) is the proportion of the floor area that meets the minimum 3% outdoor ray threshold. 5,154 unique office spaces were modeled; because there are multiple transactions for some floors (either over time and/or partial floor transactions), there are 6,267 observations in the full sample.

	All Observations				Floors with High View Access (Min. 10% sVA)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Number of nodes on floor	512	(427)	13	4,690	560	(368)	47	3,778
Total rays cast throughout floor	3.13e+06	(2.61e+06)	79443	2.87e+07	3.42e+06	(2.25e+06)	2.87e+05	2.31e+07
Number of rays that reach outside	3.18e+05	(2.06e+05)	19,723	4.13e+06	3.27e+05	(1.64e+05)	59,093	1.51e+06
Proportion of rays that reach outside	0.123	(0.056)	0.017	0.735	0.109	(0.035)	0.047	0.550
Spatial View Access, sVA_3	0.048	(0.111)	0.000	1.000	0.258	(0.149)	0.100	1.000
For all rays that reach outside, proportion reaching each view element								
Neighboring buildings	0.878	(0.153)	0.028	1.000	0.664	(0.161)	0.135	0.972
Ground	0.022	(0.043)	0.000	0.625	0.018	(0.027)	0.000	0.280
Iconic landmarks	0.011	(0.041)	0.000	0.604	0.042	(0.085)	0.000	0.604
Green spaces	0.002	(0.010)	0.000	0.199	0.005	(0.019)	0.000	0.199
Water	0.010	(0.032)	0.000	0.277	0.047	(0.065)	0.000	0.277
Sky	0.077	(0.118)	0.000	0.972	0.225	(0.111)	0.000	0.502
Observations	6,267				1,008			

node and the sVA for the floor. Table 5.1 presents a summary of the results for two samples: (1) all observations and (2) a sub-sample of floors with high view access, defined as minimum 10% sVA_3.

For the full sample, an average of 12% of the rays cast on a floorplate reach the outside. For the floors that have high view access, the cumulative average is around 11% of the outside rays. In the latter group, even though the average proportion of rays reaching outside is lower, the average sVA is significantly higher: 25.8% in the high view access group vs 4.8% in the full sample. The different between the two groups illustrates how looking at the proportion of outside rays can be misleading because the rays can be concentrated in a few nodes. The sVA metric, in contrast, considers the spread of rays across many nodes on a floorplate.

Table 5.1 includes a breakdown of the types of outside view elements that are intersected by the rays: neighboring buildings, green spaces, iconic landmarks, water and distant views, or sky. The majority of outside rays, on average 88% for all observations and 66% for the high view access group, intersect with adjacent neighboring buildings. Rays that reach the sky are the second largest group, on average 8% for all observations and 23% for the high view access group. The sky rays are not included in the MVP and sVA calculations, as discussed in Section 5.1.2, because they are closely correlated with the daylight access in the space. Rays that intersect with ground, iconic landmarks, green spaces, and water constitute between 1 to 2% across all observations and 2 to 5% in the high access group. The sharp decrease in the proportion of rays hitting these object types is not surprising because there are fewer of these elements in the urban context model. As they are less common, these are also generally the coveted elements in a viewscape.

Figure 5.11 depicts the distribution of sVA derived from the view simulations. The histogram show the distribution of sVA with three different MVP threshold values: 1%, 3%, and 5%. As discussed in Section 5.1.2, we considered these three different cut-offs in the development of the metric. This plot is a summarized version of the plots in Figure E.1 in the Appendix, which shows the sVA distribution for six different MVP specifications. Based on the rough estimation that at least 10% of the office spaces in our sample have good views (based on our knowledge of the New York office spaces, familiarity with the dataset, and anecdotal evidence), we select the thresholds to differentiate between the observations with high view access and low view access in the sample. Ultimately, we define 3% MVP and 10% sVA_3 to define high view access. These thresholds created a distribution of the results such that 16% of the observations have high view access.

While the metrics distill the view results into single numbers, the spatial distribution of view lines vary from one office to another. Figure 5.12 visualizes the view simulation rays on 15 sample floor plans. The color of each ray indicates the type of view element it intersects, and the length of the ray indicates how far it travels (scaled by 1/50). Figure 5.13 depicts the same 15 spaces with the high view access area highlighted on the floorplate, and lists the names, rent price, sDA, and sVA values for comparison. The graphic shows that the high view access area always follows the perimeter of the floorplate, however it can be concentrated in particular orientations depending on the where view sight lines exist. Looking at the visualization of the view simulation results in Figures 5.12 and 5.13, one can see the variation in the views across the sample of offices. Floors can have similar sVA values yet have different view characterization. For example, 590 Madison Ave (40th floor) and 101 Avenue of the Americas (13th floor) have sVA_3 values of 28% and 26%, respectively. Yet, as depicted in Figure 5.12, the rays cast in each floor differ in both objects seen, as well as distance and orientation of the rays.

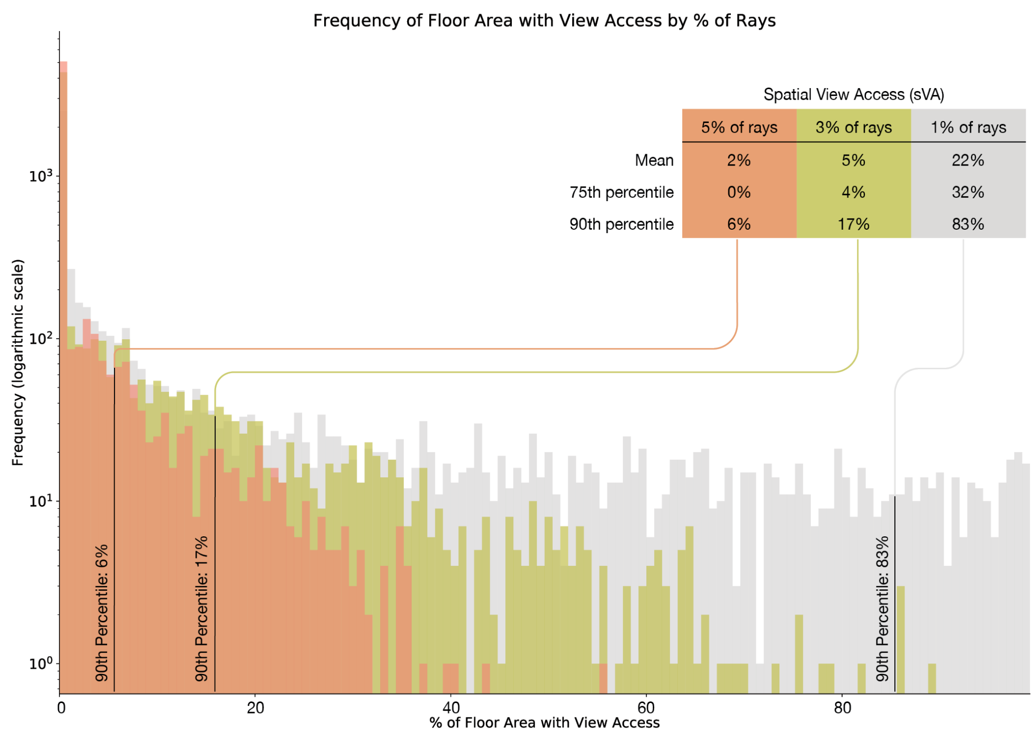


Figure 5.11: Distribution of floor-wide view access (sVA) results with three minimum view performance (MVP) thresholds: 1%, 3%, 5% of the total rays cast from a point. The y-axis of the plot is on a logarithmic scale to account for the high concentration of observations with very low sVA. The table in the top right of the plot presents the mean, 75th percentile, and 90th percentile for each threshold considered. The color of the distribution plot corresponds to the color of each threshold in the table (5% - orange, 3% - green, 1% - grey).

5.2.3 Views vs Daylight

In this dissertation, daylight and views are evaluated in parallel for the purposes of measuring the rental value of each attribute distinctly. Therefore, we devise the view metric sVA such that it does not overlap with the spatial daylight autonomy measure of a space. To complement the sDA results, we design the sVA to measure the elements of a view that are *not* related to light access. To this end, we do not consider the rays that have a direct path to the sky. We tested the metric with and without the sky rays and found that the sky rays mirror the sDA results closely and therefore do not add additional information. In other applications of the view analysis, the sky rays could be included in the calculation of MVP and sVA.

Figure 5.12: Visualization of view simulations on 15 office floors in plan view. The rays shown are at points that meet the 3% MVP requirement; if a point has no rays, it does not meet the MVP limit. The color of each line indicates what view object it intersects. The length and direction of each line indicates which way and how far it extends. The rays have been scaled down by 1/50. The address, floor number, rent value, sDA, sVA are listed in Figure 5.13.

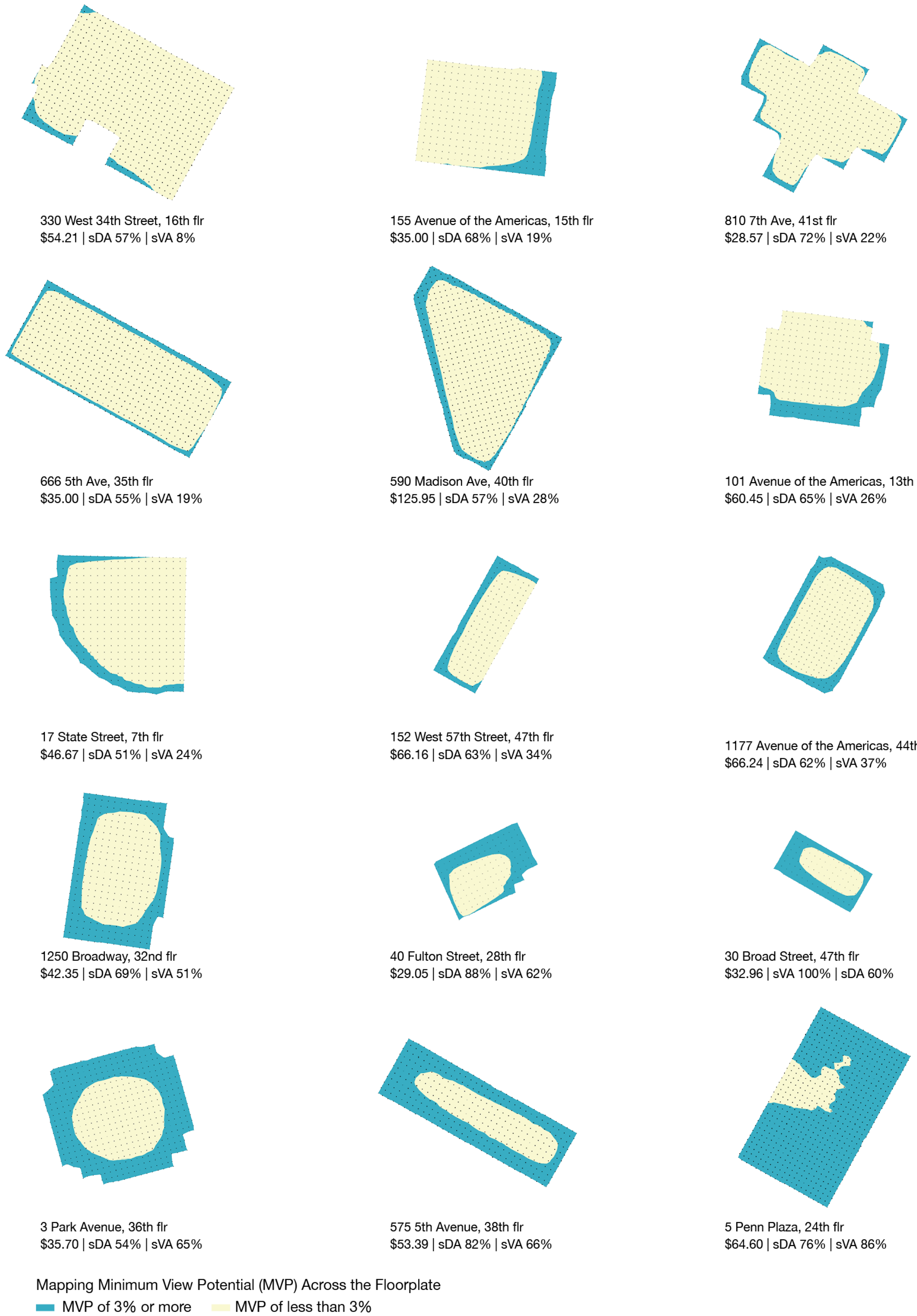


Figure 5.13: Visualization of view metric results on 15 office floors. The colored portion of the floorplate indicates the area that meets the 3% MVP threshold. For each floor, the rent value, sDA and sVA results are listed. The floors correspond to the view simulation results shown in Figure 5.12.

Figures 5.14 plots the view metric against the daylight metric. There is not a strong visually-discernable relationship between the two variables. At both low and high sDA values, the sVA numbers vary considerably. By excluding the sky rays from the view analysis, we aim to disassociate the view and daylight performance metrics. This plot supports the idea that the two variables are relatively independent of one another.

Figure 5.15 plots both daylight and views against floor number. For both daylight and views there appears to a positive relationship to floor number, i.e. height off the ground. This makes sense because the higher the floor, the more open the surroundings are to both sun exposure and views.

5.3 Discussion

In this section, we discuss validation of the view analysis method, explore how the approach can be refined, and consider incorporating internal visual connectivity into the view assessment.

5.3.1 Validation of the method

In future steps of this work, the method will be validated through user surveys to determine how closely it reflects the human perception of views. In the meantime, to this end, the hedonic pricing analysis in Chapter 6 provides some insight. While economic preferences do not directly reflect individuals' perception of a view, it is known generally in the real estate market that people pay for better views. Therefore, the work in Chapters 5 and 6 inform one another—knowing that views have value in real estate, we can test which specification of the view metric leads to the most reasonable results in the hedonic analysis. In the hedonic model, we test multiple configurations of the view metric to determine which form produces strong statistical correlation. The thresholds established for MVP (3%) and sVA (10%) were determined by testing various thresholds in the hedonic model. This will be discussed further in Chapter 6.

5.3.2 Refining the Views

In the current view analysis method, views in all orientations are counted. We cast rays 180-degrees around the analysis node, as illustrated in Figure 5.2. The reasons for this are two-fold: one, we assume that occupants will turn their heads and face different directions over time; and two, we assume a open floor plan office, thus the furniture can be oriented in different directions. Further work to refine the internal floor layout and the facade assumptions will help to refine the view analysis. Additionally, in future steps of this work, the analysis method could be modified to target particular views, such as preferred orientations—for example, views that shift over the day based on the position of the sun to best illuminate a landmark or to see sunset.

