Empirical analysis of office markets:
A spatiotemporal approach

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Berlin, February 2006 Franz Fürst

Eidesstattliche Versicherung

Hiermit erkläre ich an Eides statt, dass die an der Fakultät VIII - Wirtschaft und Management der Technischen Universität zu Berlin eingereichte Dissertation mit dem Titel "Empirical analysis of office markets –a spatiotemporal approach" eigenständig und ohne unzulässige Hilfe anderer Personen verfasst wurde, auch in Teilen keine Kopie anderer Arbeiten darstellt und insbesondere alle empirischen Ergebnisse von mir selbst ermittelt wurden, soweit sie nicht explizit als Zitate anderer Studien gekennzeichnet sind.

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Empirical analysis of office markets: A spatiotemporal approach

Executive Summary

This dissertation focuses on the empirical analysis of office real estate markets. In particular, it attempts to bridge the gap between econometric time series analysis of real estate markets and cross-sectional analysis of spatial structures. To this aim, a number of exemplary research questions are investigated using empirical data of New York City. These questions are structured around five core chapters which each address a topic of spatiotemporal office market research with crucial implications for investment and policy practice.

Following the introductory chapter is an inquiry into the dynamics of office employment in regional perspective and an exploration of the sources of agglomeration economies for office-using industries. The dynamics of office employment are investigated by calculating industry concentration indicators such as the Hirschman-Herfindahl index, the spatial Gini and the Ellison-Glaeser index. In a second stage of the employment analysis, I attempt to detect small-scale spillover effects by measuring concentration and co-agglomeration with zip code-level employment data.

Chapter 3 analyzes the impact of the September 11 terrorist attack on the New York office market. Using an event study methodology, I examine whether the attack had only a limited impact on rental prices over a number of quarterly observations in the affected submarket of Lower Manhattan or whether the direct impact of the attack was indeed more widespread across time and space. The empirical evidence suggests that although the attack constituted an exogenous market shock of unprecedented magnitude, its effects on the office market were indeed limited.

In the fourth chapter, I set out to develop and empirically estimate a simultaneous equation model that is capable of producing a contingent forecast of the aggregate Manhattan office market until 2010. The output of this model comprises three major indicators of the office market: rental rates, vacancy rates and new construction of office space.

The fifth chapter analyzes data at the more disaggregated submarket level and attempts to answer the question if sufficient portfolio diversification is at all possible within a single urban market considering that most portfolio studies recommend geographic diversification across a number of regions or even countries. To test this hypothesis, I apply cointegration analysis, Granger causality and impulse response analysis in a vector-autoregressive framework. This topic is of particular practical relevance to real estate investors who need to know whether the gains they achieve by investing in a single urban market and lower transaction costs are potentially offset by excessive risk exposure through geographic concentration.

In the sixth chapter, I analyze the determinants of office rents at the building level. To this aim, an innovative component is introduced to standard hedonic modeling by carrying out both repeated-measurement OLS and random-effects panel data analysis. Thus, I test whether locational and property-specific features are valued differently at each phase of the market cycle and across space by attempting to statistically detect structural breaks in the data. This question has potentially far-reaching consequences for both appraisal methods and future cash flow estimates as standard hedonic modeling typically does not allow for such structural differences. If structural differences do exist, however, they are not reflected in hedonic regression models that pool all time-series and cross-sectional observations.

The empirical results support the assumption that applying panel data models yields better results in capturing these dynamic processes than the standard pooled OLS modeling procedure.

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Zusammenfassung

Im Mittelpunkt der vorliegenden Dissertation steht die empirische Analyse von Büroimmobilienmärkten. Im Rahmen dieser Arbeit werden die bislang weitgehend getrennt behandelten Gebiete der ökonometrischen Zeitreihenanalyse von Immobilienmärkten einerseits und der Querschnittsanalyse räumlicher Strukturen andererseits anhand ausgewählter Themen zusammengeführt. Zu diesem Zweck wird in fünf Hauptkapiteln der Arbeit jeweils eine immobilienwirtschaftliche Fragestellung im gewählten Untersuchungsraum New York untersucht, bei der sowohl eine räumliche Differenzierung als auch eine dynamische Veränderung über die Zeit zu beobachten ist. Zunächst wird im Einleitungskapitel der theoretische und empirische Kontext der Arbeit erläutert.

Im Mittelpunkt der im zweiten Kapitel dargestellten Studie stehen die dynamische Veränderung der Bürobeschäftigten in regionaler Perspektive sowie eine Untersuchung der Agglomerationseffekte von Bürounternehmen. Zu diesem Zweck werden Konzentrationsmaße wie der Hirschman-Herfindahl Index, der räumliche Gini-Koeffizient und der Ellison-Glaeser Index für die vorliegenden Zeitreihendaten berechnet. Um auch kleinräumige Effekte messen zu können, wird diese Analyse im nächsten Schritt auf der Ebene der Postleitzahlenbezirke wiederholt.

Das dritte Kapitel analysiert den Einfluss der terroristischen Anschläge des 11. September 2001 auf den New Yorker Büromarkt. Mit Hilfe einer Event-Studie wird nachgewiesen, dass die Anschläge zwar eine bislang unbekannte Größenordnung eines exogenen Schocks darstellen, die ökonomischen Effekte auf dem Büromarkt jedoch als räumlich und zeitlich relativ eng begrenzt anzusehen sind.

Im vierten Kapitel wird ein simultanes Gleichungssystem entwickelt, das in der Lage ist, Prognosen für den Büromarkt Manhattans bis zum Jahr 2010 zu generieren. Der Output des Modells umfasst die drei Indikatoren Mieten, Leerstandsraten und Neubau von Büroflächen.

Das fünfte Kapitel geht der Frage nach, ob eine ausreichende Portfolio-Diversifizierung mit einer einzigen Objektart (Büro) sowie innerhalb eines einzigen städtischen Immobilienmarkts möglich ist. Die meisten Studien dieser Art betrachten eine Streuung der in einem Portfolio enthaltenen Immobilien über weit auseinander liegende Regionen oder Länder, ohne die damit einhergehenden Transaktionskosten zu beachten. Die Frage nach der generellen Möglichkeit einer Diversifikation durch Investition in verschiedene Teilmärkte innerhalb einer Stadt wird mit Hilfe der Kointegrationsanalyse, der Granger-Kausalität sowie einer Impuls-Response-Analyse untersucht. Die Ergebnisse der empirischen Analyse legen nahe, dass eine ausreichende Diversifikation nur unter sehr spezifischen Bedingungen möglich ist.

Im sechsten Kapitel werden die Bestimmungsfaktoren für Büromieten auf Gebäudeebene betrachtet. Zu diesem Zweck wird als innovative Komponente im hedonischen Standardverfahren ein Random-Effects Paneldatenmodell zusätzlich zur wiederholten Schätzung mit der OLS-Methode angewandt. Insbesondere wird der Frage nachgegangen, ob sich die Gewichte bestimmter räumlicher und objektspezifischer Merkmale konjunktur- und teilmarktabhängig verschieben.

Insgesamt bestätigen die Analyseergebnisse die Annahme, dass Paneldatenmodelle aufgrund der festgestellten strukturellen Unterschiede Vorteile gegenüber einfachen Regressionsmodellen bieten, weil sie geeignet sind, diese dynamischen Prozesse adäquat abzubilden.

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1. Exposition: Empirical office market analysis

Notwithstanding its essential role in realms as diverse as private investment, corporate management, project development and portfolio management, real estate economics as an academic discipline has long been relegated to the sidelines of mainstream economics. Although the importance of real estate in the capital market is almost universally recognized by economists, the number of researchers specializing in the real estate economics is still minuscule to date. In recent years, however, real estate economics has experienced increased academic appreciation driven by the insight that real estate is characterized by a set of particularities and unique features which warrant academic specialization in this field.

This dissertation builds on recent advances in real estate economics, particularly in the field of empirical office market analysis, which is the focus of the present work. In this context, econometric techniques and methods are applied to describe, explain, and predict patterns of office rental prices, construction activities, and demand for office real estate. The theoretical foundation of this dissertation draws on partial equilibrium analysis, financial theory as well as spatial economics and urban economics.

The purpose of this chapter is twofold. First, it lays out the objective and structure of the dissertation and places it in the context of real estate economics. Second, it sets the stage for the core section of this dissertation which consists of five standalone chapters united by the overarching theme of spatiotemporal office market research. Although each chapter of this dissertation contains a separate research literature review targeted at exploring the specific topic in question, the present chapter aims at providing the broader overview necessary for understanding the scope and context of the five main chapters.

1.1 Objective of this dissertation

This dissertation sets out to contribute to the nascent field of spatiotemporal office market analysis in that it combines time series methods with spatial market analysis. Instead of presenting a comprehensive treatise on extant work, it chooses a different approach in that it seeks to highlight and empirically test a number of key research questions that have both a temporal and a spatial dimension. Presently, empirical office market research addresses the questions pertaining to these two dimensions separately in either cross-sectional or time series analyses. Although a number of empirical studies examine the temporal and spatial properties of office markets, the interaction of both dimensions is still poorly understood. A synopsis of both dimensions may therefore yield additional insights into the dynamics of office markets. In a similar vein, very few studies attempted to link various aggregation levels from the overall market down to the individual building. Thus, Grissom and Liu (1994) state:

"Little work has been done in linking spatial market analysis directly to real estate analysis. […] The missing component in the market analysis process is the linkage of the quantitative techniques between the city level and the site level."

The present dissertation attempts to selectively provide this component by linking some of the previously disjointed issues. Figure 1-1 presents a tentative visualization of the 'missing link' that this dissertation attempts to provide for a set of exemplary cases. The illustration on the left hand side of the diagram represents the scope of real estate analysis and forecasting in current market research practice. While all three levels of aggregation (market, submarket, and building) are routinely surveyed and analyzed, no systematic effort is typically being made to link these levels. Thus, this approach is necessarily confined to the rather rigid assumption that submarkets and buildings develop in the same manner as the overall market. In contrast, the diagram on the right hand side shows the envisaged contribution of this dissertation research. It relaxes the assumption of constant ratios between the levels of aggregation and aims at providing a number of tools that can be useful for explaining small-scale developments. The insight gained from this research may, for instance, lead to developing disaggregated forecasting models in future research.