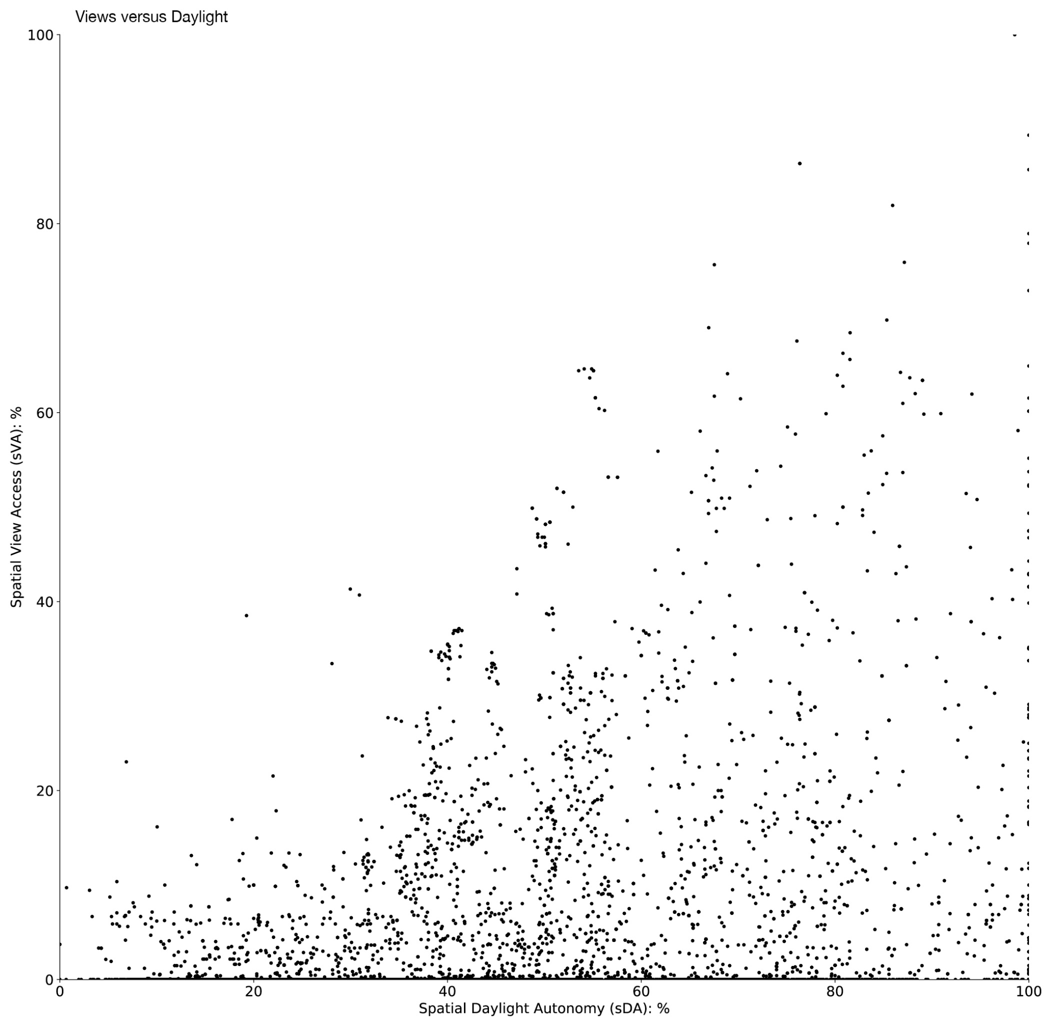


Figure 5.14: Plot: View (sVA_3) versus daylight ($sDA_{300/50\%}$). Both variables measure the proportion of the total floor area that meets a performance criteria. The plot shows that the floorplates always have a higher daylit floor area compared to area with view access, as indicated by the points being below the line $y = x$. Beyond this correlation, however, there is no discernable descriptive relationship between the variables. This is not surprising as the rays that extend to the sky are excluded from the sVA calculation. The lack of a relationship indicates that the variables are seemingly independent of one another.

5.3.3 Considering Internal Views

The full visual experience includes what one sees both inside and outside the space. The view analysis framework presented in this chapter considers only those views that one sees outside a window. In future work, it would be valuable to expand the method to account for internal views. Internal visual connections are an important aspect of how one perceives a space, arguably even more than outdoor views because the objects in sight are in close proximity to the occupant. Inside the building, visual engagement can encourage socializing and human interaction. Particularly in open work spaces, visual exposure impacts occupant satisfaction,

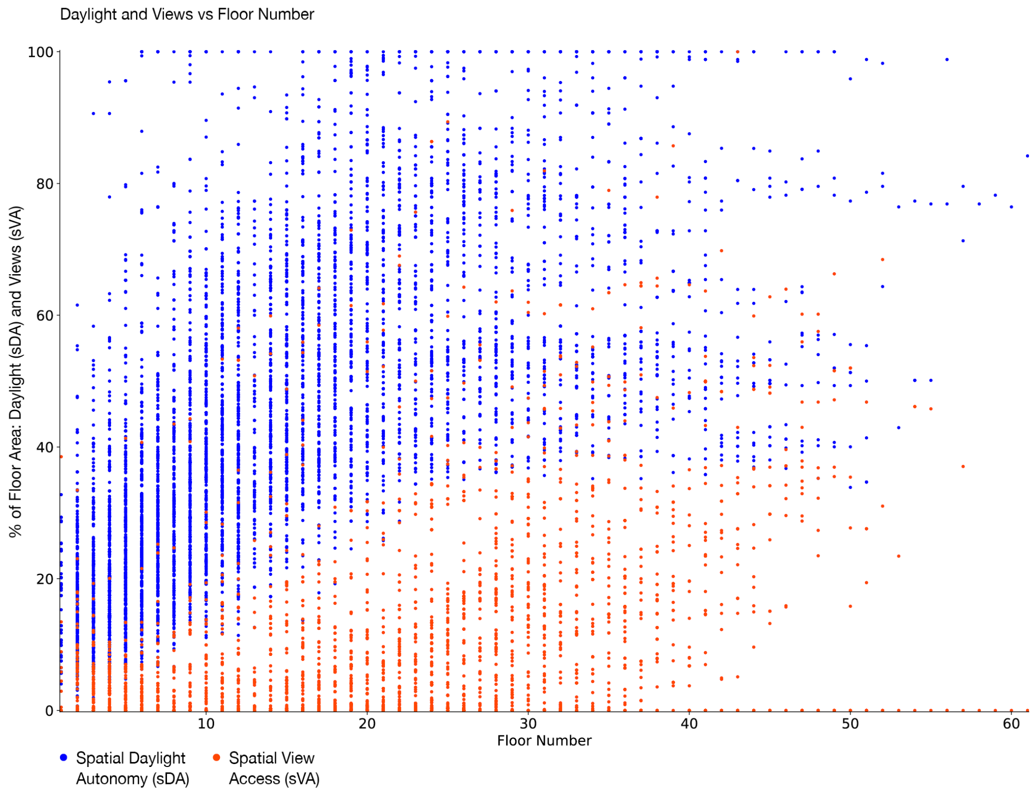


Figure 5.15: Plot: Daylight and view by floor number. The metrics for both daylight and views ($sDA_{300/50\%}$ and sVA_3) are on a scale of 0-100%, and describe the proportion of floor area that meets the daylight or view threshold. On the whole, daylight penetrates through a larger portion of the floors than view access does. There is a recognizable positive trend in daylight moving up the buildings. The views, in contrast, vary increasingly on higher floors.

collaboration, productivity, and perseverance (Bernstein and Turban, 2018; Haapakangas et al., 2018; Kim and de Dear, 2013; Kong et al., 2018; Roberts et al., 2019; Zerella et al., 2017). Moreover, internal visual elements may take the place of external views when they are not available. For example, views to vegetation inside the building may substitute a view to the natural environment where it does not exist. Studies show that these internal views to a representation of nature, either indoor vegetation or digital projections of natural scenes, are valued (Gray, 2017; Zhao et al., 2017).

By evaluating both indoor and outdoor views at once, we can more comprehensively assess the visual experience of occupants. To this end, we published a preliminary method for mapping the internal visual connectivity throughout a floorplate. Like the outdoor view analysis approach, the simulation casts rays at each sensor point, as illustrated in Figure 5.16 (Turan and Reinhart, 2019). It evaluates how much of a internal space can be seen from a single point. Building upon this work and the outdoor view analysis method presented in this chapter, there is an opportunity to further explore how the holistic visual experience can be quantitatively analyzed.

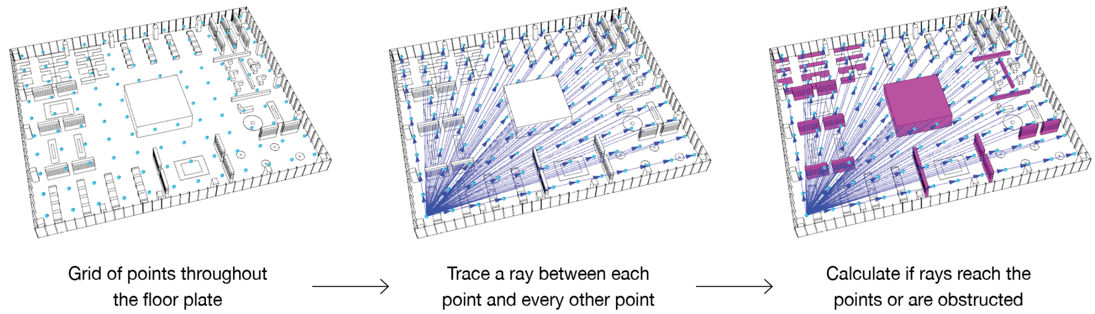


Figure 5.16: Mapping interior visual connectivity. The proposed approach, similar to the MVP, calculates the percentage of the interior space that can be seen from a particular point.

5.4 Summary of Contributions

In this chapter, we present a framework for evaluating spatially-distributed views in open plan work spaces. The method is built upon the idea that a view depends not just on select visual objects, but rather the aggregation of all objects seen in the landscape. The aim is not to measure the quality of a view, but rather to quantify the compositional elements that contribute to the overall visual experience. Previous analysis methods have evaluated views from a few select positions on a building's perimeter, looking outward to specific objects of interest. We evaluate views that occupants see as they move through a floor plate, accounting for dynamic visuals as they change position. The objectives of the method are three-fold: first, it is computationally lightweight such that it can be applied to a large sample of spaces throughout a city; second, it can be applied in parallel with daylighting analysis without significant overlap in the results; and third, it characterizes the view spatially distributed throughout a floorplate rather than at distinct points on a building's facade.

The framework evaluates views at individual nodes within an analysis grid across the entire floorplate. At the point level, the minimum view potential (MVP) represents the fraction of total rays that intersect with outdoor view objects. At the floor level, the spatial view access (sVA) summarizes how many points meet the MVP threshold.

We apply the framework to a sample of 5,154 office spaces throughout Manhattan. The results show that, using a MVP threshold of 3% to indicate high view access, on average 5% of each floor's area has high view access. For the floors with the greatest view access (90th percentile), 17% of the total floor area has high view access. The urban-scale simulations provides a distribution of the view access in office floors across Manhattan.

This simulation approach has yet to be validated. However, as will be described in Chapter 6, the approach does show statistical significance in the economic analysis. This is not a confirmation of the method's validity, yet it suggests that the method is differentiating views to some degree. This work is the first step of a more robust view evaluation method for use within architectural practice. To this end, the view analysis framework is a comprehensive computational methodology for evaluating view performance in architectural, spatially-distributed terms, using a flexible quantitative metrics that describe the occupants' visual experience in architectural space.

6. Views: Real Estate Value

This chapter presents the results of the hedonic regression analysis to measure the impact of daylight and views, together, on net effective rent observed in lease transactions. The multivariate hedonic regression model employed is an expansion of the specification in Equation 4.1, operationalized in the following functional form:

$$logY_i = \alpha + \varphi D_i + \beta B_i + \gamma L_i + \delta N_i + \omega T_i + \varepsilon_i, \tag{6.1}$$

where the dependent variable Y is the realized net effective rent per square foot for rental contract observation i. D represents two variables of interest, spatial daylight autonomy (sDA) and and spatial view access (sVA). The view metric, sVA, is included as a dummy variable indicating if a rental contract observation i has high view access—defined to be at least 10% spatial view access with 3% minimum view potential (10% sVA_3). The daylight metric is included in same form it was used in Chapter 4, as categorical variable indicating the daylight autonomy level ($sDA_{300/50\%}$ 0–55%, 55–75%, 75–100%) for rental contract observation i. B is a vector of exogenous hedonic building characteristics (such as age, class, LEED certification, etc.) of the building in which the rental contract observation i is located. L is a vector of the lease contract terms (such as lease duration, transaction floor number, landlord concessions, etc.) for rental contract observation i. N is a vector of exogenous location fixed effects by Manhattan neighborhood, defined by 24 submarkets (such as Chelsea, Financial District, Grand Central, and Times Square). T is a vector of time fixed effects by quarter and year that the lease is executed, between 2010 and 2016. φ, β, γ, δ, and ω are the estimated parameter vectors, representing the functional relationship between each independent variable and the dependent variable. ε is the error term, a vector of independent, identically distributed regression disturbances. All variables are defined in Table C1 in the Appendix.

Adding view access to the regression addresses a key limitation of the hedonic pricing model results in Chapter 4. In the previous model, the daylight performance variable (sDA) serves as a proxy for both daylight and views. Daylight levels and views are intrinsically related to one another, yet they are unique visual qualities that each add to an occupant's experience in an office space. By adding a separate variable for views, in this chapter, we disentangle the impact of the two attributes on the rent price.

6.1 Data

In total, we analyze 6,267 lease contracts signed between 2010 and 2016, located on 5,154 floors throughout Manhattan. The regression model contains all the same variables as those in the daylight only regression model (Chapter 4), with the addition of a binary variable for spatial view access, 10% sVA_3.

Table 6.1 presents the descriptive statistics (mean and standard deviation) for the lease contract data as a whole, as well as in four sub-samples: observations with *no daylight or views*, *high daylight only*, *high views only*, and *high daylight and views*. High daylight is defined to be minimum 55% $sDA_{300/50\%}$ (combining the high and very high sDA categories); high view access is defined to be minimum 10% sVA_3. 64% of the contracts in the sample have neither high daylight nor views; 19% have high daylight only; 8% have high views only; and 8% have both high daylight and views. In total, 1,008 observation, or 16% of the full sample, meets the 10% sVA_3 view threshold.

The dependent variable is net effective rent in U.S. Dollars. As in the previous regression (Chapter 4), we use the logarithmic transformation of the variable to adjust for the slight skewness of the rent price distribution and to be able to interpret the result coefficients as percentage changes.

Figure 6.1 depicts the distribution of net effective rent values for the four sub-samples, along with the mean value in each sub-sample. The average net effective rent across all observations is \$49.94 with a standard deviation of \$20.55 per square foot (\$537.55 with a standard deviation of \$221.20 per square meter). Unsurprisingly, the average net effective rent for spaces with no daylight or views is lower at \$46.14 with a standard deviation of \$16.20 per square foot (\$496.65 with a standard deviation of \$174.37 per square meter). The sub-samples for high daylight only and high views only have similar average rent values at \$54.54 and \$56.94 per square meter, respectively (\$587.07 and \$512.90 per square meter, respectively). The sub-sample of contracts with both high daylight and views, notably, has an average net effective rent of \$62.29 with a standard deviation of \$4.06 per square foot (\$670.49 with a standard deviation of \$43.70 per square meter). This is \$12, or 25%, more than the average effective rent price per square foot across the entire sample. While this descriptive statistic alone does not confirm that there is a premium, it does signal that there seems to be a positive value for both daylight and views in the office spaces. The hedonic regression presented in the following sections measures the true effect of each variable on the rent price.

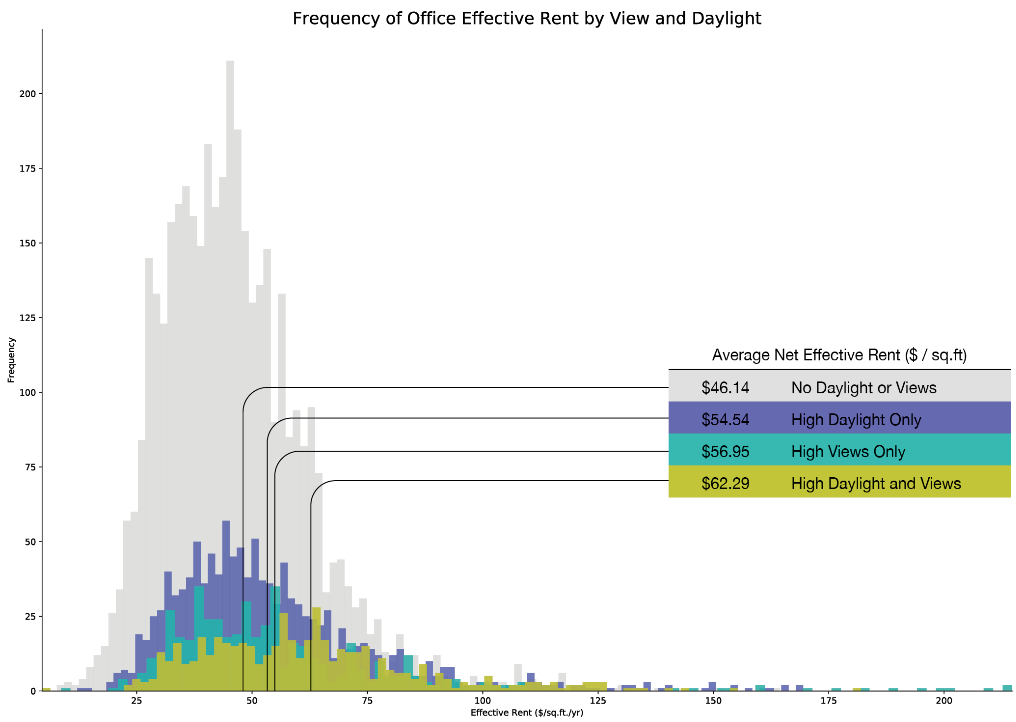


Figure 6.1: Distribution of rents by based on daylight and view performance. The four distributions show the rent price distribution for office spaces that: (1) do not meet either the daylight or view performance minimums; (2) meet the daylight but not the view performance minimum; (3) the view but not the daylight performance minimum; (4) both the view and daylight performance minimums.

Table 6.1: Summary statistics for variables included in the daylight and view hedonic model. Mean and standard deviation presented for all observations, as well as for the sub-samples representing office spaces that meet the minimum daylight and view performance thresholds separately and together.

		All Observations		No Daylight or Views		High Daylight Only		High Views Only		Daylight and Views	
Dependent Variables		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Net Effective Rent ($ per sq.ft.)		49.944	(20.551)	46.138	(16.207)	54.540	(23.463)	56.948	(29.278)	62.288	(24.391)
Log Net Effective Rent		3.839	(0.376)	3.773	(0.346)	3.921	(0.386)	3.948	(0.412)	4.058	(0.392)
Variables of Interest											
Spatial Day-	Low (0-55%)	0.724	(0.447)	-	-	-	-	-	-	-	-
light Autonomy	High (55-75%)	0.161	(0.367)	-	-	0.619	(0.486)	-	-	0.498	(0.500)
($sDA_{300/50\%}$)	Very High (75-100%)	0.115	(0.319)	-	-	0.381	(0.486)	-	-	0.502	(0.500)
Views: Minimum 10% of floor area (1 = yes)		0.161	(0.367)	-	-	-	-	1.000	(0.000)	1.000	(0.000)
Building Characteristics for Each Contract											
	A	0.545	(0.498)	0.460	(0.498)	0.572	(0.495)	0.892	(0.311)	0.818	(0.387)
Building Class	B	0.383	(0.486)	0.451	(0.498)	0.366	(0.482)	0.080	(0.272)	0.178	(0.383)
	C	0.072	(0.258)	0.089	(0.285)	0.062	(0.240)	0.028	(0.165)	0.004	(0.063)
——											
Building Age at Lease Signing (years)		67.766	(29.284)	73.225	(28.705)	67.305	(26.797)	41.669	(22.278)	51.098	(25.176)
Renovated building (1 = yes)		0.500	(0.500)	0.500	(0.500)	0.521	(0.500)	0.496	(0.500)	0.459	(0.499)
LEED Certified (1 = yes)		0.121	(0.326)	0.120	(0.324)	0.080	(0.272)	0.215	(0.411)	0.141	(0.349)
Fiber Lit Building (1 = yes)		0.950	(0.219)	0.937	(0.243)	0.954	(0.210)	0.992	(0.089)	0.998	(0.044)
Lease Contract Terms											
	0-15	0.620	(0.485)	0.826	(0.379)	0.327	(0.469)	0.227	(0.419)	0.075	(0.263)
Transaction Floor	16-30	0.276	(0.447)	0.155	(0.362)	0.553	(0.497)	0.367	(0.483)	0.484	(0.500)
Number	31-45	0.091	(0.287)	0.019	(0.136)	0.095	(0.294)	0.337	(0.473)	0.410	(0.492)
	46 and over	0.013	(0.113)	0.000	(0.000)	0.025	(0.158)	0.068	(0.252)	0.031	(0.174)
——											
	5 or less	0.393	(0.488)	0.402	(0.490)	0.428	(0.495)	0.263	(0.441)	0.365	(0.482)
Lease Duration (years)											

Table 6.1 – *Continued from previous page*

		All Observations		No Daylight or Views		Daylight Only		Views Only		Daylight and Views	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	6-10	0.423	(0.494)	0.395	(0.489)	0.499	(0.500)	0.361	(0.481)	0.527	(0.500)
	11-15	0.135	(0.342)	0.152	(0.359)	0.061	(0.239)	0.221	(0.415)	0.096	(0.295)
	16-20	0.036	(0.186)	0.037	(0.188)	0.011	(0.103)	0.118	(0.323)	0.012	(0.108)
	21-25	0.007	(0.084)	0.007	(0.084)	0.000	(0.000)	0.032	(0.177)	0.000	(0.000)
	26 or more	0.005	(0.070)	0.007	(0.081)	0.002	(0.041)	0.004	(0.063)	0.000	(0.000)
——											
Free Rent Period (months)	No free rent	0.184	(0.387)	0.196	(0.397)	0.181	(0.385)	0.118	(0.323)	0.157	(0.364)
	6 months or less free	0.546	(0.498)	0.521	(0.500)	0.656	(0.475)	0.442	(0.497)	0.584	(0.493)
	7-12 months free	0.228	(0.419)	0.240	(0.427)	0.153	(0.360)	0.299	(0.458)	0.243	(0.429)
	13-18 months free	0.035	(0.184)	0.040	(0.196)	0.009	(0.095)	0.084	(0.278)	0.012	(0.108)
	19-24 months free	0.005	(0.068)	0.002	(0.042)	0.002	(0.041)	0.038	(0.192)	0.002	(0.044)
	Over 24 months free	0.003	(0.054)	0.002	(0.044)	0.000	(0.000)	0.018	(0.133)	0.002	(0.044)
——											
Landlord Concession (Work Type)	As-Is	0.016	(0.127)	0.018	(0.131)	0.012	(0.110)	0.016	(0.126)	0.018	(0.132)
	Built to Suit	0.001	(0.025)	0.000	(0.022)	0.001	(0.029)	0.002	(0.045)	0.000	(0.000)
	New Building Installation	0.044	(0.206)	0.041	(0.199)	0.056	(0.230)	0.030	(0.171)	0.055	(0.228)
	Not Specified	0.140	(0.347)	0.141	(0.348)	0.170	(0.376)	0.048	(0.214)	0.145	(0.353)
	Other	0.001	(0.025)	0.000	(0.022)	0.002	(0.041)	0.000	(0.000)	0.000	(0.000)
	Paint & Carpet	0.002	(0.042)	0.001	(0.035)	0.002	(0.050)	0.004	(0.063)	0.002	(0.044)
	Pre-Built	0.023	(0.149)	0.019	(0.138)	0.034	(0.180)	0.008	(0.089)	0.039	(0.194)
	Tenant Improvements	0.770	(0.421)	0.777	(0.417)	0.719	(0.450)	0.886	(0.319)	0.729	(0.445)
	Turnkey	0.003	(0.058)	0.002	(0.042)	0.004	(0.064)	0.006	(0.077)	0.012	(0.108)
——											
Transaction Size (sq.ft.)		34,335	(83,088)	39,474	(92,568)	11,904	(23,163)	68,119	(1.10e+05)	14,190	(30,255)
Sublease (1 = yes)		0.118	(0.323)	0.124	(0.330)	0.089	(0.284)	0.157	(0.364)	0.100	(0.300)
Partial Floor Flag (1 = yes)		0.523	(0.500)	0.526	(0.499)	0.548	(0.498)	0.508	(0.500)	0.455	(0.498)
Multiple Floors in Lease (1 = yes)		0.237	(0.426)	0.263	(0.440)	0.150	(0.357)	0.317	(0.466)	0.167	(0.373)
Tenant Broker (1 = yes)		0.628	(0.483)	0.628	(0.483)	0.576	(0.494)	0.761	(0.427)	0.618	(0.486)
Landlord Broker (1 = yes)		0.682	(0.466)	0.676	(0.468)	0.666	(0.472)	0.771	(0.421)	0.684	(0.465)

Table 6.1 – *Continued from previous page*

	All Observations		No Daylight or Views		Daylight Only		Views Only		Daylight and Views	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of Observations	6,267		4,041		1,218		498		510	

6.2 Results

The hedonic model dissects the effective rent price of lease contracts into individual building and neighborhood characteristics, estimating the added value of each characteristic. The dependent variable, net effective rent, is the value that the tenant is willing to exchange for a bundle of qualities in the leased space that include building characteristics, lease contract conditions, relative spatial market supply and demand, and macro-economic conditions.

We estimate Equation 6.1 using ordinary least squares with robust standard errors. We find that this form of the ordinary least squares model provides the best linear unbiased estimator of coefficients with heteroskedasticity-consistent robust standard errors (White, 1980). We consider two variables of interest: daylight ($sDA_{300/50\%}$) and views (sVA_3). For daylight, the low daylight (0-55% $sDA_{300/50\%}$) level serves as the base category, and the model measures the value of high daylight (55-75% $sDA_{300/50\%}$) and very high daylight (75-100% $sDA_{300/50\%}$) relative to the base. For view access, we specify a dummy variable to identify lease contract observations for floors with at least 10% sVA_3.

Table 6.2 presents the regression results. Column (1) presents the results of the model that includes only the daylight variable of interest sDA. The incremental build up of this model is explained in Chapter 4, Section 4.2. Column (2) presents the results of the model with both variables of interest, spatial daylight autonomy and spatial view access. Column (3) incorporates the interaction effects between daylight and views to complete the fully-specified model results. Column (4) presents results for a trimmed distribution, eliminating the lease contract observations with the top 1% of net effective rent values. All models control for location fixed effects, time fixed effects, building characteristics, lease contract terms, and the interaction between daylight and floor number.

The main results of the regression, presented in column (3) show that the model explains up to 59.7% of the variation in net effective rent. This is in line with the earlier established daylight-only model in column (1), as well as with previous studies that use the same data (Liu et al., 2016; Chegut and Langen, 2019). In this model, the results for daylight (sDA) are nearly identical as those in the daylight-only model: spaces with high daylight (55-75% $sDA_{300/50\%}$) have a 5.3% premium over spaces with low daylight, while spaces with very high daylight command a 6.4% premium over spaces with low daylight.[1] The view access (sVA) results show that, alongside the daylight impacts on net effective rent, spaces with high view access (10-100% sVA_3) have a 6.3% premium over spaces with low view access (0-10% sVA_3). To illustrate these values, consider a standard office space with low daylight and low view access that transacts for $50.00 per square foot ($538.20 per square meter). The same space with *high daylight and low views* would transact for 5.3% more or $52.60 per square foot ($566.19 per square meter), ceteris paribus. Alternatively, the same space with *high view access*

[1] For ease of interpretation of the results, the regression coefficients are converted into percentage changes in net effective rent (Y) by taking the exponent of both sides of Equation 6.1 and applying the approximation $e^x \sim 1 + x$. Thus, for example, the fitted coefficient of 0.053 for high daylight actually has a fractional effect on Y of $e^{0.053} = 1.054$. The approximation results in a marginal variation in the percentages that is less than the standard error for most coefficients.

and low daylight would transact for 6.4% more or $53.20 per square foot ($572.64 per square meter), ceteris paribus. The condition in which the space has both high daylight and high view access will be explored separately in Section 6.2.2.

The building characteristics and lease contract terms stay relatively unchanged between the daylight-only model in column (1) and the daylight and view access model in column (3). In most cases, the coefficients shift by 0.001-0.002, less than the standard error for the term. All of the building characteristics maintain a coefficient within this margin. The lease term characteristics that change are the following: The impact of 21-25 year lease terms (relative to 6-10 year lease terms) decreases from 20.4% to 19.2%. The discount for 19-24 months of free rent (relative to 0-6 months) shifts from -13.0% to -14.7%; and for over 24 months free, the discount shifts from -6.5% to -7.2%. The landlord concessions with the greatest impact increase slightly, namely the impact of a pre-built unit increases from 9.9% to 10.2% and a turnkey unit decreases from 14.1% to 13.7%. There is a decrease in the value of high floor numbers for all categories, especially for the highest floor numbers (floor 46 and over), for which the premium decreases from 32.1% to 27.0%. In Chapter 4 we identified that there is collinearity between daylight and floor number, and include an interaction term in the model to account for it. Similarly, there may be some collinearity between view access and floor number, though the relationship not as strong as depicted in Figure 5.15.