There are two main reasons for choosing a spatiotemporal approach for the research questions at hand. First, office markets are far more volatile and subject to greater oscillations than residential real estate. It is therefore crucial for investors to understand the cyclical dynamics of the office market as well as the spatial impact of market cycles in order to achieve optimal timing of their investment decisions. Second, as implied by urban economic theory, office uses are characterized by a steep rent gradient thus yielding a pattern of highly unequal rental rates depending –*ceteris paribus*- on the location of a particular building. Therefore, investors wishing to determine the risk and expected income flows of a given property depend on accurate predictions of a location's potential.

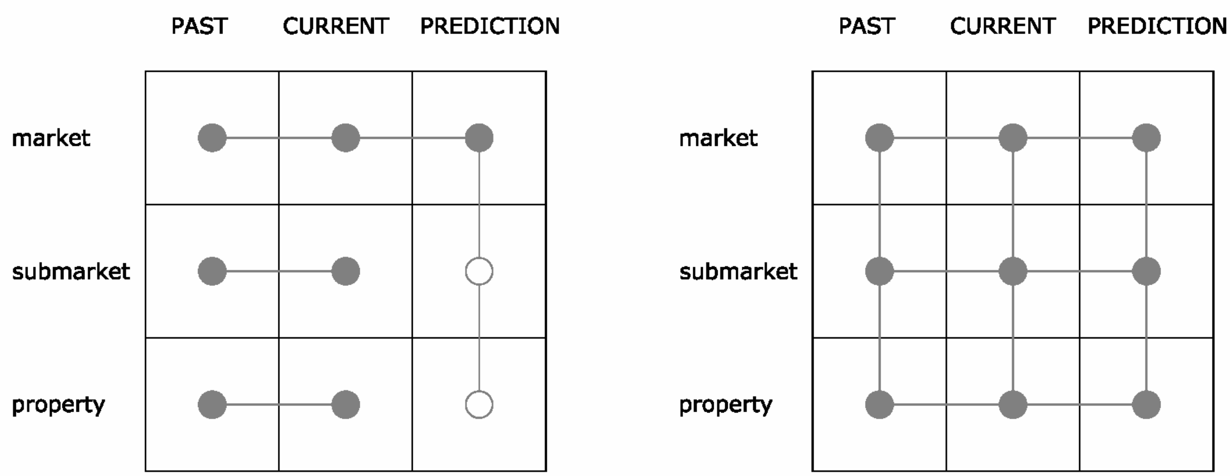

Figure 1-1: Research objective of this dissertation: Replacing the rigid assumption of constant ratios between spatial units (left) by integrating small-scale information (right).

1.2 Structure of this dissertation

This dissertation is structured around five core chapters which each address a topic of spatiotemporal office market research with crucial implications for investment and policy practice (see Table 1-1). Following the introductory chapter is an inquiry into the dynamics of office employment in a regional perspective and an exploration of the sources of agglomeration economies for office-using industries in Chapter 2. The dynamics of the office market are captured using standard measures of industry concentration such as the Hirschman-Herfindahl index, the spatial Gini and the Ellison-Glaeser index. In a second stage of the employment analysis, I attempt to detect indications of small-scale spillover effects by analyzing zip code-level employment data. Chapter 3 analyzes the impact of the September 11 terrorist attack on the New York office market. Using an event study methodology, I examine whether the attack had only a limited impact on rental prices over a number of quarterly observations in the affected submarket of Lower Manhattan or whether the direct impact of the attack was indeed more widespread across time and space. A particular case in point is the analysis of the displaced tenants of the World Trade Center. Despite being an arguably extreme and unique case, their relocation and reconfiguration patterns are particularly valuable for studying agglomeration effects and the locational behavior of office-using companies. In the fourth chapter, I set out to develop and empirically estimate a simultaneous equation model that is capable of producing a contingent forecast of the aggregate Manhattan office market up until 2010. The output of this model comprises three major indicators of the office market: rental rates, vacancy rates and new construction of office space. The fifth chapter analyzes data at the more disaggregated submarket level and attempts to answer the question if sufficient portfolio diversification is at all possible within a single urban market considering that most portfolio studies recommend geographic diversification across a number of regions or even countries. To test this hypothesis, I apply cointegration analysis, Granger causality and impulse response analysis in a vector-autoregressive framework. This topic is of particular practical relevance to real estate investors who need to know whether the gains they achieve by investing in a single urban market and lower transaction costs are potentially offset by excessive risk exposure through geographic concentration. In the sixth chapter, I analyze the determinants of office rents at the building level. To this aim, an innovative component is introduced to standard hedonic modeling by carrying out both repeated-measurement OLS and random-effects panel data analysis. Thus, it will be tested whether locational and property-specific features are valued differently at each phase of the market cycle and across space by attempting to statistically detect structural breaks in the data. This question has potentially far-reaching consequences for both appraisal methods and future cash flow estimates as standard hedonic modeling typically does not take into account such structural differences. If structural differences do exist, predicting rental rates with hedonic regression models could be improved by taking into account these structural differences across time and space.

Table 1-1: Structure of the dissertation and levels of aggregation

Chapter	*Level of aggregation*
(1) Introduction: Spatial and temporal dimensions of office market research	
(2) Dynamics of office employment in regional perspective	Region
(3) The New York City office market: exploratory analysis and event study of the September 11 attack	Region/City
(4) Forecasting the aggregate Manhattan market with a simultaneous equation model	City
(5) Submarket volatility and the single market hypothesis: Is sufficient portfolio diversification possible within a single metropolitan office market?	Submarkets
(6) Panel analysis of office building characteristics	Buildings
(7) Conclusions	

1.3 Scope of this dissertation within real estate economics

As proposed by Wendt (1974), real estate economics can best be thought of as a systematic synthesis of theories and methods sampled from a variety of paradigms. Figure 1-1 illustrates this multidisciplinary nature of the field. As visualized in the figure, real estate economics draws on both neoclassical economics and institutional economics. The neo-classical approach has been dominating the academic research literature in economics since the 1930s by virtue of its enormous capacity for formalizing theories and hypotheses. In contrast, institutional economics perceives economic decisions as derivative of social institutions which in turn are subject to evolution as the underlying cultural and social preferences change (Langlois 1989). These paradigms of general economics are conveyed to the more narrow field of real estate economics through four contributing subdisciplines: urban land economics, regional science, regional/urban economics and finance. The theoretical principles and axioms of the neo-classical as well as heterodox (i.e. institutionalist) paradigms are nested within these four subdisciplines albeit with varying emphasis. They also differ with regard to their foundation in either micro- or macro-economics.

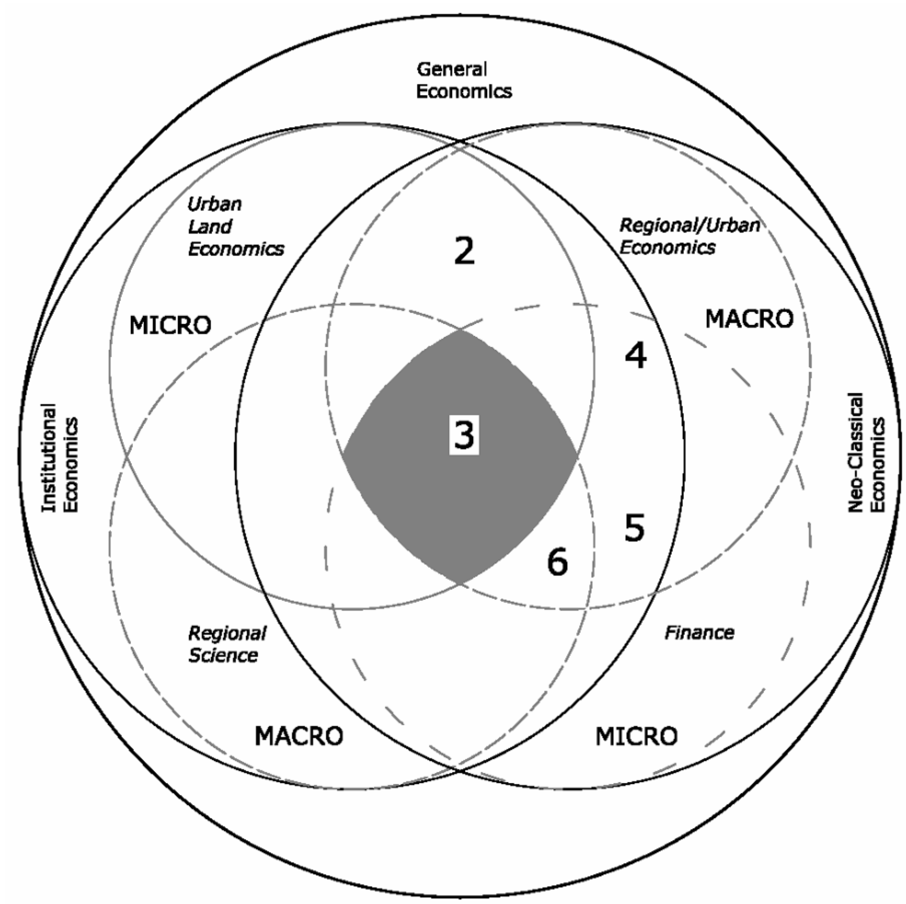

Figure 1-2: Assignment of core dissertation chapters (compare Table 1-1 for numbering) to the dimensions and paradigms of real estate economics. Source: Adapted from DeLisle and Sa-Aadu (1994)

While the scheme as illustrated in Figure 1-1 is by no means an exhaustive and undisputed characterization of real estate economics, it provides a valuable framework within which the contributions of this dissertation can be placed.[1] The analysis of office employment and agglomeration effects of Chapter 2 of this dissertation primarily draws on methods from the disciplines regional science, urban land economics and regional/urban economics but excludes finance.

[1] For a more thorough discussion of the epistemological and disciplinary roots of real estate economics see DeLisle, Sa-Aadu (1994).