Like the building and lease term characteristics, the time and location fixed effects are relatively stable with the addition of views to the model. The macroeconomic conditions, represented by the transaction period (year-quarter from 2010 to 2016), show a steady positive increase in the price starting in late 2011 (relative to 2010, quarter 1). The location fixed effects, represented by the Manhattan submarkets (i.e. neighborhoods), have sizable impact on the net effective rent, ranging from -41.3% to 40.0% depending on the submarket (relative to Grand Central). All of the coefficients, including the time and location fixed effect variables, are presented in Table F1 in the Appendix.

6.2.1 View Access Variable: Robustness Checks

The view metric sVA_3 is a continuous variable from 0 to 100%. We tried specifying the variable in its continuous form as well as in incremental steps. These formulations of the view variable either showed weak or no statistical significance. When we instead specify the variable as a dummy indicator (as it is in the final specification), it is both statistically and economically significant, resulting in a positive 6.4% impact on the net effective rent with a standard error of 1.7%. From these results, one can infer that the dummy form of the variable may align better with the occupants' perception of views: that the space either has views or not. Like with daylight variation, occupants may not recognize small changes in daylight but instead label a space as either with a view or not. This is an area for potential future work, specifically incorporating user surveys to better understand how people observe and judge views in space.

Table 6.2: Hedonic pricing regression: daylight and view results. The dependent variable is the logarithm of net effective rent per square foot ($/sq.ft.). Column (1) presents the regression results of the model that includes only the daylight variable of interest sDA (from Chapter 4). Column (2) presents the results of the model containing both the daylight and views variables of interest, sDA and sVA. Column (3) incorporates the interaction effects between daylight and views, and presents the fully-specified model results. Column (4) presents results for a trimmed distribution, eliminating the lease contract observations with the top 1% of net effective rent values.

Variables	(1) Daylight Only	(2) Daylight + Views	(3) +Interactions	(4) Trimmed
Daylight: Spatial Daylight Autonomy (Base Level: $sDA_{300/50\%}$ 0-55%)				
High Daylight	**0.052*****	**0.051*****	**0.053*****	**0.044*****
(sDA 55-75%)	[0.014]	[0.014]	[0.014]	[0.014]
Very High Daylight	**0.063****	**0.060****	**0.064****	**0.063****
(sDA 75-100%)	[0.027]	[0.027]	[0.027]	[0.027]
Views: Spatial View Access, (Base Level: sVA_3 0-10%)				
High View Access	-	**0.037*****	**0.063*****	**0.044*****
(sVA_3 10-100%: 1 = yes)	-	[0.012]	[0.017]	[0.016]
Building Class (Base Level: Class A)				
Class B Building	-0.114***	-0.113***	-0.113***	-0.116***
	[0.010]	[0.010]	[0.010]	[0.010]
Class C Building	-0.200***	-0.199***	-0.200***	-0.203***
	[0.017]	[0.017]	[0.017]	[0.016]
Building Age at Lease Signing (years)	-0.010***	-0.010***	-0.010***	-0.010***
	[0.001]	[0.001]	[0.001]	[0.001]
Building Age, Squared	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Renovated Building (1 = yes)	0.040***	0.041***	0.040***	0.050***
	[0.007]	[0.007]	[0.007]	[0.006]
LEED Certified (1 = yes)	0.004	0.002	0.002	0.007
	[0.010]	[0.010]	[0.010]	[0.010]
Fiber-Lit Building (1 = yes)	0.022	0.021	0.021	0.019
	[0.016]	[0.016]	[0.016]	[0.016]
Lease Term Duration (Base Level: 6-10 years)				
Lease term 5 years or less	-0.047***	-0.047***	-0.047***	-0.041***
	[0.008]	[0.008]	[0.008]	[0.008]
Lease term 11-15 years	0.061***	0.060***	0.059***	0.056***
	[0.010]	[0.010]	[0.010]	[0.010]
Lease term 16-20 years	0.097***	0.097***	0.096***	0.085***
	[0.018]	[0.018]	[0.018]	[0.017]
Lease term 21-25 years	0.204***	0.197***	0.192***	0.194***
	[0.043]	[0.043]	[0.043]	[0.043]
Lease term 26 years or more	0.057	0.056	0.056	0.051
	[0.051]	[0.051]	[0.051]	[0.049]
Free Rent Period (Base Level: 0-6 months)				
No free rent	0.023**	0.024**	0.024**	0.022**
	[0.009]	[0.009]	[0.009]	[0.009]

Table 6.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)
7-12 months free	-0.033***	-0.034***	-0.033***	-0.024***
	[0.009]	[0.009]	[0.009]	[0.009]
13-18 months free	-0.054**	-0.056***	-0.056***	-0.048**
	[0.021]	[0.021]	[0.021]	[0.021]
19-24 months free	-0.130**	-0.141***	-0.147***	-0.113**
	[0.055]	[0.054]	[0.054]	[0.056]
Over 24 months free	-0.065**	-0.070***	-0.072***	-0.061**
	[0.027]	[0.027]	[0.026]	[0.027]
Transaction Size (sq.ft.)	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Sublease (1 = yes)	-0.171***	-0.171***	-0.171***	-0.160***
	[0.011]	[0.011]	[0.011]	[0.011]
Partial Floor Flag (1 = yes)	0.038***	0.039***	0.038***	0.030***
	[0.008]	[0.008]	[0.008]	[0.008]
Multiple Floors in Lease (1 = yes)	0.007	0.009	0.009	0.007
	[0.010]	[0.010]	[0.010]	[0.010]
Tenant Broker (1 = yes)	0.010	0.010	0.010	0.014*
	[0.008]	[0.008]	[0.008]	[0.008]
Landlord Broker (1 = yes)	0.035***	0.036***	0.036***	0.030***
	[0.009]	[0.009]	[0.009]	[0.009]
Landlord Concessions / Work Done (Base Level: Tenant Improvements)				
As-Is	0.041	0.040	0.041	0.033
	[0.029]	[0.029]	[0.029]	[0.029]
Built to Suit	-0.044	-0.041	-0.046	-0.017
	[0.069]	[0.066]	[0.067]	[0.059]
New Building Installation (NBI)	0.065***	0.065***	0.065***	0.066***
	[0.012]	[0.012]	[0.012]	[0.011]
Not Specified	0.032***	0.032***	0.032***	0.040***
	[0.009]	[0.009]	[0.009]	[0.009]
Other	0.012	0.017	0.018	0.019
	[0.056]	[0.056]	[0.055]	[0.056]
Paint & Carpet	0.058	0.054	0.052	0.068
	[0.059]	[0.060]	[0.060]	[0.056]
Pre-Built	0.099***	0.101***	0.102***	0.106***
	[0.021]	[0.021]	[0.021]	[0.020]
Turnkey	0.141***	0.135***	0.137***	0.134***
	[0.040]	[0.040]	[0.041]	[0.039]
Transaction Floor Number (Base Level: Floors 0-15)				
Transaction Floor Number 16-30	0.121***	0.116***	0.112***	0.104***
	[0.010]	[0.010]	[0.011]	[0.010]
Transaction Floor Number 31-45	0.225***	0.203***	0.187***	0.176***
	[0.021]	[0.022]	[0.023]	[0.023]
Transaction Floor Number 46+	0.321***	0.292***	0.270***	0.162***
	[0.069]	[0.069]	[0.069]	[0.059]
Interaction Effect: sDA Level x Transaction Floor Number				

Table 6.2 – *Continued from previous page*

	(1)	(2)	(3)	(4)
High sDA x Trans. Floor 16-30	-0.030	-0.030	-0.022	-0.025
	[0.020]	[0.020]	[0.020]	[0.019]
High sDA x Trans. Floor 31-45	-0.027	-0.026	0.006	-0.014
	[0.033]	[0.033]	[0.037]	[0.036]
High sDA x Trans. Floor 46+	0.073	0.081	0.118	0.219**
	[0.093]	[0.092]	[0.093]	[0.087]
Very High sDA x Trans. Floor 16-30	-0.042	-0.043	-0.034	-0.023
	[0.031]	[0.031]	[0.032]	[0.031]
Very High sDA x Trans. Floor 31-45	-0.070*	-0.066*	-0.038	-0.031
	[0.038]	[0.038]	[0.040]	[0.040]
Very High sDA x Trans. Floor 46+	-0.233**	-0.210*	-0.186*	-0.099
	[0.113]	[0.115]	[0.113]	[0.105]
Interaction Effect: Daylight (55% sDA minimum) x View Access (10% of floor area minimum				
Daylight x View Interaction	-	-	-0.051**	-0.022
	-	-	[0.023]	[0.022]
Location Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	–	Yes	Yes	Yes
Constant	3.928***	3.925***	3.923***	3.935***
	[0.034]	[0.034]	[0.034]	[0.034]
Observations	6,267	6,267	6,267	6,205
R-squared	0.602	0.603	0.603	0.594
F Adj R2	0.596	0.597	0.597	0.588

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.2.2 Interaction of Daylight and Views

As discussed in Section 5.2.3, view and daylight are closely related. If there are good views, often there is also good daylight, and vise versa. We deliberately specify the daylight (sDA) and views (sVA) metrics to disentangle the two properties. Yet, it is impossible to disassociate them completely. To test whether there is collinearity between the variables, we interact sDA and sVA, as presented in column (3). The interaction term is multiplication of the sVA dummy variable with a single sDA variable that includes both high and very high daylight (55-75% and 75-100% sDA) observations. Interacting the view metric with each categorical sDA bin (55-75% and 75-100% individually) yielded very small sample sets therefor we group all daylight values between 55-100% into one variable.

The interaction term represents the conditional impact of having both high daylight *and* high view access. The results show that the interaction term has a -5.1% impact on the net effective rent with a standard error of 2.3%. This means that, for a space with *high daylight and high view access*, the impact of both variables on net effective rent is the addition of +5.3%

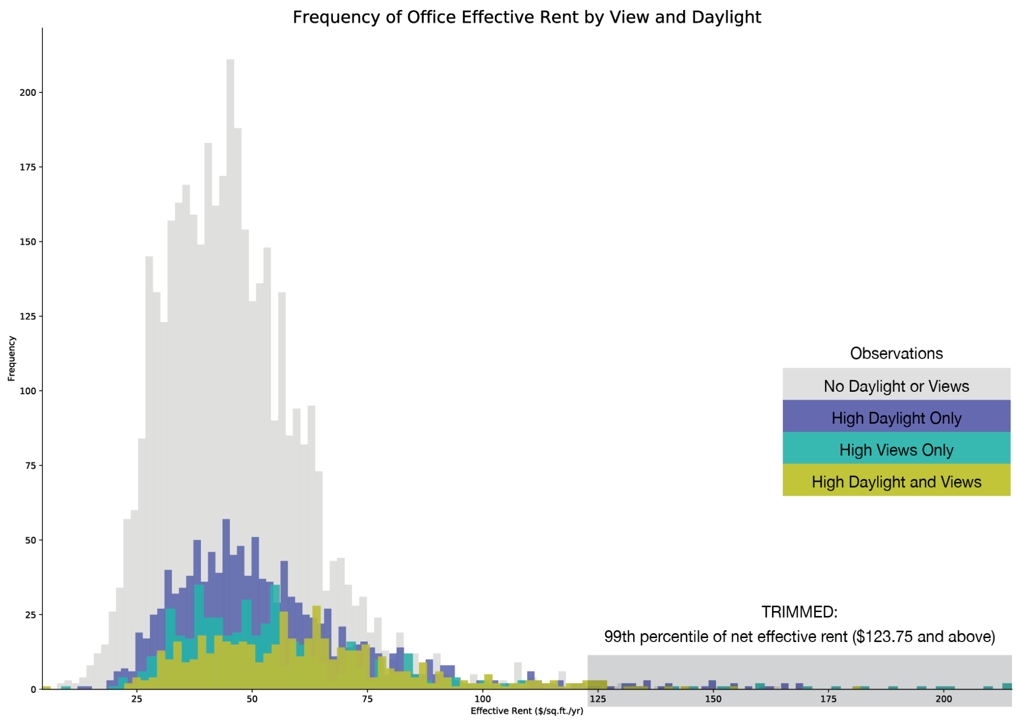


Figure 6.2: Distribution of rents by daylight and rent performance indicating the top 1% of observations that are trimmed in the fourth specification of the hedonic model. Table 6.4 presents the summary statistics for the net effective rent, daylight, and view access for the trimmed observations.

for high daylight, +6.3% for high views, and -5.1% for the interaction between daylight and views, resulting in a combined impact of +6.5%. Conceptually, the -5.1% coefficient for the interaction term indicates that there is value to having both high daylight and high views, however it is not necessarily much greater than having each quality on its own.

The 2.3% standard error for the interaction coefficient indicates that, while statistically significant, the effect of the interaction is relatively dispersed. Nevertheless, the result for the interaction effect is somewhat surprising, given that both daylight and views are highly valued in real estate. We expect that having both qualities in a space would yield to a higher premium than either characteristic on its own. These results prompt avenues of further investigation into the relationship between daylight and views, to better understand how people differentiate between the two visual qualities.

6.2.3 Outliers

The distribution of net effective rent has a strong positive skew. While the mean net effective rent is $49.94 (with std. dev. $20.55), the top 1% of the observations have rent values between $123.75 and $214.75, as shown in Table 6.3. To test the robustness of the final hedonic specification, we run the same model with a trimmed sub-sample. In the trimmed sample, the top 1% of the observations are eliminated, leaving observations in the interval [0, 0.99). This eliminates 62 observations, all with a net effective rent of $123.75 or above. Figure 6.2 highlights on the histogram the upper tail portion of observations trimmed from the sample. Table 6.4 summarizes the rent, daylight, and view access statistics for the observations in the trimmed top 1%.

The results of the model run with the trimmed sample are presented in column (4) of Table 6.2. In this case, the model explains up to 58.8% of the variation in net effective rent. This is, surprisingly, a slightly lower adjusted R^2 than in the full model specification in column (3). The coefficients for variables of interest decrease but maintain their statistically-significant positive effect on the net effective rent. The coefficient for very high daylight shifts slightly from 6.4% to 6.3%; and the coefficient for high daylight decreases from 5.3% to 4.4%. The view access variable coefficient shifts from 6.3% to 4.4%. This decrease in the coefficient values is logical given that the most expensive rented spaces tend to have high daylight and high view access.

Notably, in the trimmed model, the interaction between daylight and views loses significance completely. The elimination of the interaction term implies that there is no collinearity between the variables, and that the value of daylight and views are independent of one another. While this is unlikely to be completely true—human perception of these qualities are interrelated—the result suggest that there are likely dynamics between daylight and views in the upper tail of the observations that we are not capturing in the current model. This is is an area for further exploration moving forward.

6.3 Discussion

While evaluating daylight and views as independent variables provides insight into their individual impacts on rent prices, there are limitations to the approach. Notably, in order to separate the two characteristics, we disregard views of the sky. Computationally analyzing the sky exposure in a view is similar to assessing solar exposure. Therefore, to avoid overlap in the daylight and views, we do not consider sky exposure in the view metric. This constraint should be re-evaluated in future work.

Broadly, daylight and views are two visual qualities that are closely related. Is their impact on the value of office rents inherently dependent on one another? In the hedonic model presented in Chapter 4, we postulated that the daylight variable was likely serving as a proxy for both daylight and views. While both qualities are valued in the real estate market, we question if they can be valued as independent characteristics. The results presented in this chapter suggest that while they are collinear, each has its own economically and statistically significant value. The addition of the view variable does not change the previously established value premium of daylight; the values for both high and very high daylight shift by 0.01, as presented in Table 6.2 columns (1) and (3). However, the significance of the interaction term indicates that their mutual presence in a space impacts their value. When both high daylight and high view access exist in a space, their combined value is 6.5%—just over the impact of

Table 6.3: Net effective rent: detailed summary statistics, including the minimum, maximum, and 99^{th} percentile. The first column describes the statistics for the full sample and the second column describes the statistics for rent contract observations that have both high daylight and high view access.

Net Effective Rent ($ per sq.ft.)	All Observations	High Daylight and Views
Mean	49.94	62.29
Std.Dev.	20.55	24.39
Minimum	4.50	4.53
Maximum	214.75	181.97
99th Percentile	**123.75**	**133.40**
Observations	6,267	510

Table 6.4: Descriptive statistics of rent value, daylight, and view access for top 1% of lease contract observations. These are the 62 observations that are cut in the trimmed sample.

	Mean	Std. Dev.	Min	Max
Net Effective Rent ($ per sq.ft.)	152.27	(23.86)	125.38	214.75
Spatial Daylight Autonomy, $sDA_{300/50\%}$ (%)	57.9	(11.3)	12.2	92.7
Spatial View Access, sVA_3 (%)	13.7	(18.2)	00.0	68.5
Observations	62			

either characteristic on its own. This finding encourages further investigations into how both daylight and views are characterized in space, and how occupants value each quality. Utilizing empirical real estate data, we can continue to explore how the each both visual attributes manifest in economic preferences.

6.4 Summary of Contributions

In this chapter, we measure the financial impact of daylight and views on the rental price of office spaces in Manhattan. We carry out a hedonic pricing regression to identify the impact that each property has on the net effective rent for office leases. The hedonic method disentangles the value that individual characteristics have on the overall rental price of the property. In this approach, the value of the daylight and view attributes is independent of the other building, neighborhood, and lease contract characteristics included in the model.

The results, presented in column (3) of Table 6.2, show that spaces with high levels of daylight (55-100% $sDA_{300/50\%}$) have a 5 to 6% premium over spaces with low daylight; and spaces with high access (10-100% sVA_3) to views have a 6% premium over spaces with low access to views. Because daylight and views are closely entwined, their combined impact on rent price is considered with the inclusion of an interaction term that accounts for their collinearity. Accounting for their interaction, we find that the value of spaces with *both* high daylight and view access, similarly, is 6%. This result indicates that there is value to having both high daylight and high views, however it is not necessarily greater than having each quality on its own.

To test the robustness of the interaction term, we run the model on a trimmed sub-sample that excludes the observations with top 1% of observations by transacted rent price (i.e. 62 of the 6,267 lease contract observations). The trimmed model results maintain a positive coefficient on the daylight and view variables while eliminating the interaction term. The result of the trimmed model indicates that there may be dynamics in the upper tail of the rent observations that are not considered in the current model.

The 5 to 6% impact of daylight and view access on the net effective rent, both individually and together, is comparable in magnitude to other building attributes and lease characteristics that a tenant considers when choosing an office space. For example, a renovated building has a premium of 4.0%, relative to a non-renovated building. Amongst landlord concessions, a new building installation has a 6.5% added value and a turnkey property has a 13.7% added value, relative to tenant improvements.[2] Recognizing that daylight and views have statistically and economically significant value proportionate to these other qualities can drive decision-making of various stakeholders in commercial building production and management. It is well known that daylight and views positively impact the health and well-being of occupants of a building; the results of this chapter indicates that the benefits translate into economic terms, too.

[2]Compstak defines tenant improvements as the negotiated allowance landlord returns to tenant to renovate or improve space leased.

Part IV: Impact, Outlook and Conclusion

The association with capital, while withdrawing from a project of architectural autonomy, opens new avenues for questioning architecture's relationship to the world, to allied fields, and to cultural economy. The relationship with capital provides both limitations and opportunities for architectural production that make its engagement with the world messier and more complex. Innovation in architectural production occurred not only in design, materials, aesthetics, and technology, but also in finance.

Sara Stevens, *Developing Expertise: Architecture and Real Estate in Metropolitan America*

7. Conclusion

In this dissertation, I quantitatively examine the relationship between architectural performance attributes and financial value of commercial office spaces. I specifically evaluate two design attributes: daylight and views. Previous chapters motivated the work; reviewed background literature; presented results of the daylight and views performance analysis; introduced an original view evaluation method for an urban context; and measured the value of the visual design attributes using a hedonic pricing model. This final chapter summarizes the contributions of the dissertation, examines the relevance and directions for future work, discusses the impact, and offers concluding remarks.

7.1 Dissertation Contributions

It is well accepted that daylight and views add value to a space, particularly offices. Brokers and developers cite the premium for these features based on their own experiences (Kaysen, 2017). Real estate listings nearly always mention natural light and views. The marketing material for a new office building will reliably include renderings of rooms with floor-to-ceiling glazing that have expansive vistas and light flooding in. Yet, despite the industry-wide acknowledgement of their value, up to this point, there has been no study to measure the premium for daylight and views across a real estate market. This work, for the first time, identifies the value for daylight and views for commercial offices in Manhattan.

Beyond the specific quantitative outputs, however, the dissertation integrates methods of computational architectural performance simulation and statistical real estate finance modeling to examine the value of building spatial attributes in a new way. The hybrid research foundation produces both new methodological frameworks and novel analytical results. This dissertation makes the following particular contributions:

1. Manhattan-wide daylight performance dataset: Chapter 3 presents a method for simulating spatially-distributed daylight at the urban scale. Through the proposed approach, we create an original dataset of spatial daylight autonomy (sDA) performance

results in office spaces throughout Manhattan. The average $sDA_{300/50\%}$ throughout the floors is 43%, with a standard deviation of 23%. The median $sDA_{300/50\%}$ is 39%. Sixteen percent of the floors have high daylight autonomy (i.e., $sDA_{300/50\%}$ between 55% and 75%) and 12% have very high daylight availability ($sDA_{300/50\%}$ over 75%).

2. View analysis methodology: Chapter 5 introduces an original computational method for simulation views in an urban context, as well as the metrics minimum view potential (MVP) and spatial view access (sVA), by which the views can be quantitatively described. The MVP describes how much of an outdoor view can be seen from one point in the analysis area, and is measured as a percentage of total rays cast from that point that intersect view elements in the urban context. sVA is a measurement of the sufficiency of MVP viewing potential in an indoor space. It is defined as the percentage of the analysis area that has a minimum viewing potential.

3. Manhattan-wide view performance dataset: In Chapter 5, additionally, the proposed view analysis method is applied to create an original dataset of sVA performance results in offices spaces throughout Manhattan. The average sVA_3 for the office floors is 4.8% with a standard deviation of 11%. Of the 6,267 lease contracts in sample, 1,008 or 16% of the spaces have at least 10% sVA_3, the minimum threshold set for a high view access.

4. Value of daylight and views: Chapters 4 and 6 measure the premium for daylight and views in commercial office rent prices. The results show that spaces with high levels of daylight (55% and above $sDA_{300/50\%}$) have a 5 to 6% premium over spaces with low daylight (less than 55% $sDA_{300/50\%}$). Spaces with high access to views (10% and above sVA_3) have a 6% premium over spaces with low access to views (less than 10% sVA_3). The combined value of spaces with *both* high daylight and view access, similarly, is 6%, indicating that the impact of daylight and views together is significant but is not additive. These values are ceteris paribus, or independent of all other building, lease, location, and time characteristics included in the hedonic model.

5. Hybrid design performance-finance analysis: Methodologically, this dissertation combines design performance simulation with real estate financial modeling. The approach is conceptually illustrated in Figure 7.1. By combining theory and methods from both worlds, the work interrogates the conception of spatial attributes in buildings simultaneously as architectural elements and financial assets.

   The hybrid approach is demonstrated in the development of the view analysis methodology presented in Chapter 5. Assuming that views are economically valued in buildings (as is conventionally well-accepted), we test a range of sVA thresholds in the hedonic regression to identify which cut-off results in a coefficient that reflects the market value of views. Based on the hedonic model results, we select 3% MVP and 10% sVA_3. These are rough ballpark values that need to be further tested and validated. Nevertheless, the iterative performance-finance approach allows for new information to guide the development of methods.

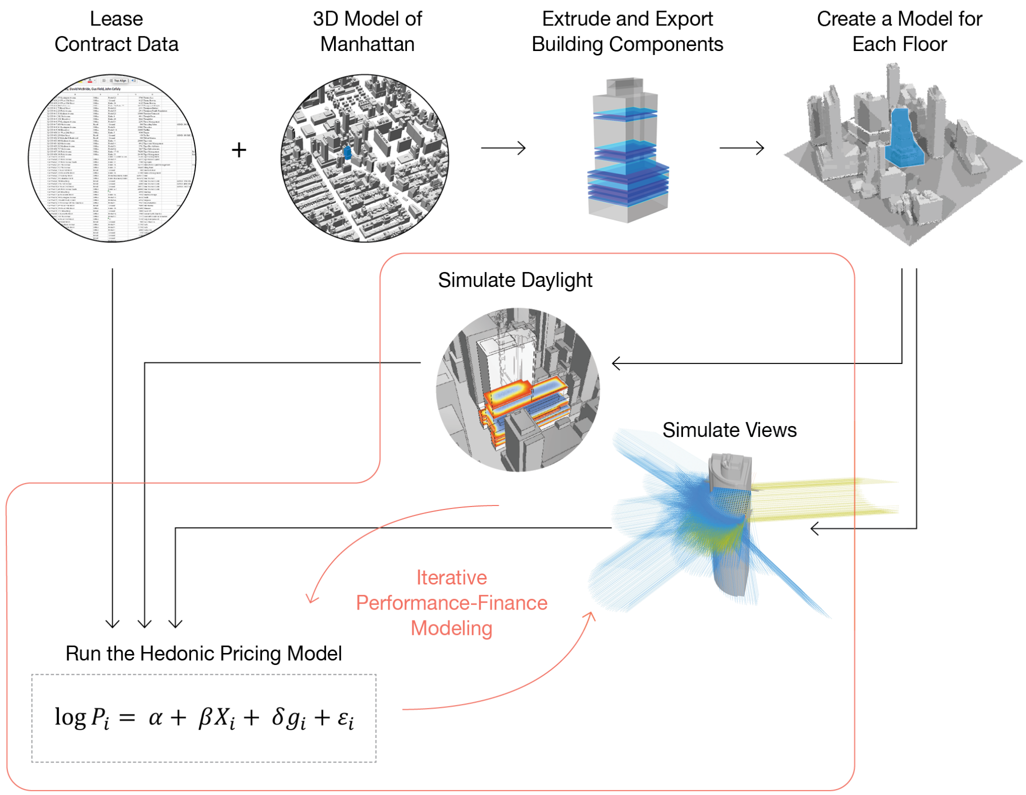


Figure 7.1: Iterative performance-finance methodological workflow. The workflow introduced in Chapter 1 (Figure 1.2) is shown again here with the addition of the red polygon, which conceptually represents the hybrid performance-finance methodology that is developed and used in this dissertation. The financial data inform the development of the performance simulations; and inversely, the building performance methods inform how a building's spatial and architectural attributes are specified in the financial models. Notably, data is the foundation of both urban-scale performance simulations and the hedonic analysis. As the amount and resolution of data in cities increase, the performance-finance approach to studying buildings becomes evermore feasible.

7.2 Relevance and Impact

This work has conceptual, practical, and cultural relevance to those engaged in the planning, design, and operation of building. For one, it frames the value of specific design attributes in economic terms. At the same time, it provides new approaches to urban-scale design performance analysis and real estate modeling.

7.2.1 Defining and Delineating the Value(s) of Design

In this dissertation, value is defined as the economic worth of an attribute. However, as discussed in Chapters 1, there are different types of value—social value and environmental value, for example. For daylight and views, the social value of the attributes is their impact on occupant health and well-being; and the environmental value of daylight is its role in reducing a building's electrical lighting load (but also detrimentally increasing solar heat gain). Rarely is the financial value of daylight and views cited as the driver of architectural design. Yet, in real estate, the economic worth is often the decision-making force. Architectural critic Jacob Moore and historian Susanne Schindler write that "[...] for most forms of real estate development, a property's exchange value (how much its sale will bring on the market) is more important than its use value (what functional benefit it brings to its residents)" (Martin et al., 2015). In short, financial returns drive the production of buildings. This raises questions about the purpose of buildings: Who is the building for and what need is it fulfilling? To evaluate the social and environmental impacts of buildings, it is imperative to question the existing dynamics and evaluate how the dominance of capital steers design.

Eugene Kohn, architect and co-founding partner of Kohn Pedersen Fox (KPF), acknowledges the domineering role of finance in architectural practice, writing about office buildings: "A building conceived strictly as a financial instrument takes on a different character from one that is viewed as a place of work—a source of productivity and a home during working hours—as well as an important component of the urban or suburban environment." While Kohn acknowledges the authority of financial forces, he maintains faith in the financiers:

> It is most critical to realize that the tenants and their willingness to pay for quality also influences the product. There obviously must be a balance between the two goals—one is short-term economics, and the other is the quality of the building and the work environment. The best developers and REITs [real estate investment trusts] strike this balance. They are confident that companies will pay higher rent for quality buildings, thus yielding a proper return for the investor, the risk taker. (2002)

Kohn has an optimistic outlook about the existing system and believes in the economic equilibrium of supply and demand. This is a premise worth challenging. Can buildings be made differently? In the face of public health vulnerabilities and climate change, we should evaluate all levers in the building production process. Unpacking the complex relationship between social, environmental, and economic values in the built environment is beyond the scope of this dissertation. However, the hybrid iterative methodology I use to evaluate the value of daylight and views is an approach to evaluate linkages between various systems in building production.