Chapter 3 (the impact study of 9/11 attack) is based on precepts and publications from all four disciplines. The scope of Chapter 4 (forecasting of the aggregate market) is more narrowly defined at the intersection of microeconomic finance and macroeconomic urban economics -although the assumption of market imperfections and the existence of time lags in the empirical model places it outside strict neoclassical boundaries. Similarly, Chapter 5 applies methods derived from financial portfolio analysis and urban economics to the question of intracity diversification with the same limitations as stated above. Finally, Chapter 6 can be assigned to the three disciplines regional science, urban/regional economics and finance in that it uses definitions of spatial variables stemming from regional science and urban/regional economics and applies these explanatory variables in the context of estimating rental income streams (i.e. finance).

Overall, this dissertation is a contribution to office market research which is also a fairly recent field of study within economics. Despite individual research studies in the context of urban economics and regional science in earlier periods, the field came to fruition only with the advent of powerful computers arguably because of the heavy data load involved in these studies. In a study of the San Francisco market, Rosen (1984) was among the first to develop an empirically testable model of urban office markets, which performed reasonably well. Pollakowski, Wachter and Lynford (1992) expanded the work of Rosen and added a spatial dimension to office market models. By the early 1990s, many econometric studies of urban office markets had been undertaken. In a critique of the existing practice, Shilton (1994) identified a number of problems inherent in the use of office market models. He described the causes and consequences of what appears to be the key problem of all empirical office market research: missing or inaccurate data. Although the quality and scope of available datasets has improved greatly over the last ten years particularly with regard to office employment data, there remain some serious problems. The identification of office employment became considerably easier with the introduction of the NAICS (North American Industry Classification System) standard. The emergence of real estate research companies compiling large datasets with detailed and up-to-date collections of rental and vacancy rates also helped to improve the general quality of the data. There remain doubts, however, particularly with regard to the accuracy of the vacancy rate.[2] This indicator is plagued by a number of problems, one of the more serious among these being the existence of so-called shadow space not captured in market surveys which will be discussed in more detailed later on.

1.4 Case study New York City

The empirical context of this dissertation is the New York City office market. New York provides nearly ideal conditions for empirically testing the research questions put forth in this dissertation. With more than 350 million square feet of office space, it is one of the largest and most differentiated office markets in the world, providing rich datasets on micro-level spatial specialization of its submarkets. Due to its density and its position as one of the world's prime office markets, it is also exceptionally well researched in terms of the breadth and depth of datasets at all levels of spatial aggregation. Besides applying a series of other real estate and office employment data, the present dissertation draws on a unique set of time series data on more than one thousand Manhattan office buildings compiled by the CoStar Group. None of the European office markets, including Germany, offers the datasets required for conducting disaggregated analyses at the building level, at least not to academic researchers. The specifics of each dataset will be laid out in detail in the chapter in which it is used for empirical tests.

The two main characteristics of the New York office market are its vast size and the high degree of specialization of buildings, submarkets, and office-using companies. In a regional perspective, New York is undergoing significant changes in its spatial structure. While the degree of regional centralization of office space (56.7% within the core central business districts of Midtown and Downtown Manhattan) is the highest compared to all other major US cities (Lang 2000), suburban growth in office space, particularly along the northern New Jersey waterfront has generated a more decentralized pattern of office space in the region in recent years. Even within the core area of Manhattan itself, a number of new locations have emerged as new business centers, typically driven by the expansion of particular industries. One of the most dynamic emerging office corridors stretches along Broadway from Times Square to Columbus Circle and houses mainly

[2] This can be exemplified by a quick comparison of current local office market reports. In their reports for the third quarter of 2005, Newmark Real Estate indicate a total vacancy rate of 9.9% in Midtown Manhattan, Grubb & Ellis quote a rate of 7.4% and CB Richard Ellis report 7.1%.

entertainment and multi-media firms (Moss 1999). The completion of several new office high-rises around Times Square has led to an influx of financial services and business services companies. Another potential expansion area has been identified on the Far West Side of Midtown Manhattan, west of Ninth Avenue. Massive transport infrastructure investments and a comprehensive development scheme will be necessary, however, to develop the area as envisioned.

Office employment in Manhattan has fluctuated considerably over the last three decades without any significant secular growth. Despite this slow growth in employment, the occupied office space shows a clear expansive trend over the last decades. This growth, however, is almost entirely due to an increase in office space per worker. I will explore this phenomenon in more detail in Chapter 4 (Forecast of the Manhattan office market).

1.5 The time dimension of office market research: Real estate cycles

It is not within the scope of this dissertation to replicate the vast theoretical body of knowledge on general business cycles and longer-term economic cycles as developed by Schumpeter (1927), Kuznets (1930), Kondratieff (1935) and more recently by Nobel prize winners Kydland and Prescott (1990) to name only some of the more illustrious proponents of economic cycle research. Hence, this section is limited to a brief outline of the characteristics of real estate cycles as far as it is necessary to comprehend the underpinnings of the empirical research presented in the following chapters. Albeit not as extensively researched as general business cycles, cyclical movements of real estate markets have become a primary research subject in the past decade (e.g. Clapp 1993, Barras 1994; Kummerov 1999; Wheaton 1999). In essence, most of these studies find empirical support for the Cobweb theorem which postulates an inherent sluggishness of markets in adapting to changes in the demand structure. Lagged responses to market conditions are characteristic of the office real estate market because planning and construction of buildings is a long-term process despite recent advances in building technology which accelerate the construction process. The stylized abstraction of the real estate cycle as depicted in Figure 1-3 distinguishes four phases: recovery, expansion, peak, and decline. Mueller (1999) demonstrated that each phase of the cycle is connected to a distinct pattern of changes in rental rates, occupancy rates and new construction of office space. Thus, the four phases are defined horizontally by the position of current occupancy (i.e. all office space that is currently occupied and not vacant) to long-term average occupancy (LTAO). The peak point is defined as the origin of a dividing vertical line between positive growth of occupancy rates and the subsequent contraction. At the same time, it is also considered the demand/supply equilibrium point since it marks the moment in the cycle when supply of office space catches up and equals demand. As new construction of office space continues and new buildings become available, the market is pushed off the equilibrium again and occupancy falls below the threshold of the LTAO, marking the beginning of the decline phase which is characterized by excess supply. It is important to note here that the term equilibrium as used in this context is merely a simple ratio of demand for space versus supply of space. A hypothetical equilibrium price or rental rate which is more intricate to determine will be introduced in Chapter 4 as part of constructing the forecasting model. The second illustration at the bottom of Figure 1-3 gives a description of the prevailing features at each phase of the cycle. It demonstrates that changes in demand are not immediately recognized in the marketplace because companies initially accommodate additional office workers within the fixed amount of leased-up space before they are able to adjust their space needs with new lease transactions. Moreover, rental rates are lagged as well because information about price changes spreads gradually and selectively among both landlords and tenants. Although it may appear counterintuitive, construction and delivery of new space is not halted immediately and continues despite rising vacancy rates in the decline phase. The reason for this time lag is that completing office development projects is a complex task with a planning horizon of several years necessary for acquiring and assembling the site, finishing the architectural and urban design, obtaining a building permit, putting together a viable financing concept and physically constructing the building. Once the implementation of an office development project has reached a certain stage (for instance, when construction of the building has already started) it has already passed the point-of-no-return. In this case, buildings will be completed regardless of the market situation. Development projects that have not passed that point-of-no-return may be put on hold until market conditions improve or may be discarded completely depending on the individual circumstances. At the aggregate market level, the time lag structure resulting from the long periods of planning and construction exacerbates the amplitude of the market cycle.

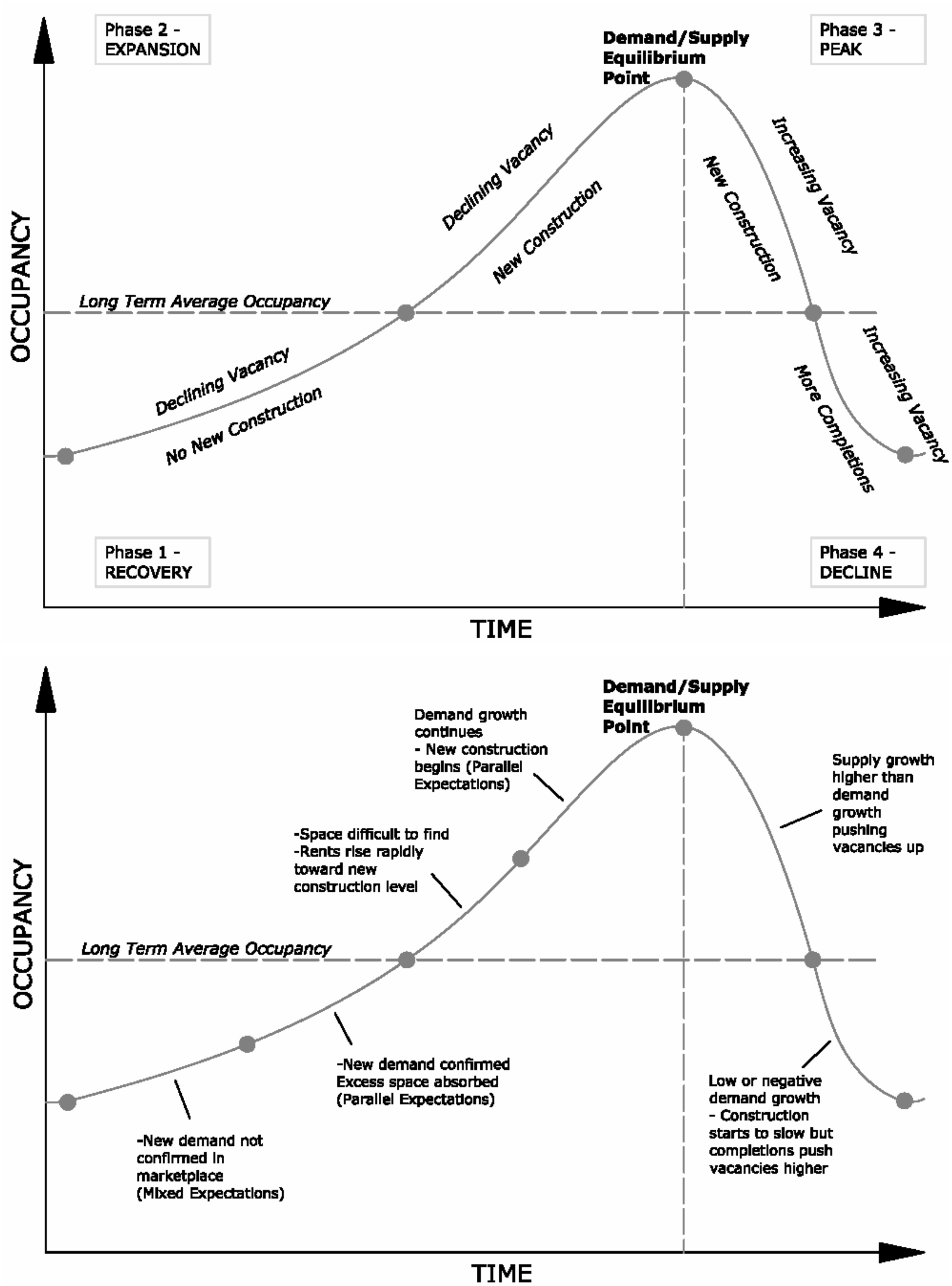

Figure 1-3: *Characteristics of a stylized real estate cycle model.*

Source: Adapted from Mueller (1999).