In the following two sections, I discuss juxtapositions of different types of value that are particularly relevant to the daylight and view analysis in this dissertation: tenant value versus occupant value, and occupant value versus environmental value. I differentiate these as follows: tenant value is the economic worth of spatial attributes, as the tenant pays the rent; occupant value is the social worth, as the occupants' experience the impacts of the building attributes as they spend time in the space; and environmental value encompasses the contributions that the attributes make to the sustainability and environmental performance of the building.

Figure 7.2: Renderings of One Vanderbilt, a new office building under construction next to Grand Central Terminal in Manhattan. The tower, projected to be completed in late 2020, is developed by SL Green Realty Corporation and designed by Kohn Pedersen Fox (KPF). The interior renderings romanticise daylight and views, exaggerating the visual attributes to an unrealistic extent. All renderings come from the building's website *onevanderbilt.com* (SL Green, 2020).

7.2.2 Tenant Value vs Occupant Value

In selecting an office property, a tenant is often evaluating a vacant space, such as those depicted in the photos in Chapter 1, Figure 1.1. If the building is new construction, then they might see idealized renderings of the space, like those of One Vanderbilt, a new office tower under construction in Manhattan, shown in Figure 7.2. The building, design by KPF, is marketed as a world-class office building that caters to today's office culture. The interior renderings present a romanticized picture of the work environment. With unobstructed floor-to-ceiling glazing, the views are spectacular. However, the flood of light into the space as shown would probably result in uncomfortable glare and excessive solar heat gain. To combat this, most likely, these large panes of glass will be accessorized with shading devices that control the daylight penetration and block a portion of the view. Simply put, the office space that takes shape once occupied will differ from the office space considered by the tenant when they are considering a rental property.

Tenants are wise enough to consider the realities and recognize the needed modifications when evaluating potential spaces. Even so, the experience of being in the space once it is occupied cannot be fully anticipated in advance. Therefore, the occupants' experience in the space, and subsequently the value they place on spatial attributes in the space may differ from the values of the tenant. The disparity between idealized and real office environment is exemplified by open office plans. In theory, open office arrangements encourage engagement and collaboration between occupants. As such, it is an attractive model for organizations. It is the spatial layout that dominates the current office property market—the renderings of One Vanderbilt in Figure 7.2 are a case in point. However, as popular as open floor plans are for tenant organizations, studies show that occupants in these spaces interact less with one another and long for visual and sound privacy (Bernstein and Turban, 2018; Kim and De Dear, 2013). There is a dissonance between the airy open office plan romanticized in real estate marketing images and the reality experienced by the occupants. This discrepancy is an area for further research, to better understand how not only the rent-paying tenant but also the space-occupying workers value attributes of a space.

7.2.3 Tenant Value vs Environmental Value

The renderings of One Vanderbilt in Figure 7.2 portray floor-to-ceiling glazing with unbridled sunlight flowing through. As mentioned in the previous section, this facade condition would, in reality, lead to glare discomfort and excessive solar heat gain. For office buildings, which are cooling-dominated environments, the solar gain from uncontrolled daylight penetration is an added energy burden. Daylight design in a building requires balancing the lighting and thermal needs (Reinhart, 2014). Daylight penetration reduces the electrical lighting load but adds to the cooling needs in a space. The increased heat gain is particularly an issue for buildings with high window-to-wall ratios, i.e. most new construction. In New York City office buildings, on average, lighting accounts for 13% and space cooling accounts for 11% of of total source energy use (Urban Green Council, 2017).

In terms of financial value, the results of this dissertation show that high daylight has 5 to 6% value over low daylight spaces. To evaluate the trade-off between energy operating costs and rental value of daylight, we need to consider the utility expenses for the office buildings. The structure of leases in our sample vary such that in some cases the tenant pays for utilities, while in others the owner pays.[1] According to the Building Owners and Managers Association, utilities in commercial office buildings costs on average $2.14 per sq.ft. (2018).[2] Based on our sample, average office rent in Manhattan is $50 per sq.ft.—5% value for high daylight

[1] The breakdown of lease types in the data sample is presented in Table D1 in the Appendix.

[2] It should be noted that this value is not specific to New York.

equates to $2.50 per sq.ft, roughly the equivalent of the utility costs. However, given that lighting and cooling are a fraction of this total utility expenses, there is a significant premium to higher daylight even with added energy costs.

This presents a troubling picture for energy efficiency measures in office buildings. If the premium for daylight outweighs the added utility costs, there is no incentive to increase energy efficiency. For this reason, regulations such as New York City's Local Law 97 (LL97), enacted in 2019, are critical. The law requires that all public and private buildings over 25,000 square feet meet prescribed energy intensity limits to reduce city-wide emissions 40% by 2030 and 80% by 2050, in line with Paris Agreement objective. LL97 applies to about 50,000 buildings or 60% of NYC's total built area, a mix of multi-family residential and commercial (Urban Green Council, 2019). Regulations such as LL97 can be used to balance the financial trade-offs between tenant preferences and environmental performance. Identifying the real estate value of the design attributes, as in this dissertation, is one step toward this sort of economic balancing.

7.3 Directions for Future Work

The work presented in this dissertation poses multiple avenues for further examination. There are several areas in which more work can be done:

- Validation and development of the building assumptions: We made several assumptions about building envelope and interiors in the construction of the 3d geometric model for the daylight and view simulations. Namely, we assumed a 30% window-to-wall ratio on all buildings, a 11-foot floor to ceiling height, and an open floorplate with no core. Moving forward, these assumptions should be reconsidered. The window-to-wall ratios can be specified for each building based on measurements taken off of the facade (see Section 3.1.3). It is more difficult to obtain information about the interior layout and dimensions of each floor in the sample. However, by evaluating the building footprints, age, structural system, and heights, it may be possible to building typologies that more closely reflect the interior layout in each building.
- Further development of the view methodology: The view analysis method introduced in this dissertation is a preliminary framework for evaluating spatially-distributed views in an urban context. The proposed approach should be further developed and tested. Most importantly, the method and metrics should be validated through a human subject survey. Doing so will shed light on whether the metrics reflect what people in fact prefer in views. Additionally, the computational approach used in the view analysis could be further explored. Ray-casting is a technique that, while accurate for modeling daylight, is not ideal for view assessment. Incorporating image-based techniques into the analysis may further the simulated depiction of views.
- Expansion of the design-finance analysis: The hedonic models presented in Chapters 4 and 6 may serve as a framework for integrating design performance analysis into future pricing regressions. The real estate finance analysis approach used in this work can be

applied to different cities around the world.[3] The hedonic analysis can also be applied to different building typologies, such as residential structures; or different property markets, namely the asset market. Lastly, other types of building performance simulation can be used to introduce new parameters in the hedonic model. Beyond daylight and views, environmental conditions that vary spatially such as outdoor thermal comfort or air quality may be evaluated.

- Contextualize the design-finance work: The design value measured through the hedonic analysis provides insight into the value that tenants place on daylight and views. However, the person deciding on the lease terms for a space is not necessarily the person who will occupy the space (especially for large commercial tenants). Therefore, the value measured in the hedonic regressions does not necessarily reflect the value that *occupants* place on the attributes. Further work should be done to compare the rent premium that commercial tenants pay with the impact that daylight and views has on the people in the space. This could be done through occupant surveys. Moreover, there is an opportunity to explore whether the economic value placed on daylight and views is reflective of their impact on health, well-being, and productivity of the people inside the space. An expansion of the methodology can inform building codes and regulations, as well as tie into public health data to understand environmental impacts of buildings on people.

7.3.1 The Evolution of Workplace Environments

The notion of the ideal office space is evolving. The changing climate, economy, technologies, and culture all feed the metamorphosis of workplace spatial arrangements. Over time, the quintessential office has shifted from the large daylit hall of the Larkin Building, to the corner office on the top floor of a skyscraper, to open-plan workspaces, and most recently to the shared and flexible co-working model (Russell, 2000; Weijs-Perrée et al., 2019). As history has shown, the development of office typologies responds directly to the times. There are countless examples of this—one is the evolution of European office spaces in the 1980s: "The need to give nearly every office a window inspired a great deal of architectural innovation in Europe," writes architecture critic James Russell. "The push for a window and fresh air came out of an ecological sensibility and a suspicion of mechanically treated air that is deep seated in the culture of many Northern European countries" (Russell, 2000).

We are at a similar transformational crossroads today. There is a move away from the open-plan arrangement as people recognize their negative effects on occupant well-being and productivity (Colenberg et al., 2020). Most recently, the COVID-19 pandemic of 2020 has re-centered attention on occupant health in the workplace. At the same time, climate change

[3] In this expansion of the work, it is worth considering that office leasing arrangements vary from one global region to another. In some places, for example, it is more common for a company to own their workplace building. In these cases, it would be worthwhile to apply the model to an asset market, to consider the sales transaction of properties in place of rental contracts. Moreover the physical typology of the offices change from place to place, with different workplace code requirements (Russell, 2000).

necessitates radically rethinking how we design, construct, and manage buildings. Pressing health and environmental concerns, along with the prevalence of mobile technology, raise questions about the functionality, efficiency, and purpose of conventional office spaces. Flexible remote working arrangements may completely upend the traditional office: tenants may opt out of long-term commitments to any one space, and businesses may allow employees to work from anywhere (as some already do) (Kelly, 2020). As such, office real estate will also evolve. The challenges of conventional office spaces that pertain to health and environmental issues are mainly spatial in nature—they are associated with either the organization of the space or the conditioning of the space. Building science, as a discipline, evaluates these very conditions. As daylight and views are modeled in this dissertation, so can other indoor environmental conditions be computationally analyzed. At this moment when the nature and purpose of workplaces are being rethought, applying building performance methods alongside financial models can inform the next incarnation of the office.

7.4 Final Remarks

The value of daylight and views in buildings, from an experiential and human health standpoint, is well-known. In the financial models that inform investment decisions, however, these visual design attributes are often considered qualitatively and vaguely. In this dissertation, I translate the benefit of these attributes into quantified economic terms to provoke action: by knowing the financial value of specific spatial qualities, project teams are given new agency to advocate for high-performing architectural design; at the same time, economically valuing individual design attributes can inform building codes and policy. Recognizing the preferences of those on the demand-side of real estate reveals what indoor environmental strategies may be naturally adopted by the market. Where specific measures are not preferred by tenants, there is an opportunity for regulations to step in. For example, while tenants are willing to pay for spaces with preferable visual characteristics, they may not as overtly value indoor environmental attributes that impact air quality, acoustics, and thermal comfort. In these cases, codes serve to ensure attention is paid to these aspects of the building. Particularly for design elements that directly contribute to occupant health or environmental sustainability, recognizing the economic worth can be used by stakeholders to push for change.

Daylight and views are attributes of the visual experience that are shaped directly by architectural design. They are features that impact the health and well-being of the occupants, as well as contribute to the delight of spatial perception. As such, they are experienced by individuals in a building at a human level. Yet, in real estate, the experiential quality of daylight and views can be lost in the tally of building specifications. Moving beyond simplification of these qualities, this work integrates the nuance of visual attribute performance into financial analysis. Measuring the economic value of daylight and views distributed throughout a space provides a new way through which to frame the building's relationship to both its occupants and its surrounding world.

A. Data and Variable Descriptions

Table A1: Summary and description of datasets used in the dissertation. Some data is used only in the view analysis work (Chapters 5 and 6)—these datasets are noted in the table.

Data Source	Description
CompStak	CompStak is a database of crowd-sourced commercial lease contract data that is cross-checked against multiple broker submissions. It includes net effective rent (the actual amount of rent paid by tenant, i.e. the starting rent minus landlord concessions), as well as contract characteristics (space type, least transaction type, lease term duration, rent free period, sublease, transaction floors, tenant broker, landlord broker, and landlord concessions) and building characteristics (building class, building age, and renovation year) (CompStak Inc., 2018).
New York City Department of Information Technology and Telecommunications (NYC DOITT): 3D Building Massing Model; Green Spaces and Hydrography planimetric basemap (*green spaces and hydrography maps used in the view analysis only*)	The NYC DOITT three-dimensional building massing model is based on a 2014 aerial survey of the city, developed to a mix of Level of Detail (LOD) 1 and 2. LOD is a standard specification used in building information modeling to indicate the resolution to which the model is developed (NYC Department of Information Technology & Telecommunications, 2016b). GIS data of the green spaces and waterways around Manhattan are additionally used in the view analysis model (NYC Department of Information Technology & Telecommunications, 2016a; NYC Department of City Planning Information Technology Division, 2018a).

(Table A1 continued from previous page.)

Data Source	**Description**
New York City Department of City Planning: MapPLUTO	The MapPLUTO dataset from the NYC Department of City Planning provides additional building characteristics (NYC Department of Planning, 2016).
Green Building Information Gateway (GBIG)	The GBIG database, authored by the U.S. Green Building Council, lists LEED certified projects around the world (U.S. Green Building Council, 2018).
Geotel	The Geotel telecommunications infrastructure database lists the buildings that are fiber lit (are connected to a high-speed fiber optic cable) (GeoTel, 2018).
Curbed New York: Map of NYC Iconic Buildings (*used in view analysis only*)	A list of 30 iconic buildings throughout the five boroughs of New York City (with 22 located in Manhattan) published online by Curbed New York in 2019 (Curbed, 2019).

B. Window-to-Wall Ratio Survey Results

We assume a 30% WWR for all of the office spaces. To validate the WWR assumption, MIT graduate student Ana Alice McIntosh visually surveyed all buildings with floors in the sample. Using images of the buildings from Google Earth and Google Maps, Ana measured the area of window on each facade in Rhino. The distribution of primary facade WWR values are presented in Figure 3.3. Based on the facades in the sample she created a catalog of window typologies, depicted in Figure B.1.

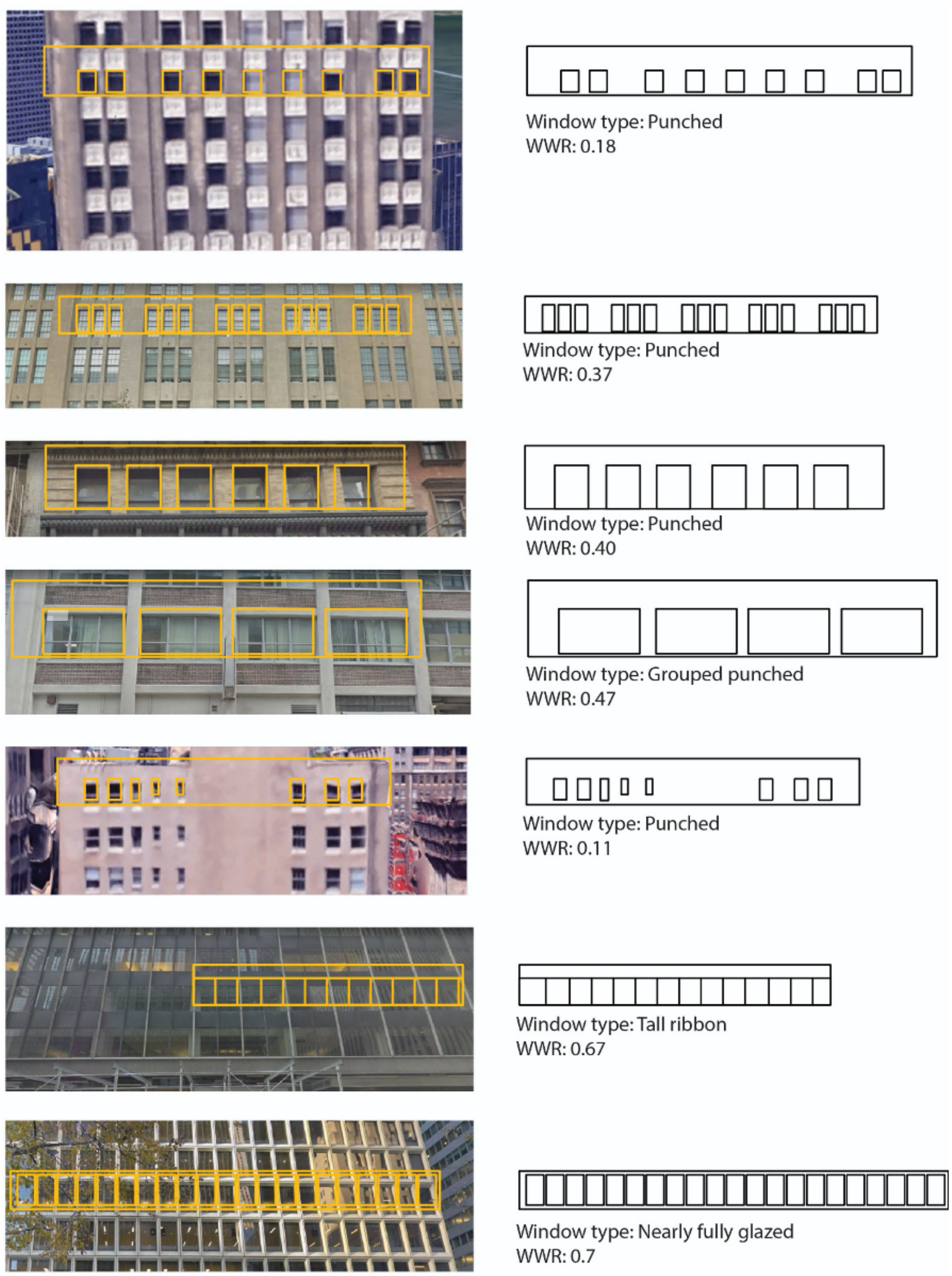


Figure B.1: Measured window-to-wall ratio examples. *Figure credit: Ana Alice McIntosh*

C. Hedonic Model Specification Variable Descriptions

Table C1: Description of variables in the hedonic model specifications presented in Chapters 4 and 6.

Variable	Description
Dependent Variable	
Net effective rent	We use the net effective rent in U.S. Dollars as our dependent variable. CompStak defines net effective rent as the "actual amount of rent paid (subtract[ing] lease concessions from starting rent)" CompStak Inc. (2018). In the model we use the logarithm of the net effective rent to adjust for right skewness and to be able to clearly interpret the resulting coefficients. We drop observations for which the net effective rent is not listed.
Variables of Interest	

(Table C1 continued from previous page.)

Variable	**Description**
Spatial daylight autonomy ($sDA_{300/50\%}$)	$sDA_{300/50\%}$ is a value between 0 and 100% indicating how much of a floor receives minimum 300 lux for 50% for all occupied hours ($sDA_{300/50\%}$). We assume the occupied hours to be standard office work hours from 8am to 6pm, Monday through Friday. We assume the occupied hours to be standard office work hours from 8am to 6pm, Monday through Friday. We separate the results into three categories: low daylight (0-55%), high daylight (55-75%), and very high daylight (75-100%). The ranges are based on the LEED recommended 55% and 75% thresholds for good daylight autonomy in commercial office spaces U.S. Green Building Council (2013). We adopt these thresholds because they are widely applied and understood within the building sector, and currently guide the daylighting design of contemporary buildings.
Spatial view access (sVA_3)	sVA_3 is a value between 0 and 100% indicating how much of a floor receives at least 3% minimum view potential (MVP) at each analysis point. The MVP is measured as a fraction of total rays cast from that point that intersect view elements that were tagged in the urban model. 6,111 rays are cast from each point. The metric credits rays that intersect with the following view elements: iconic landmarks, green spaces, water/distant view rays, and neighboring buildings and ground beyond 18-feet from the origin point. *Included in view and daylight hedonic specification (in Chapter 6) only.*
Market Conditions (Location Fixed Effects)	

(Table C1 continued from previous page.)

Variable	Description
Submarket	We use Compstak's submarket (i.e. neighborhood) categorization to control for the location fixed effects. There are 24 submarkets represented in the data: Chelsea, City Hall Insurance, Columbus Circle, Financial District, Gramercy Park Union Square, Grand Central, Hudson Square, Hudson Yards, Madison/Fifth Avenue, Midtown Eastside, Murray Hill, NoHo Greenwich Village, North Manhattan (no observations), Park Avenue, Penn Station, Sixth Avenue, SoHo, Times Square, Times Square South, Tribeca, UN Plaza, Upper Eastside, Upper Westside, World Trade Center. During estimation, we consider the categorical location fixed effects relative to a base submarket, Grand Central. Figure 4.1 presents the net effective rent by submarket.
Macroeconomic Conditions (Time Fixed Effects)	
Period of transaction	We transform the lease transaction commencement date into time periods to control for macroeconomic conditions in the economy, so-called time fixed effects over the January 2010 to December 2016 lease period. To do so, we divide commencement dates into year-quarter intervals. During estimation, we consider the categorical time fixed-effects relative to a base period, year 2010, quarter 1.
Contract Term Condition Variables	
Space type	Consider only "Office" spaces; we drop other space types.
Lease transaction type	Consider only "New Lease" spaces; we drop other types.

(Table C1 continued from previous page.)

Variable	Description
Lease term duration	Full length of the lease in years. We include all leases that are less than 50 years long, divided into 5-year categories: 0-5 years, 6-10 years, 11-15 years, 16-20 years, 21-25 years, 26 and over. 72% of the leases are for 10 years or less. We drop the four outlier observations with a lease duration over 50 years. We estimate the incremental value of lease duration relative to a base lease term, 6-10 years.
Free rent period	Duration of rent-free period in months. We divide the data into 6-month categories: no free rent, 6 months or less, 7-12 months, 13-18 months, 19-24 months, over 24 months. We estimate the incremental value of rent-free periods relative to a base rent-free period, 6 months or less.
Transaction size	The amount of square feet leased by the tenant. This is the size of the *total* space leased, which can include multiple floors and/or partial floors. Included as a continuous variable.
Sublease	A binomial variable denoting contracts that allow sublease provisions or not (1 = Yes, 0 = No).
Partial floor contracts	A binomial variable denoting contract-floor that is for partial floor, and does not encompass the full floor space (1 = Yes/Partial, 0 = No/Entire).
Multiple floor contracts	A binomial variable denoting contract-floor that is part of a multiple floor contract (1 = Yes/Multiple floor contract, 0 = No/Single floor contract).
Tenant broker	A binomial variable denoting leases that have a tenant broker or tenant brokerage firm listed (1 = Yes/Tenant broker, 0 = No/No tenant broker or brokerage firm listed).

(Table C1 continued from previous page.)

Variable	Description
Landlord broker	A binomial variable denoting leases that have a landlord broker or landlord brokerage firm listed (1 = Yes/Landlord broker, 0 = No/No landlord broker or brokerage firm listed).
Landlord concessions / work type	All landlord concession types are included as categorical variables ("as-is", "tenant improvements", "built to suit", "new building installation", "paint and carpet", "pre-built", "turnkey", "other"). One additional category "not specified" is added for observations where the landlord concession is not listed. We estimate the incremental value of each lease concession relative to a base lease concession type, tenant improvements.
Transaction floor number	Transaction floors are divided into 15 floor intervals (0-15, 16-30, 31-45, 46 and over). We estimate the incremental value of floor height relative to a base floor height, floors 0-15.
Building Characteristic Variables	
Building class	Buildings are listed as categorical variables (Building Class A, B, or C). We drop observations for which the class is not listed. We estimate the incremental value of building class relative to a base building class, Class A.
Building age	We calculate the age of the building in the year of the lease transaction, taking the difference between the transaction year and the year the building was built. We include both the building age and the square of the building age in the model. Included as a continuous variable.
Renovated building	A binomial variable denoting buildings that are renovated (1 = Yes/Renovated, 0 = No/Not renovated).

(Table C1 continued from previous page.)

Variable	Description
LEED certification	A binomial variable denoting buildings that have a LEED certification (1 = Yes/LEED certified building, 0 = No/No LEED certification). If a building has multiple full-building LEED certifications, we keep only the latest certification. We consider only full-building certifications in this analysis, excluding certifications that do not apply to office buildings, such as retail or school certifications. We drop certifications that are for individual floors or spaces within a building, as they do not apply to the full building.
Fiber lit buildings	A binomial variable denoting buildings that are fiber lit (1 = Yes/Fiber lit, 0 = No/Not fiber lit). Observations that have no data are assumed to be not fiber lit.

D. Breakdown of Lease Types

Table D1: Breakdown of lease types in the office lease contracts sample

Lease Type	Frequency	Percent	Cum.Percent
Full Service	744	11.87	11.87
Gross	53	0.85	12.72
Modified Gross	1,404	22.40	35.12
Double Net (NN)	1	0.02	35.14
Triple Net (NNN)	8	0.13	35.26
Net	15	0.24	35.50
Net of Electric	324	5.17	40.67
Not Listed	3,718	59.33	100.00
All Observations	6,267	100.00	

Types of leases as defined in the Compstak data dictionary (CompStak Inc., 2018):

- Full Service/Gross Lease: Landlord is responsible for covering all operating expenses.
- Modified Gross Lease: Tenant pays portion of operating expenses in addition to base rent.
- Double Net/NN Lease: Tenant responsible for covering some operating expenses such as property taxes and insurance, but landlord will cover maintenance expenses (CAM).
- Triple Net/NNN Lease: Tenant responsible for base rent, as well as three types of operating expenses: property tax, insurance, and maintenance (CAM).

Note: Net and net of electric leases are not explicitly defined in the Compstak data dictionary.

E. View Metric Threshold Study: Distribution Plots

To determine the appropriate thresholds for the new view metrics, we evaluate a range of possible numbers and identify which results in a reasonable distribution of the results. We considered three values for the MVP threshold: 1%, 3%, and 5%. We also consider two different distance limits for the neighborhood and ground rays: 18-feet (3-meters) and 150-feet (50-meters). The plots in Figure E.1 show the distribution of sVA across all floors in the sample based on the six different specifications.

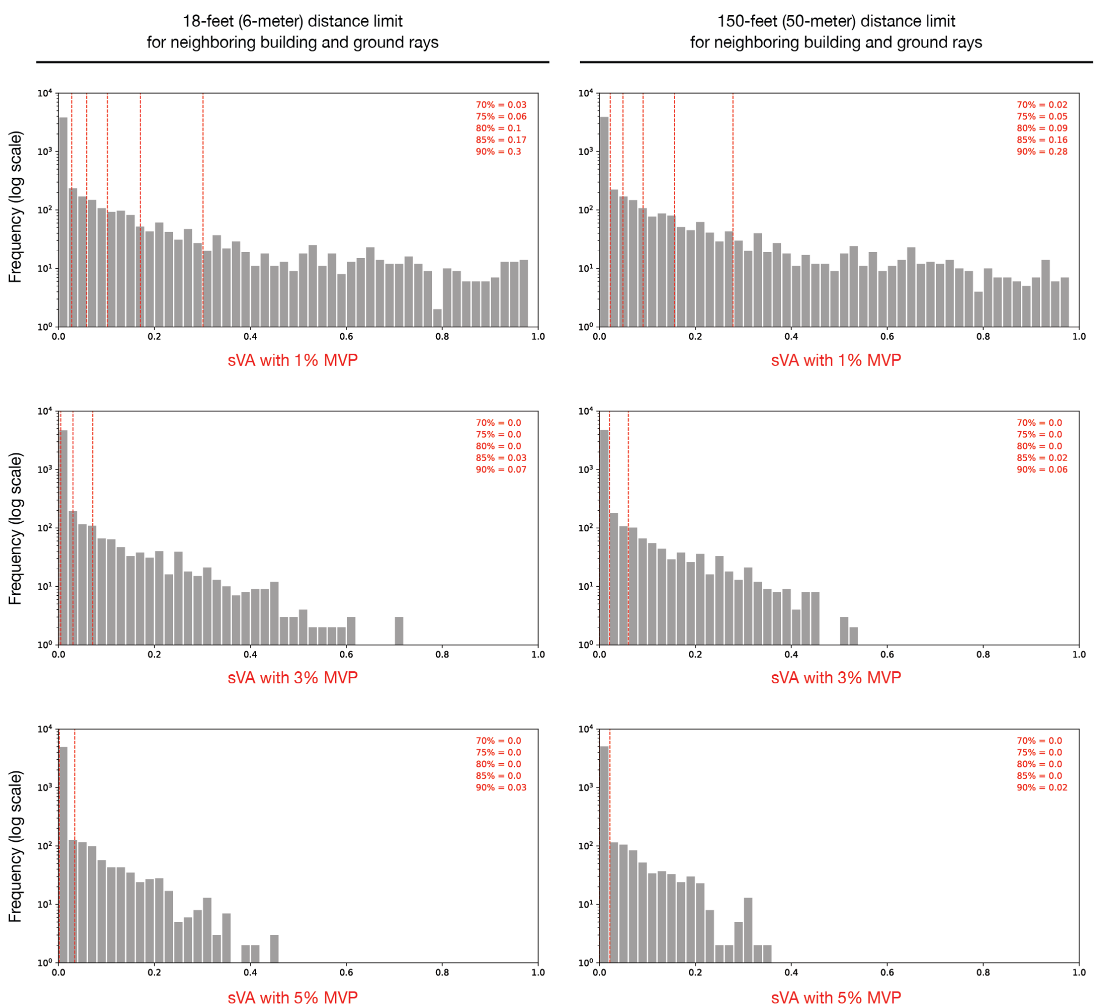


Figure E.1: View metric threshold study: distribution plots. We considered three values for the MVP threshold: 1%, 3%, and 5%. We also consider two different distance limits for the neighborhood and ground rays: 18-feet (3-meters) and 150-feet (50-meters). The plots show the distribution of sVA across all floors in the sample based on the six different specifications. In the top right corner of each plot, in red, a range of percentiles are listed (70th to 90th) are listed for each table. The red vertical lines indicate graphically where these percentiles fall within the distribution. Note: the y-axis on each plot is in log scale to account for the large number of observations at the low end of sVA.