In order to specify the implications of the market phases visualized in Figure 1-3, Table 1-2 shows how each of the four phases is reflected in standard indicators of office market research. The table describes both the absolute level of the respective indicator at the beginning of a given phase and the subsequent change ('trend') during that phase (Fürst 2003). At the beginning of the recovery phase leasing activity increases, new space is absorbed and vacancy rates decline. According to Figure 1-3, the signals sent through changes in absorption and vacancy are initially not recognized by the marketplace and rental rates remain stable until the occupancy rate exceeds the LTAO threshold at the beginning of the expansion phase. In contrast to this lagged response during market recovery, the sensitivity of rental rates to deteriorating market conditions is generally higher, arguably because the delivery of new office space aggravates the imbalance of supply and demand during the decline phase of the market.

Further along the stylized phases of the market cycle, as absorption continues at a high rate and office space becomes increasingly scarce, rental rates begin to rise rapidly once vacancy rates fall below a certain threshold (whose exact value has to be determined empirically and separately for each market). Although absorption and vacancy rates begin to slow at the peak of the market cycle due to scant availability of new space, rental rates continue to rise. New construction does not occur during the recovery and expansion phases of the market due to the time lags described above. It is not until the beginning of the peak phase that large-scale new construction of office buildings is completed. As new space is being released to the market in very short time intervals at or around the peak phase, rental rates decline precipitously in response to the new demand-supply ratio. The decline phase may also be exacerbated by eroding demand (which in turn entails reduced occupancy rates) although this is not always the case. A further important indicator is the capitalization rate, which is defined as the ratio of annual return on an individual property divided by the price of the property. In principle, the greater the perceived risk of a given real estate investment, the higher the capitalization rate will be. Hence, the desired return on that investment will also be higher as investors expect a premium to reward them for the increased risk. Along the timeline of the market cycle, capitalization rates begin to decline as perceptions of the office market become more favorable during the expansion phase. Capitalization rates typically reach their lowest point during the peak of the cycle and increase during the decline phase as investors fully recognize the inherent risk of the investment. This adaptation of investors' perceptions and capitalization rates typically occurs with a time lag due to frictions between the space market and the capital market. The length of this cycle may vary empirically although empirical studies report an average duration of seven years (Shilton 1998) to ten years (Wheaton 1987).

Table 1-2: Typical phases of the real estate market cycle and their manifestations in major market indicators. Source: Fürst 2003.

		Recovery	*Expansion*	*Peak*	*Decline*
Absorption	*Level*	*low*	*intermediate (exceeds new construction)*	*high*	*negative*
	Trend	↗	↑	↗	↓
Vacancy	*Level*	*high*	*below 'natural' rate*	*severe shortage of space*	*above 'natural' rate*
	Trend	↘	↓	↘	↗
Rental rates	*Level*	*low*	*intermediate*	*high*	*intermediate or low*
	Trend	→	↗	↑	↓
New construction	*Level*	*low*	*low*	*intermediate*	*high (exceeds absorption)*
	Trend	→	→	↗	↑
Capitalization rates	*Level*	*high*	*intermediate*	*low*	*high*
	Trend	→	↘	↓	↗

This stylized model of the real estate cycle has been criticized extensively for assuming market agents with no or myopic foresight of market developments. Faulty predictions are often due to trend extrapolations in times of prosperity and overly optimistic expectations of future market developments. DiPasquale and Wheaton (1996) demonstrate how the assumption of either myopic or perfect-foresight agents determines the severity of cycles. More recently, regression models and other sophisticated methods of market research such as neural network models, genetic algorithms (Bee-Hua 2000) and cellular automata (Batty 1998) have been applied to elucidate the pathway of expected future developments. It remains to be seen, however, whether the refinement and application of these methods as decision-support systems will contribute to a more 'farsighted' behavior of market agents and a flattening out of the real estate cycle. It is to be suspected, however, that real estate cycles will continue to occur as long as the underlying factors 1) asymmetric information, 2) time lags in market response and 3) heterogeneity in risk averseness of market agents persist.

1.6 The spatial dimension of office market research: Intraurban locations and the evolution of submarkets

As demonstrated in the previous section, endogenous cycles arise in office markets because of the long time lags of planning and constructing new supply and the long-term nature of most commercial leases. Most of the research on real estate market cycles, however, is aspatial in that it assumes a simultaneous adjustment of all intraurban locations to changing supply and demand relations at the metropolitan level. Very few studies seek to combine cross-sectional and time series office market data at the intra-urban level (Mourouzi-Sivitanidou 2002). The following chapters of this dissertation address some of these issues to enhance the knowledge about market dynamics in various phases of the market cycle and the nature of intraurban spatial competition.

Overall, two major strands of models can be discerned as to their treatment of intraurban and spatial differences: One that considers the metropolitan area a single real estate market and another that postulates that submarkets are highly fragmented and in many cases out-of-sync with the overall development of a metropolitan area. The former research tradition bases its assumptions on urban location theory which implies that the relative price differences between intra-urban submarkets remain stable over time irrespective of cyclical oscillations in absolute prices (constant ratio hypothesis). This stability is ascribed to the high degree of intraurban mobility of office tenants, a high price elasticity of demand and possibilities to arbitrate in a situation of mispricing (DiPasquale and Wheaton 1996). The possibility of moving from one location to another within a city at relatively low transaction costs ensures that a unitary and consistent pricing scheme prevails throughout a metropolitan area. Following this theory, a change in the relative price hierarchy of an urban market is only possible if major changes in either the physical attributes of particular locations or in transportation and communication technologies occur. Numerous empirical studies have shown that an elaborate functional division of labor exists indeed between various submarkets in a metropolitan area. This division of labor is reflected in the spatial organization patterns of office firms, such as front office – back office divisions (Shilton 1999, Schwartz 1992, Hanink 1997, Sivitanidou 1996). It is thus pertinent that processes of evolving locational specialization be integrated into a reliable forecast model in addition to emulating the mechanics of price and rental rate movements.

All of these factors are said to ensure that each metropolitan area forms a functional market where the hierarchy of locations remains unchanged unless massive alterations of the built environment occur. Thus, econometric models which are based on the single market assumption typically control rent variations between submarkets with dummy variables (Wheaton and Torto 1995). Based on the results of an empirical analysis, Mueller and Laposa (1994) note that distortions in submarket pricing can occur in the short run although submarket conditions are bound to converge towards the metropolitan rental equilibrium in the medium and long run.

The second group of researchers postulate that office markets are not fully efficient, office buildings are not close substitutes for each other and market transparency is generally low (Evans 1995). Due to the 'lumpy' nature of real estate transactions, sunk costs as defined by Baumol and Willig (1981) are regularly generated as substantial amounts of time and money are invested in a real estate transaction. The corollary of this is that monopolistic market structures are likely to arise whenever transaction costs, barrier to entry, and sunk costs are high. Empirical evidence in the context of office markets points to the fact that economic fragmentation of spatial submarkets exists (Sivitanidou 1995, 1996, Bollinger et al. 1998), arguably because of the high search and transaction costs inherent in the real estate market.

Evans (1995, 21) argues that market inefficiencies are caused by the heterogeneity of individual properties in a metropolitan market, the infrequency of market transactions and the limited number of bidders and sellers in any given market transaction. He identifies several aggravating factors arising from market inefficiencies that tend to reinforce each other. For example, in an inefficient market, real estate brokers can potentially act unethically by taking advantage of various information deficits on the part of clients. These moral hazard structures which are characterized by gains from ultimately unethical behavior enabled by asymmetrical information contribute to even more fragmented and intransparent markets.

In an empirical study of the Orlando office market, Archer (1997) found that there is at least limited evidence of a transitory and in some cases even permanent segmentation of submarkets. Moreover, he finds that segmentation of submarkets is continuous rather than divided by sharp boundaries. In an empirical test, the inclusion of structural features failed to improve overall market forecasts while the inclusion of dynamic features (history of occupancy and rental rates) yielded better results. Slade (2000) estimated rent determinants during market decline and recovery but did not consider any explicitly spatial variables. Dolde and Tirtiroglu (1997) found distinct patterns of temporal and spatial diffusion of real estate prices using GARCH-M methods.

Capturing neighborhood and transport accessibility effects

The importance of spatial variables in hedonic modeling is almost universally acknowledged in the literature. The broad variety and potential cross-influence of spatial variables poses a number of intricate problems, however. The goal of hedonic modeling should be to maximize the efficiency of the estimators while minimizing information loss due to elimination of important variables. In an effort to categorize spatial variables, Can (1996) proposed to distinguish between adjacency and neighborhood effects. Adjacency effects which are externalities and spillover effects due to the geographic position of a property relative to other points of reference (i.e. other properties, transportation infrastructure) can be captured by geostatistical methods and various accessibility measures. Neighborhood effects, which are perceived or observable characteristics of an area, also have an impact upon property prices and rental rates although their contribution to price formation is more difficult to measure.