F. Full Expression of the Hedonic Regression Results

Table F1: Hedonic pricing regression: unabridged table with all variables presented (including location and time fixed effects). The dependent variable is the logarithm of net effective rent per square foot ($/sq.ft.). Column (1) presents the regression results of the model that includes only the daylight variable of interest sDA (from Chapter 4). Column (2) presents the results of the model containing both the daylight and views variables of interest, sDA and sVA. Column (3) incorporates the interaction effects between daylight and views, and presents the fully-specified model results. Column (4) presents results for a trimmed distribution, eliminating the lease contract observations with the top 1% of net effective rent values. This is an expanded version of Table 6.2; at the same time, column (1) in this table is an expanded version of column (5) in Table 4.2.

Variables	(1) Daylight Only	(2) Daylight + Views	(3) +Interactions	(4) Trimmed
Daylight: Spatial Daylight Autonomy (Base Level: $sDA_{300/50\%}$ 0-55%)				
High Daylight	**0.052*****	**0.051*****	**0.053*****	**0.044*****
(sDA 55-75%)	[0.014]	[0.014]	[0.014]	[0.014]
Very High Daylight	**0.063****	**0.060****	**0.064****	**0.063****
(sDA 75-100%)	[0.027]	[0.027]	[0.027]	[0.027]
Views: Spatial View Access, (Base Level: sVA_3 0-10%)				
High View Access	-	**0.037*****	**0.063*****	**0.044*****
(sVA_3 10-100%: 1 = yes)	-	[0.012]	[0.017]	[0.016]
Building Class (Base Level: Class A)				
Class B Building	-0.114***	-0.113***	-0.113***	-0.116***
	[0.010]	[0.010]	[0.010]	[0.010]
Class C Building	-0.200***	-0.199***	-0.200***	-0.203***
	[0.017]	[0.017]	[0.017]	[0.016]
Building Age at Lease Signing (years)	-0.010***	-0.010***	-0.010***	-0.010***
	[0.001]	[0.001]	[0.001]	[0.001]
Building Age, Squared	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Renovated Building (1 = yes)	0.040***	0.041***	0.040***	0.050***
	[0.007]	[0.007]	[0.007]	[0.006]
LEED Certified (1 = yes)	0.004	0.002	0.002	0.007

Table F1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	[0.010]	[0.010]	[0.010]	[0.010]
Fiber-Lit Building (1 = yes)	0.022	0.021	0.021	0.019
	[0.016]	[0.016]	[0.016]	[0.016]
Lease Term Duration (Base Level: 6-10 years)				
Lease term 5 years or less	-0.047***	-0.047***	-0.047***	-0.041***
	[0.008]	[0.008]	[0.008]	[0.008]
Lease term 11-15 years	0.061***	0.060***	0.059***	0.056***
	[0.010]	[0.010]	[0.010]	[0.010]
Lease term 16-20 years	0.097***	0.097***	0.096***	0.085***
	[0.018]	[0.018]	[0.018]	[0.017]
Lease term 21-25 years	0.204***	0.197***	0.192***	0.194***
	[0.043]	[0.043]	[0.043]	[0.043]
Lease term 26 years or more	0.057	0.056	0.056	0.051
	[0.051]	[0.051]	[0.051]	[0.049]
Free Rent Period (Base Level: 0-6 months)				
No free rent	0.023**	0.024**	0.024**	0.022**
	[0.009]	[0.009]	[0.009]	[0.009]
7-12 months free	-0.033***	-0.034***	-0.033***	-0.024***
	[0.009]	[0.009]	[0.009]	[0.009]
13-18 months free	-0.054**	-0.056***	-0.056***	-0.048**
	[0.021]	[0.021]	[0.021]	[0.021]
19-24 months free	-0.130**	-0.141***	-0.147***	-0.113**
	[0.055]	[0.054]	[0.054]	[0.056]
Over 24 months free	-0.065**	-0.070***	-0.072***	-0.061**
	[0.027]	[0.027]	[0.026]	[0.027]
Transaction Size (sq.ft.)	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Sublease (1 = yes)	-0.171***	-0.171***	-0.171***	-0.160***
	[0.011]	[0.011]	[0.011]	[0.011]
Partial Floor Flag (1 = yes)	0.038***	0.039***	0.038***	0.030***
	[0.008]	[0.008]	[0.008]	[0.008]
Multiple Floors in Lease (1 = yes)	0.007	0.009	0.009	0.007
	[0.010]	[0.010]	[0.010]	[0.010]
Tenant Broker (1 = yes)	0.010	0.010	0.010	0.014*
	[0.008]	[0.008]	[0.008]	[0.008]
Landlord Broker (1 = yes)	0.035***	0.036***	0.036***	0.030***
	[0.009]	[0.009]	[0.009]	[0.009]
Landlord Concessions / Work Done (Base Level: Tenant Improvements)				
As-Is	0.041	0.040	0.041	0.033
	[0.029]	[0.029]	[0.029]	[0.029]
Built to Suit	-0.044	-0.041	-0.046	-0.017
	[0.069]	[0.066]	[0.067]	[0.059]
New Building Installation (NBI)	0.065***	0.065***	0.065***	0.066***
	[0.012]	[0.012]	[0.012]	[0.011]
Not Specified	0.032***	0.032***	0.032***	0.040***

Table F1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	[0.009]	[0.009]	[0.009]	[0.009]
Other	0.012	0.017	0.018	0.019
	[0.056]	[0.056]	[0.055]	[0.056]
Paint & Carpet	0.058	0.054	0.052	0.068
	[0.059]	[0.060]	[0.060]	[0.056]
Pre-Built	0.099***	0.101***	0.102***	0.106***
	[0.021]	[0.021]	[0.021]	[0.020]
Turnkey	0.141***	0.135***	0.137***	0.134***
	[0.040]	[0.040]	[0.041]	[0.039]
Transaction Floor Number (Base Level: Floors 0-15)				
Transaction Floor Number 16-30	0.121***	0.116***	0.112***	0.104***
	[0.010]	[0.010]	[0.011]	[0.010]
Transaction Floor Number 31-45	0.225***	0.203***	0.187***	0.176***
	[0.021]	[0.022]	[0.023]	[0.023]
Transaction Floor Number 46+	0.321***	0.292***	0.270***	0.162***
	[0.069]	[0.069]	[0.069]	[0.059]
Interaction Effect: sDA Level x Transaction Floor Number				
High sDA x Trans. Floor 16-30	-0.030	-0.030	-0.022	-0.025
	[0.020]	[0.020]	[0.020]	[0.019]
High sDA x Trans. Floor 31-45	-0.027	-0.026	0.006	-0.014
	[0.033]	[0.033]	[0.037]	[0.036]
High sDA x Trans. Floor 46+	0.073	0.081	0.118	0.219**
	[0.093]	[0.092]	[0.093]	[0.087]
Very High sDA x Trans. Floor 16-30	-0.042	-0.043	-0.034	-0.023
	[0.031]	[0.031]	[0.032]	[0.031]
Very High sDA x Trans. Floor 31-45	-0.070*	-0.066*	-0.038	-0.031
	[0.038]	[0.038]	[0.040]	[0.040]
Very High sDA x Trans. Floor 46+	-0.233**	-0.210*	-0.186*	-0.099
	[0.113]	[0.115]	[0.113]	[0.105]
Interaction Effect: Daylight (55% sDA minimum) x View Access (10% of floor area minimum				
Daylight x View Interaction	-	-	-0.051**	-0.022
	-	-	[0.023]	[0.022]
Location Fixed Effect: Submarket in Manhattan (Base submarket: Grand Central)				
Chelsea	-0.034*	-0.040**	-0.040**	-0.041**
	[0.020]	[0.019]	[0.019]	[0.019]
City Hall Insurance	-0.323***	-0.328***	-0.329***	-0.327***
	[0.026]	[0.026]	[0.026]	[0.026]
Columbus Circle	-0.059***	-0.059***	-0.059***	-0.052***
	[0.016]	[0.016]	[0.016]	[0.016]
Financial District	-0.409***	-0.410***	-0.413***	-0.403***
	[0.011]	[0.011]	[0.011]	[0.011]
Gramercy Park Union Square	0.040***	0.036***	0.036***	0.031**
	[0.013]	[0.013]	[0.013]	[0.013]
Hudson Square	0.085***	0.078***	0.081***	0.078***
	[0.024]	[0.024]	[0.024]	[0.024]

Table F1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
Hudson Yards	-0.384***	-0.397***	-0.398***	-0.407***
	[0.112]	[0.110]	[0.110]	[0.111]
Madison/Fifth Avenue	0.257***	0.254***	0.253***	0.226***
	[0.013]	[0.013]	[0.013]	[0.013]
Midtown Eastside	-0.064***	-0.066***	-0.067***	-0.064***
	[0.016]	[0.016]	[0.016]	[0.016]
Murray Hill	-0.111***	-0.115***	-0.114***	-0.113***
	[0.015]	[0.015]	[0.015]	[0.015]
NoHo Greenwich Village	0.077***	0.075***	0.075***	0.072**
	[0.029]	[0.029]	[0.029]	[0.028]
Park Avenue	0.251***	0.253***	0.253***	0.205***
	[0.018]	[0.018]	[0.018]	[0.016]
Penn Station	-0.130***	-0.137***	-0.139***	-0.130***
	[0.015]	[0.015]	[0.015]	[0.015]
Sixth Avenue	0.090***	0.089***	0.087***	0.089***
	[0.016]	[0.016]	[0.016]	[0.016]
SoHo	0.160***	0.155***	0.155***	0.149***
	[0.024]	[0.024]	[0.024]	[0.024]
Times Square	-0.093***	-0.093***	-0.096***	-0.088***
	[0.019]	[0.020]	[0.020]	[0.020]
Times Square South	-0.125***	-0.129***	-0.129***	-0.126***
	[0.012]	[0.012]	[0.012]	[0.012]
Tribeca	-0.101**	-0.107***	-0.105**	-0.109***
	[0.042]	[0.041]	[0.041]	[0.041]
UN Plaza	0.061	0.065	0.060	0.064
	[0.126]	[0.123]	[0.126]	[0.131]
Upper Eastside	0.403**	0.401**	0.400**	0.399**
	[0.196]	[0.196]	[0.196]	[0.201]
Upper Westside	0.028	0.028	0.028	0.036
	[0.089]	[0.089]	[0.089]	[0.090]
World Trade Center	-0.296***	-0.312***	-0.321***	-0.299***
	[0.021]	[0.021]	[0.021]	[0.021]
Time Fixed Effect: Transaction Commencement Date, year and quarter (Base level: 2010, Q1)				
2010, Q2	-0.047*	-0.047*	-0.046*	-0.048*
	[0.028]	[0.028]	[0.028]	[0.028]
2010, Q3	-0.035	-0.035	-0.034	-0.036
	[0.028]	[0.028]	[0.028]	[0.028]
2010, Q4	-0.016	-0.017	-0.017	-0.016
	[0.024]	[0.024]	[0.024]	[0.024]
2011, Q1	0.027	0.026	0.028	0.024
	[0.024]	[0.024]	[0.024]	[0.024]
2011, Q2	0.027	0.026	0.028	0.019
	[0.025]	[0.025]	[0.025]	[0.025]
2011, Q3	0.093***	0.092***	0.094***	0.087***
	[0.026]	[0.026]	[0.026]	[0.026]
2011, Q4	0.079***	0.077***	0.079***	0.069***
	[0.025]	[0.025]	[0.025]	[0.025]
2012, Q1	0.093***	0.093***	0.093***	0.089***

Table F1 – *Continued from previous page*

	(1)	(2)	(3)	(4)
	[0.024]	[0.023]	[0.023]	[0.023]
2012, Q2	0.116***	0.115***	0.116***	0.111***
	[0.025]	[0.024]	[0.024]	[0.024]
2012, Q3	0.110***	0.110***	0.111***	0.102***
	[0.025]	[0.025]	[0.025]	[0.024]
2012, Q4	0.131***	0.131***	0.132***	0.117***
	[0.028]	[0.028]	[0.028]	[0.027]
2013, Q1	0.154***	0.153***	0.153***	0.144***
	[0.023]	[0.023]	[0.023]	[0.023]
2013, Q2	0.137***	0.136***	0.136***	0.123***
	[0.025]	[0.025]	[0.025]	[0.025]
2013, Q3	0.212***	0.212***	0.213***	0.197***
	[0.026]	[0.026]	[0.026]	[0.025]
2013, Q4	0.197***	0.196***	0.197***	0.193***
	[0.025]	[0.025]	[0.025]	[0.025]
2014, Q1	0.229***	0.229***	0.231***	0.225***
	[0.024]	[0.024]	[0.024]	[0.024]
2014, Q2	0.238***	0.235***	0.236***	0.222***
	[0.024]	[0.024]	[0.024]	[0.024]
2014, Q3	0.323***	0.321***	0.322***	0.304***
	[0.024]	[0.024]	[0.024]	[0.023]
2014, Q4	0.278***	0.277***	0.278***	0.275***
	[0.026]	[0.026]	[0.026]	[0.026]
2015, Q1	0.309***	0.308***	0.310***	0.300***
	[0.026]	[0.026]	[0.026]	[0.025]
2015, Q2	0.351***	0.351***	0.353***	0.337***
	[0.025]	[0.025]	[0.025]	[0.024]
2015, Q3	0.383***	0.381***	0.382***	0.370***
	[0.025]	[0.025]	[0.025]	[0.024]
2015, Q4	0.333***	0.331***	0.334***	0.314***
	[0.029]	[0.029]	[0.029]	[0.028]
2016, Q1	0.389***	0.388***	0.390***	0.371***
	[0.027]	[0.027]	[0.027]	[0.026]
2016, Q2	0.396***	0.396***	0.396***	0.379***
	[0.028]	[0.028]	[0.028]	[0.028]
2016, Q3	0.396***	0.394***	0.394***	0.381***
	[0.027]	[0.027]	[0.027]	[0.027]
2016, Q4	0.474***	0.473***	0.476***	0.465***
	[0.032]	[0.032]	[0.032]	[0.031]
Constant	3.928***	3.925***	3.923***	3.935***
	[0.034]	[0.034]	[0.034]	[0.034]
Observations	6,267	6,267	6,267	6,205
R-squared	0.602	0.603	0.603	0.594
F Adj R2	0.596	0.597	0.597	0.588

Robust standard errors in brackets

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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