Although not widespread in office market research, spatio-temporal models are a well-established strand of research in the housing market analysis. The most widely-accepted models include Clapp's local regression Model (LRM), Dubin's maximum likelihood estimation of the hedonic regression and Case's hedonic price model of homogenous districts and nearest neighbor residuals (Case et al 2003).

Rent gradients and agglomeration effects

One of the earliest references to the existence of cross-sectional fragmentation can be found in Hoyt (1939) who observed that cities are composed of submarkets radiating outwards from the center thus forming different zones of land use. Today, there exists a host of studies on intrametropolitan office submarkets (Clapp 1980; Ihlanfeldt and Raper 1990; Mills 1990; Hanink 1997; Bollinger et al 1998). The starting point of such considerations is the stylized fact that scarcity of urban land ensures the allocation of an 'optimal' use for a given parcel under market conditions, thus determining rents and property values (Alonso 1964; Dokko and Edelstein 1992). The highest and best use of a site is dependent on the bid rent for a specific use which in turn is determined by the expected additional utility an agent will derive from a specific location. The resulting bid rent functions form a pattern of real estate price gradients that are inversely related to distance from the Central Business District under the assumption of a monocentric city.

What induces these locational advantages that cause companies to pay such vastly different rents in different locations? One crucial factor in the formation of office clusters is the existence of knowledge spillovers at various geographic levels. In an empirical study of the microfoundations and geographic levels of agglomeration economies, Rosenthal and Strange (2001) found evidence that such knowledge spillovers operate almost exclusively at the small-scale level. The authors conclude from their observations that such spillovers evaporate rapidly across space. When analyzing agglomeration effects in this context, it is helpful to break down agglomeration economies into two types of effects: localization economies or Marshall-Arrow-Romer (MAR) externalities which are dependent on the size of a particular industry within a city and urbanization economies (also termed Jacobs externalities) which are dependent on the overall size of a city's economy (Henderson 1997). Following this definition, localization economies refer to savings in production costs that a firm achieves by sharing industry-specific input factors with companies of the same industry or by gaining joint access to a large pool of workers with specialized skills relevant to the particular industry or trade. Urbanization economies, which are more broadly defined, apply to all urban location factors such as transportation infrastructure, public utilities, information services and other factors that are simultaneously relevant for a number of industries and exhibit decreasing average costs with large-scale production (McDonald 1997, 37).

Following this line of argumentation, both small-scale localization and urbanization economies can contribute to a fragmentation of submarkets because they imply a greater differentiation of locations within a city and hence imperfect substitutability of locations and individual properties. Assuming that office-using firms are different regarding their locational preferences, demand for office space will not be distributed evenly over a city's submarkets but will instead be directed by the growth patterns of various office-using industries and their locational preferences. As will be demonstrated later on, submarkets matching the locational preferences of information technology firms experienced a particularly dynamic development during the so-called dotcom boom.

Metropolitan office markets: homogenous entity or fragmented submarkets?

The existence of distinct submarkets within urban real estate markets has been confirmed by a large number of studies. The highly localized patterns of occupancy and rental rate determination found in these studies are evidence of fragmentation. Market fragmentation occurs when the boundaries separating relatively homogeneous market areas exert a significant influence on the level of commercial leasing activity and price formation. In principle, there are both structural and spatial forces that lead to a less than perfectly integrated local office market. In this context, structural fragmentation refers to distinct submarkets marked by individual property characteristics (as reflected in the Class A/B/C distinction) whereas spatial fragmentation is brought about by the features of a particular location (e.g. accessibility by mass transit or the prestige of an area). Empirical studies find that structural and spatial fragmentation overlap frequently because certain types of properties are more prone to prevail in an area with specific locational characteristics. For instance, it is highly likely that the office properties found in an area with a very good locational profile will itself be of very high quality itself with state-of-the-art communication infrastructure and above-average design and amenities. While it is statistically possible to control for the impact of structural and spatial variables separately, this would in effect eliminate the information on the simultaneous occurrence of both types of fragmentation and their causal interrelationships.

A widespread problem plaguing hedonic analyses is spatial dependence or autocorrelation (Bourassa et al 2005). It is caused by covariance in the errors of nearby properties in a hedonic price estimation. Given the similarities in the prices of characteristics within a submarket, errors are more likely to be correlated within submarkets than across submarkets. Therefore, controlling for submarkets in hedonic equations can substantially reduce estimation errors. This can be accomplished in a variety of ways. Simple methods include incorporating a series of dummy variables for the submarkets, estimating a separate equation for each submarket, or adjusting predicted values using the errors within each submarket.

In fragmented markets, two comparable products, which are considered close substitutes, can differ widely in the prices achieved in two or more separate submarkets. According to neoclassical economic theory, such a phenomenon cannot persist over an extended period since arbitrage mechanisms will cause prices in all submarkets to converge. The ability of tenants to move from temporarily overpriced to underpriced areas within a city is another factor that ensures a unitary pricing scheme.

Spatial arbitrage mechanisms and intra-urban mobility are said to ensure that each metropolitan area forms a functional market. The hierarchy of locations within a city remains unchanged unless massive alterations of the built environment occur. Thus, econometric models which are based on the single market assumption simply control rent variations between submarkets with dummy variables without analyzing the dynamic relationship between these submarkets (Wheaton and Torto 1995). The underlying theoretical view of this strand of office market analysis is that distortions in submarket pricing relative to the overall market may occur in the short run although submarket conditions are bound to trend towards the metropolitan rental equilibrium in the medium and long run (Mueller and Laposa 1994).

There is no general consensus in the literature whether it is preferable in the context of a hedonic analysis to include predefined submarkets (for example as defined in standard real estate market reports) or apply principal component analysis or other methods to generate new submarkets with maximum discriminatory power. For example, Bourassa, Hoesli and Peng (2003) demonstrate that applying algorithms to calculate submarkets leads to significant improvements in the accuracy of predictions based on a market-wide hedonic equation. Ugarte, Goicoa and Militino (2004) apply mixture models which simultaneously estimate hedonic equations and classify transactions into non-geographic submarkets. Although not widespread in office market research, spatio-temporal models are a well-established strand of research in housing market analysis. These models include Clapp's local regression Model (LRM), Dubin's maximum likelihood estimation of the hedonic regression and Case's hedonic price model of homogenous districts and nearest neighbor residuals (Case et al 2004). Recent housing studies incorporate a host of sophisticated geostatistical methods derived from spatial econometrics (Kim, Phipps and Anselin 2003). In these models, the relationship between an individual property and neighboring properties are typically captured in a matrix of weights or by a distance function based on a fitted (semi-)variograms. The present study includes several spatial variables which will be explained in detail in the next section.

Atack and Margo (1998) examined the price gradient theorem in a study of New York City using historical data from 1835 to 1900. To eliminate the distorting effect of changes in real estate inventory over such a long period of time, the authors only considered sales of vacant lots in the hedonic regression and used distance from City Hall in Manhattan as an independent variable to explain land prices. The authors find that improvements in public transportation and socio-economic changes led to a gradual flattening of the price gradients over time even before the advent of the automobile.

Most studies on the intrametropolitan distribution of office space are based on a simplified suburb-central city dichotomy within which spatial changes in a market are explained. Micro-locational effects within an inner-city market, however, such as the Manhattan office market, have remained largely unexplored. Clapp (1980) noted that rents vary considerably within a very small distance. By the same token, a modification on any site within the existing urban fabric is bound to alter the property values of neighboring sites. For example, following the construction of major building projects significant changes in rental and property values can be detected on adjacent sites. Dunse, Leishman and Watkins (2002) showed in two case studies of Edinburgh and Glasgow using hedonic analysis and several statistical indicator tests that evidence on the overall existence of the submarket phenomenon is inconclusive for both cities. They argue that further empirical testing for submarket existence is necessary. Sivitanidou (1995) demonstrates that spatial supply-side constraints such as existing zoning regulations are also important factors in explaining office market development. Thrall (2002) notes that real estates cycles are often confined to relatively small areas within a city. He cites maintenance-based cycles, areas with buildings of a predominant vintage and spatially focused investment cycles as causes of spatially confined submarket cycles. Typically, suburban office cores experience only one life-cycle whereas core areas such as Manhattan undergo multiple construction- (re-)investment/renovation cycles and submarkets are more likely to be in a continuous renewal process as older buildings are being renovated and newer buildings are gradually replacing obsolete ones. These small-scale factors are usually not accounted for by models that fail to acknowledge intertemporal heterogeneity of the stock (Dombrow, Knight and Sirmans 1997).

Can (1996) examines the presence of spatial segmentation, or different pricing schemes in the housing market, based on geographic location. She contends that if neighborhood effects enter as direct determinants of housing prices, such as a premium, then one can assume a uniform housing market under investigation, since there will be one price schedule. In contrast, if neighborhood differentials lead to varying attribute prices, one can assume the presence of independent price schedules, thus the existence of a spatially segmented market. Within a cross-sectional framework, Can uses both spatial switching regressions and expansion methodology as means of incorporating spatial variability in house price models within a hedonic framework. Using data from 3,770 housing transactions in the Miami MSA in the third quarter of 1990, Can finds evidence of market segmentation using a spatial contextual expansion model with a quadratic trend. The majority of studies on the significance of submarkets applies principal component analysis or cluster analysis to generate homogenous submarkets. In the present study, no attempt is being made to generate new submarkets with the aim of maximizing statistical homogeneity *within* the submarkets and heterogeneity *between* the submarkets since the application of such a methodology may lead to circular reasoning (i.e. submarkets are first constructed based on homogeneity and heterogeneity criteria to then test for homogeneity and heterogeneity of these submarkets. Instead, the submarket delineation as used by practitioners in market research is being used to test whether fragmentation can be detected even without prior application of statistical grouping methods.

Having now laid out the objectives and scope of the dissertation along with a brief introduction into the temporal and spatial dimensions of office market research, we proceed with the first of the core chapters of this dissertation, the analysis of office employment.

2 Agglomeration effects and the changing spatial distribution of office employment in the New York region

This chapter examines the spatial dynamics of office employment in the New York region. The empirical analysis presented here addresses three key issues. First, little is known about geographic concentration outside of the manufacturing sector and hardly any consistent empirical work has been done on the spatial dynamics of office-using industries. Taking similar studies of the manufacturing sector as a point of departure, this paper simply takes a step back to answer the basic question: do establishments in the office-using sectors tend to be spatially concentrated in the New York region? If so, have recent changes in office employment been more dynamic in the Manhattan core or in the more peripheral counties of the agglomeration? Secondly, the regional employment analysis is extended by introducing some simple measures of labor productivity for office-using industries and by comparing productivity growth in the core to that of the outer region. Thirdly, the regional county-level analysis is complemented with a more disaggregated analysis of co-agglomeration in office using industries at the zip code level. To this aim, measures of co-agglomeration are calculated for all possible combinations of industries and the distribution of these measures is examined.

These three topics can be condensed to three essential questions: 1) How concentrated is office employment in Manhattan, the center of the New York region and what changes have occurred in the ratio between the urban core and the suburban periphery in recent years? 2) Is labor productivity in office-using industries similar in the core and periphery and how can potential differences be explained by structural features? 3) What conclusions can be reached from zip code level analysis of co-agglomeration of office industries regarding the existence of small-scale spillovers?

2.1 Introduction

Employment dynamics of office-based service industries are a main determinant of the demand for office space and an integral part of contemporary metropolitan economies. This is particularly true for Manhattan where FIRE (finance, insurance and real estate) and other office-using industries account for over 40 percent of total employment. In Lower

Manhattan, office jobs make up approximately 75 percent of all jobs (data source: Bureau of Labor Statistics 2005). At the regional level, suburban areas have experienced strong growth in office space and employment growth virtually throughout all metropolitan areas. In contrast, growth in inner cities has been more modest and in some cases even negative. Lang (2000) reports that in the aggregate US market office space almost tripled within one decade (1979-1989) whereas central city office space grew only by 90 percent. During the 1990s, growth of suburban office inventories slowed down remarkably, allowing inner cities to partially regain their competitiveness. Construction of new office space was 280 million square feet in inner cities and 234 million square feet in the suburban areas at the national level. This long-term trend towards more decentralized office is partially counteracted by the requirement of frequent face-to-face contacts in knowledge intensive industries. Glaeser and Kahn (2001) report that financial and business services, research and development activities, and technology development are among the industries that are strongly dependent on face-to-face communication. In addition, Rauch (1993) found knowledge spillovers in dense urban environments with a high employment density to be a source of significant productivity gains. Schwartz (1992) contends, however, that suburban proximity as found, for instance, in campus-style suburban office parks may be sufficient to replicate the proximity and communication patterns found in Central Business Districts. In a similar vein, Chang and Coulson (2001) reported that employment growth in central cities is associated with complementary suburban growth but also found cases in their empirical study where suburban growth occurred as substitutive growth at the expense of the urban core. In the face of conflicting empirical evidence, it is pertinent to briefly review the theoretical foundations of agglomeration economies before commencing the empirical analysis.

2.2 The concept of agglomeration economies

Cities have a number of distinct features that enhance their competitiveness over more peripheral areas. First, the diffusion of information among firms regarding research and development, labor, financing, and marketing strategies is particularly high in cities (Blair 1993). Transfer costs and unit costs are lower, labor productivity and management efficiency are higher (Hoover and Giarratani 1985). These locational advantages are transmitted via agglomeration economies. The term 'agglomeration economies' denotes a variety of distinct processes that result in spatial concentration of economic activities at various geographic levels. Three microfoundations of agglomerative forces have been defined in the literature: (1) knowledge spillovers, (2) labor market pooling, and (3) input sharing (Rosenthal, Strange 2001). When analyzing agglomeration effects in this context, it is helpful to break down agglomeration economies into two types of effects: localization economies or Marshall-Arrow-Romer (MAR) externalities which are dependent on the size of a particular industry within a city and urbanization economies (also termed Jacobs externalities) which are dependent on the overall size of a city's economy (Henderson 1997). Following this definition, localization economies refer to savings in production costs that a firm achieves by sharing industry-specific input factors with companies of the same industry or by gaining joint access to a large pool of workers with specialized skills relevant to the particular industry or trade. Urbanization economies, which are more broadly defined, apply to all urban location factors such as transportation infrastructure, public utilities, information services and other factors that are simultaneously relevant for a number of industries and exhibit decreasing average costs with large-scale production (McDonald 1997, 37).

More specifically, two sources of agglomeration economies are reported in the literature: natural advantage and spillover effects which I will outline briefly before proceeding to the empirical analysis of the New York region.

Natural Advantage

The basic precept of the theory of natural advantages is that absolute differences in the size of agglomerations create competitive advantages for larger regions. The higher density and absolute size of the agglomeration is in turn caused by an initial favorable endowment of a place with natural advantages that triggers the creation of an urban settlement at that particular location. Natural advantages include proximity to natural resources, high soil quality and a location along navigable waterways.

Based on assumptions derived from the Heckscher-Ohlin interregional trade model (Ohlin 1933, Leamer 1993), we may express the concept of natural advantage more formally by considering a model with *N* firms and *I* spatial markets at the state, county, zip code or some other level of aggregation. Next, the *k*th firm enters that region (*i*) which maximizes profits in the following fashion:

$$\log \pi_{ki} = \log \overline{\pi_i} + g_i(\upsilon_1, \ldots, \upsilon_{k-1}) + \varepsilon_{ki} \tag{1}$$

where $\log \pi_{ki}$ is profit accruing to firm *k* located in region *i*. Firm *k*'s profits are a function of $\log \overline{\pi_i}$, the profit of an average firm in *k*'s industry in region *i*; which in turn depends on a number observable and unobservable regional features. Moreover, profit is also a function of $g_i(\upsilon_1, \ldots, \upsilon_{k-1})$-the spillover effects of all other firms located in region *i*. Finally, profit is also a function of random exogenous shocks $\{\varepsilon_{ki}\}$. Next, if $g_i(\upsilon_1, \ldots, \upsilon_{k-1}) \equiv 0 \quad \forall\, i$, then the model reduces to a standard conditional logistic model—conditioned on the realizations of the profits $\{\overline{\pi}_i\}$. Next, we impose the following two restrictions on the model:

$$E_{\overline{\pi}_1, \ldots, \overline{\pi}_M} \frac{\overline{\pi}_i}{\sum_j \overline{\pi}_j} = x_i \tag{2}$$

$$\operatorname{var}\left(\frac{\overline{\pi}_i}{\sum_j \overline{\pi}_j} \right) = \eta^{na} x_i (1 - x_i) \quad \text{where } \eta^{na} \in [0,1] \tag{3}$$

Equation 2 yields the likelihood of *k* locating in region *i*. The parameter η^{na} indicates the importance of natural advantages in a given region. A value of η^{na} close to zero implies that the region does not have any natural advantages, while a value of one implies that the natural advantages of that region dominate all other regions. Consequently, all firms find their optimum by locating in the region where η^{na} =1.

Spillovers

The model presented in the previous section does not take into account efficiency gains for firm k due to input sharing and spillover effects. Therefore, we modify Equation 1 to incorporate these effects in the following way:

$$\log \pi_{ki} = \log \overline{\pi_i} + \lambda^s \sum_{l \neq k} e_{kl}(1-u_{il})(-\infty) + \varepsilon_{ki} \quad (4)$$

In this model, $\{\varepsilon_{ki}\}$are Bernoulli discrete random variables equal to one with probability $\lambda^s \in [0,1]$, and equal to zero with probability $1-\lambda^s$. The variable u_{il} is a dichotomous variable that equals one if establishment l is in region i, or zero otherwise. Spillover effects are captured by the probability parameter λ^s. This parameter includes various types of spillover effects. In turn, the value of this parameter may be interpreted as the propensity of firms to agglomerate.

Comparing the importance of natural advantages to spillover effects, Krugman (1993) demonstrates that natural advantages (which he terms 'first nature') are of negligible importance compared to agglomeration effects ('second nature') which by and large are sufficient to explain the existence of agglomerations in an interregional trade model. Decomposing the impact of various spillover effects in empirical studies is not a straightforward task, however. In an attempt to define spillover effects more precisely, Glaeser, Kallal, Scheinkman, and Schleifer (1992) examine the role of technological spillovers in the growth of cities. They find support for the assumption that spillovers between industries may be more important than spillovers within an industry. They also conclude that competition and economic diversity supports employment growth while significant specialization is an impediment to growth. Jaffe, Trajtenberg, and Henderson (1993) measure technological spillovers using patent citation data. In the present dissertation, spillovers are empirically measured by the degree of association (correlation) between excess small-scale concentrations of office-using industries. The empirical work of Rosenthal and Strange (2001) further confirms that knowledge spillovers are measurable only at the zip code level (or comparably small spatial units) arguably because they tend to attenuate rapidly across space. The present analysis takes up this zip code level and customizes it to fit the data and specific research questions at hand.

2.3 Methodology and data

In order to analyze the dynamics of office employment in the New York region, I calculate four types of concentration measures: the location quotient, the Hirschman Index and the locational Gini coefficient and the Ellison-Glaeser-Index.

Concentration indices

The most basic measure among these is the location quotient which is formally defined as:

$$LQ = \frac{e_{ij}^{t}}{e_{j}^{t}} \div \frac{E_{i}^{t}}{E^{t}} \quad (5)$$

where e_{ij}^{t} is employment in a given industry *i* in region *j* in year *t*. E_{i}^{t} is national employment in industry *i*. The location quotient approach compares the concentration of employment in a given industry and spatial unit to that industry's share at the aggregated national level. LQ values below 1.0 indicate that an industry has relatively fewer employees in a given spatial unit compared to the national level whereas a value above 1.0 indicates that an industry's share in the economy of a spatial unit is higher than it is in the national reference system. In the location analysis literature, LQ values above 1.0 are also interpreted as indicative of comparative regional economic specialization. LQ values above 1.0 are also routinely used to identify export industries in an export-base framework (Klosterman 1990).

The Hirschman-Herfindahl Index (HHI) takes into account the relative size and distribution of the competitors in a market and varies from 0 to 10000, where zero represents no concentration at all and 10,000 represents a perfect spatial monopoly. It is calculated by squaring the market share of each unit competing in the market (counties, in our case) and then summing the resulting numbers.

$$HHI = \sum_{i=1}^{N} \left(\frac{x_i}{X} \right)^2 \quad (6)$$

where x_i is the number of office workers in location *i* and *X* is the total number of office workers in all regions. Markets in which the HHI is between 1000 and 1800 points are considered to be moderately concentrated and those in which the HHI is in excess of 1800 points are considered to be markedly concentrated.

The spatial Gini coefficients are based on industry employment normalized by the overall industry-mix and distribution of the CMSA in the following form:

$$G = \sum_{i=1}^{N} \left(\frac{z_i}{Z} - \frac{x_i}{X} \right)^2 \tag{7}$$

where z_i is the number of workers of a particular office-using industry in location, Z represents the total number of workers of that industry in all regions, x_i is the number of all office workers in location i and X is the total number of office workers in all regions.
An industry which is not geographically concentrated more than the overall aggregate job distribution has a coefficient of 0. The coefficient approaches 1 with increasing spatial concentration of an industry. Spatial Ginis were applied, among others, by Krugman (1991) and Audretsch and Feldman (1996) to measure spatial concentration and to assess economic innovation. One of the advantages of the Gini coefficient is that it eliminates the size effect resulting from the fact that large employment and population centers are more likely to have larger numbers of workers in any given industry regardless of their industry-specific specialization. As Ellison and Glaeser (1997) point out, however, the Gini coefficient may overestimate concentration for some industries with relatively few plants. A positive value of the spatial Gini may also arise in a situation where an industry is merely made up of a small number of large plants (possibly due to industry size or internal economies of scale) with no agglomerative force present that causes the concentration. The authors propose an index which eliminates the distorting influence of industrial structure, which takes the following form:

$$E(\gamma) \equiv \frac{G - \left(1 - \sum_i x_i^2\right) HHI}{\left(1 - \sum_i x_i^2\right)(1 - HHI)} \equiv \frac{\sum_{i=1}^{M} (s_i - x_i)^2 - \left(1 - \sum_{i=1}^{M} x_i^2\right)^2 \sum_{j=1}^{N} z_j^2}{\left(1 - \sum_{i=1}^{M} x_i^2\right)\left(1 - \sum_{j=1}^{N} z_j^2\right)} \tag{8}$$

where G is the spatial Gini, HHI is the Hirschman-Hefindahl Index, s_i is the share of industry employment in region i, x_i is the share of total employment in region i, and z_i is the share of establishment employment of the industry. In the Ellison-Glaeser Index, the inclusion of the term $(1-\sum_i x_i^2)$ ascertains that E(γ)=0 when neither agglomerative spillover forces nor natural advantage are present. A zero value of γ indicates a perfectly random location process whereas positive γ values can be interpreted as excess concentration. It is not possible, however, to undertake any causal analysis of agglomeration effects with these measures. As Ellison and Glaeser (1997) point out, excess agglomeration as measured by E(γ) may result from either the presence of natural advantages or spillover effects. It is not possible to disentangle the impacts of both factors with the Ellison-Glaeser index since the cause of agglomeration of a particular industry may be pure natural advantage, pure agglomeration spillovers or a combination of both factors.

Datasets

The empirical analysis of this chapter is based on two main datasets, the County Business Patterns and the more disaggregated ES-202 data.

County Business Patterns (CBP) is an annual federal data series that provides standardized data on employment and wages by industry and county. This series is widely used in employment research to study the economic activity of detailed geographic areas over time and to benchmark time series data between economic censuses. CBP data excludes self-employed individuals, private household workers, railroad employees, agricultural employees, and most government employees. Since 1998, it has classified industry using the new North American Industry Classification System (NAICS). Before 1998, it used the previous Standard Industry Classification (SIC) system. Economy.com, a private data supplier whose CBP datasets are utilized to calculate the concentration measures described above, has attempted to reconcile SIC and NAICS data at the county level. As a consequence of these efforts, the dataset used here provides a continuous time series of employment at county level from 1984 through 2004.

ES202 Employment Data is the second major data series applied in this analysis. It comprises the New York State Department of Labor (DOL) Covered Employment and Wages data which is a quarterly time series of the number of workers and companies as well as the dollar amounts of aggregate wages by detailed industry and zip code of firm location. DOL collects this information from employers covered by New York State's Unemployment

Insurance Law. ES202 data cover approximately 97 percent of New York's nonfarm employment, providing a virtual census of employees and their wages as well as the most complete universe of employment and wage data, by industry, at the state, regional, county, and zip code levels. The data used for this study defines industry according to the older Standard Industrial Classification system (SIC) for 1992 through 2001 and the newer North American Industry Classification System (NAICS) for 2000 through 2003. Because the SIC and NAICS have not been made compatible at the zip code level, the small-scale analysis focuses only on the years organized according to the SIC system.

A known problem with using ES202 data for this type of analysis is that firms do not always report jobs where they are actually located, as the reporting form asks, but instead at the address of the company's headquarters or accounting service. While this may somewhat distort the picture of how jobs are distributed across zip codes, the main trends will nonetheless be visible. Another problem with ES202 data is that it suppresses data for zip codes with fewer than three employers in the SIC for confidentiality reasons. To remedy this problem, I apply a suppression correction algorithm. If observations were available for other years in the series (i.e. years when the number of reporting companies in an SIC rose above two) I calculated employment for the suppressed cases by applying the per-firm average taken from those other years. Where employment information was missing for whole series (because number of firms in zip code was continuously below three), no adjustments were made. The upward adjustment of employment numbers due to suppression correction ranged from 0.04 percent of total employment in 2001 to 0.27 percent in 1992. Further correction of cases with no valid observations would probably increase employment totals at the same order of magnitude.

For the purpose of this research, *office employment* is defined as including the NAICS categories 51 Information, 52 Finance and insurance, 53 Real estate, 54 Professional, scientific, & technical services, 55 Management of companies and enterprises and 56 Administrative & support services. Excluded from the latter category are 5621Waste Collection, 5622 Waste Treatment and Disposal and 5629 Remediation and Other Waste Management Services. This definition is widely used for public and private research, among others by the New York City Office of Management and Budget (2003).

2.4 Results

The development of regional office employment in the New York area largely echoes the broader national and international trends. The most important among these long-term trends is the growing importance of suburban office locations compared to central city locations. Figure 2-1 demonstrates that Manhattan had more office jobs at the beginning of the 1980's than all other thirty counties of the CMSA combined.[3] Over the course of the following two decades, the CMSA counties outside of Manhattan added more than half a million office workers while Manhattan office employment stagnated. It is also evident from the graph that the impact of the two business cycles in the observed period is reflected in both Manhattan and outer CMSA employment. While Manhattan office employment oscillates cyclically by an order of magnitude of 100,000 office workers, the other CMSA counties exhibit a clear secular growth pattern in office employment. Although employment growth in the outer CMSA appears dynamic compared to Manhattan, it is rather sluggish in the larger comparison of US national growth. In fact, the national employment growth rate in the last three decades of the Twentieth Century is more than double that of the New York-New Jersey-Connecticut CMSA (Hughes, Nelson 2002). It would be premature, however, to conclude that the figures signal a massive decentralization of office jobs. Until the 1980's, the New York region was one of the most highly concentrated in the country with more than 50 percent of office jobs being clustered in only one out of 31 counties on a land area that accounts for a mere 0.2 percent of the entire metropolitan area. In fact, Manhattan is unique in that it is the only county in the US in which the number of workers (2.2 million in 2003) permanently exceeds the number of local residents (estimated 1.6 million in 2003) despite the ongoing decentralization trend.[4]

Another caveat regarding these comparisons is that large percentage gains are more easily achieved in regions with no or little previous office employment while growth in the Manhattan and other mature markets requires large growth in absolute numbers.

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[3] The Consolidated Metropolitan Statistical Area (CMSA) consists of 31 counties in four states (New York, New Jersey, Connecticut, and Pennsylvania) which form an agglomeration of roughly 20 million inhabitants and 13,000 square miles. See Census.gov for geographic and other details regarding the CMSA counties.

[4] Employment is total non-farm payroll employment, source: Bureau of Labor Statistics, Economy.com. Source of population estimate: U.S. Census Bureau: State and County QuickFacts.

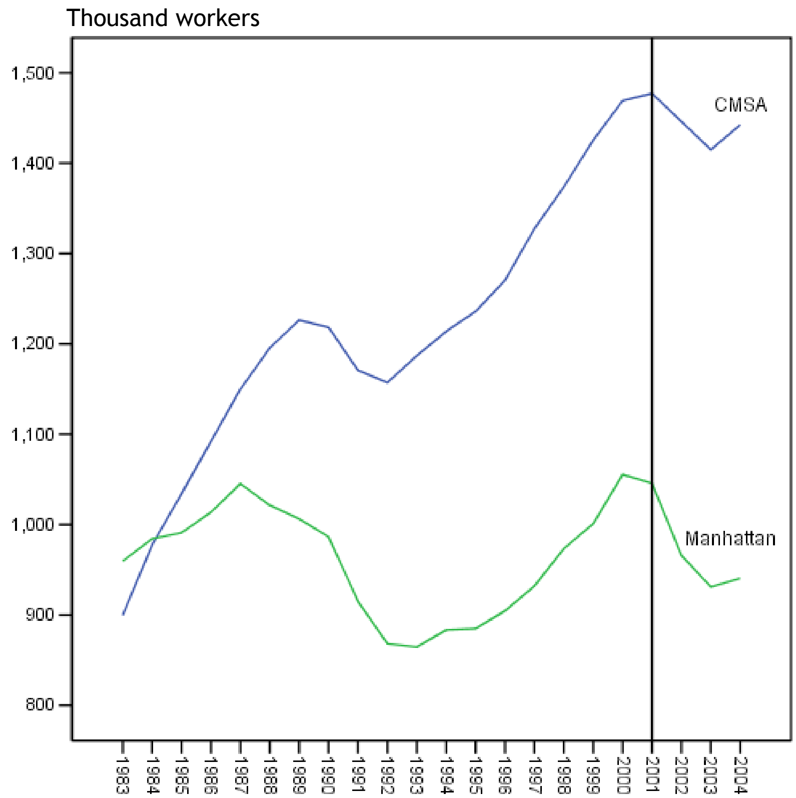


Figure 2-1: Office employment in Manhattan versus the CMSA counties ***outside*** *of Manhattan from 1983-2004 in thousands of workers. Sources: Bureau of Labor Statistics, Economy.com*

Turning to a more detailed analysis of the regional distribution of office employment, Table 2-1 and Table 2-2 present the empirical values of two standard measures of concentration as described in the previous section using County Business Pattern data. Table 2-1 shows the results of this calculation for county-level HHI values in the NAICS categories that are considered primarily office-using industries. Following the common definition of the threshold value where industries with an HHI value above 1800 are considered highly concentrated, three sectors qualify as such: information, finance and insurance and professional and technical services. Administrative and support services are the least concentrated activities. All industries have become less concentrated in the observed period from 1998 through 2003 with the exception of NAICS category 51 (Information).

Table 2-1: County-level Hirschman-Herfindahl Indices of office-using industries by county in the NY-NJ-CT CMSA

	1998	1999	2000	2001	2002	2003
Information (NAICS code 51)	1710	1876	1859	1982	1904	2016
Finance and Insurance (52)	2606	2830	2692	2618	2355	2339
Real estate (53)	1811	1542	1491	1646	1583	1431
Professional and technical services (54)	1968	1929	1913	1846	1758	1587
Management of companies (55)	1484	1246	1124	1313	1447	970
Administrative/support services (56)	1171	1078	1048	1052	976	937
all office-using industries	1836	1736	1683	1771	1658	1472

The values for the spatial Gini (Table 2-2) largely confirm the developments identified in the HHI analysis with finance and insurance being the most concentrated industry group in the New York CMSA and administrative and support services being the least concentrated. Looking at the changes over time within the analyzed period shows that all office-using industries have experienced employment decentralization to varying degrees throughout the analyzed period with the sole exception of the information industry (NAICS code 51).

Table 2-2: Spatial Gini of office-using industries in the NY-NJ-CT CMSA

	1998	1999	2000	2001	2002	2003
Information (NAICS code 51)	0.12822	0.1835	0.1845	0.16897	0.15675	0.19920
Finance and Insurance (52)	0.25487	0.31203	0.28815	0.25431	0.24884	0.26286
Real estate (53)	0.15992	0.18180	0.13999	0.12586	0.17281	0.15249
Professional and technical services (54)	0.18782	0.21992	0.21254	0.18344	0.16453	0.16971
Management of companies (55)	0.19299	0.21146	0.18006	0.15525	0.19046	0.19462
Administrative/support services (56)	0.07784	0.10138	0.09099	0.05896	0.05245	0.07497
all office-using industries	0.15110	0.18354	0.17253	0.13999	0.15675	0.14200

The gamma indices reported in Table 2-3 point in a similar direction. The decentralization process is less pronounced in the gamma values, however. While the information industry experienced significant centralization during the observed period, the five other major office-using industry groups remained relatively close to their initial levels. The general interpretation of the γ is not straightforward, however. Some empirical studies apply a rule of thumb where $\gamma > 0.05$ are defined as highly concentrated whereas $\gamma < 0.02$ are defined as not very concentrated (Ellison and Glaeser 1997, Rosenthal and Strange 2001), which we also follow in our interpretation. While management of companies (55) and administrative and support services (56) are not significantly concentrated, finance and insurance (52) exhibits an extraordinarily high degree of concentration that persists throughout the analyzed period. The high value is indicative of individual industries in the financial services industries contained in this group that are clustered in a few selected locations in Midtown and Downtown Manhattan. In the next step, the 2-digit industry groups are decomposed into 4-digit industry groups and the spatial units are disaggregated from counties to zip code level to obtain a more fine-grained analysis.

Table 2-3: *Ellison-Glaeser gamma indices of office-using industries in the NY-NJ-CT CMSA*

	1998	1999	2000	2001	2002	2003
Information (NAICS code 51)	0.054	0.154	0.116	0.103	0.058	0.134
Finance and Insurance (52)	0.223	0.290	0.262	0.222	0.217	0.232
Real estate (53)	0.142	0.167	0.119	0.103	0.158	0.133
Professional and technical services (54)	0.184	0.220	0.212	0.180	0.159	0.164
Management of companies (55)	0.045	0.069	0.028	0.005	0.043	0.047
Administrative and support services (56)	0.040	0.067	0.056	0.019	0.012	0.037
all office-using industries	0.098	0.136	0.123	0.085	0.106	0.087

In addition to the measures reported in the tables above, the spatial dynamics of office employment in the New York region can be illustrated with a series of maps.[5] Figure 2-2 shows the density distribution of office employment per square mile for the CMSA counties. With an average of 40,000 office workers per square mile, Manhattan exhibits by far the greatest density of all counties. This extraordinary density and the small-scale agglomeration spillover effects resulting from it are the basis of a more detailed zipcode-level analysis in the next step. Employment density diminishes gradually departing from Manhattan, resulting in a pattern of three concentric rings around the regional core. Figure 2-3 shows the percentage changes in office employment from 1998 until 2001 and Figure 2-4 from 2001 until 2002 at the county level (annual averages). During the first

[5] Maps in this study were generated by the author using the software system ArcGIS 9.1 by ESRI.

period (1998-2001) all counties experienced growth in office employment with the exception of only two counties (Essex and Pike Counties). The highest relative growth occurred predominantly in the New Jersey counties of the CMSA whereas Manhattan experienced the highest growth in absolute numbers. In the second period (2001-2002), the combined effect of the economic recession and the September 11 attack resulted in significant losses of office employment in most areas except some counties in the New Jersey in the southern and southwestern part of the CMSA. Manhattan experienced some of the sharpest declines in office employment both in absolute and relative terms. Two counties in the immediate vicinity of Lower Manhattan, Hudson County and Brooklyn showed an increase in office employment even after 9/11 due to office-using companies relocating from Manhattan to these neighboring office clusters in the wake of the attack.

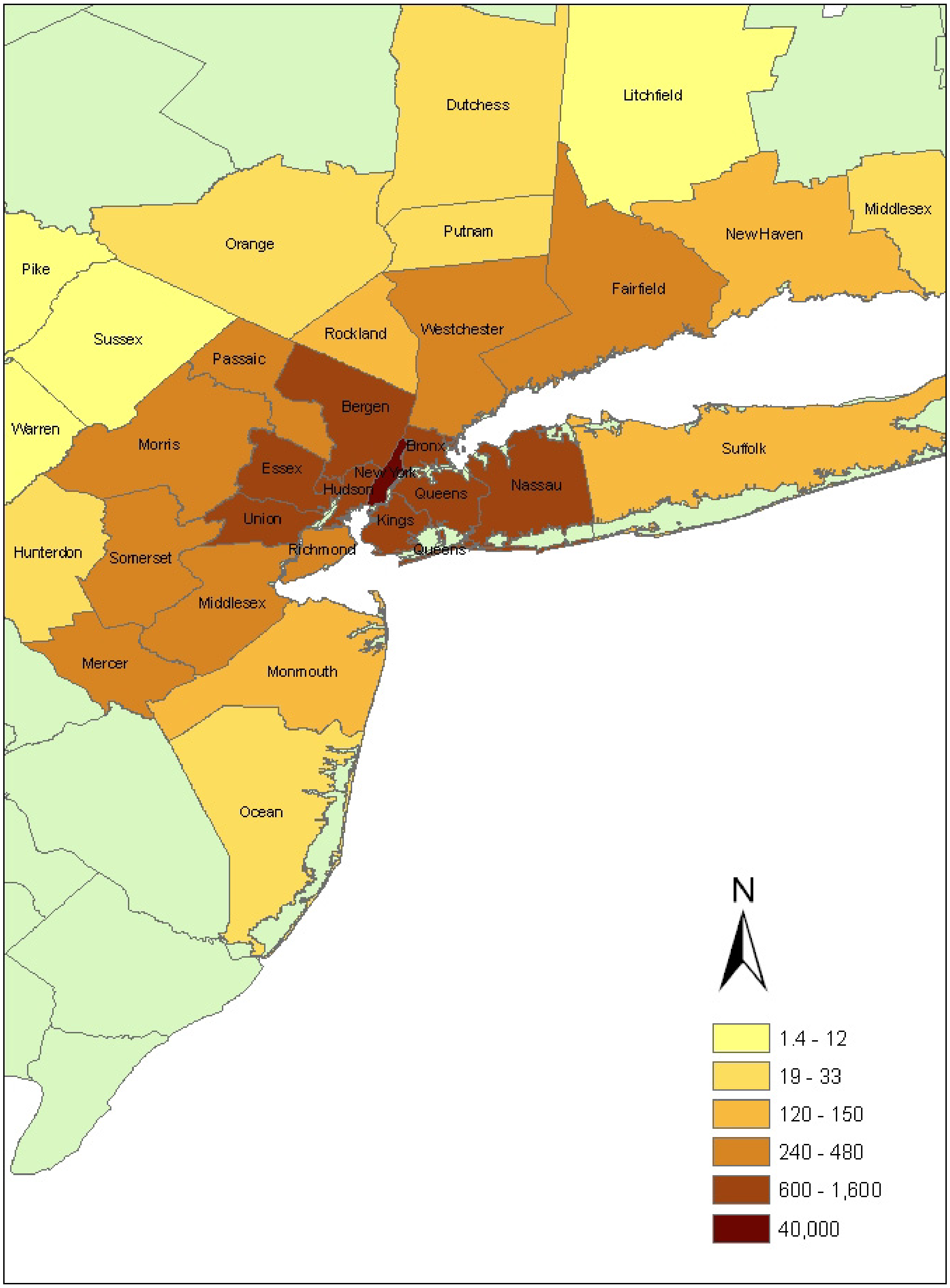


Figure 2-2: Office employment per square mile. Data: County Business Patterns, 2002

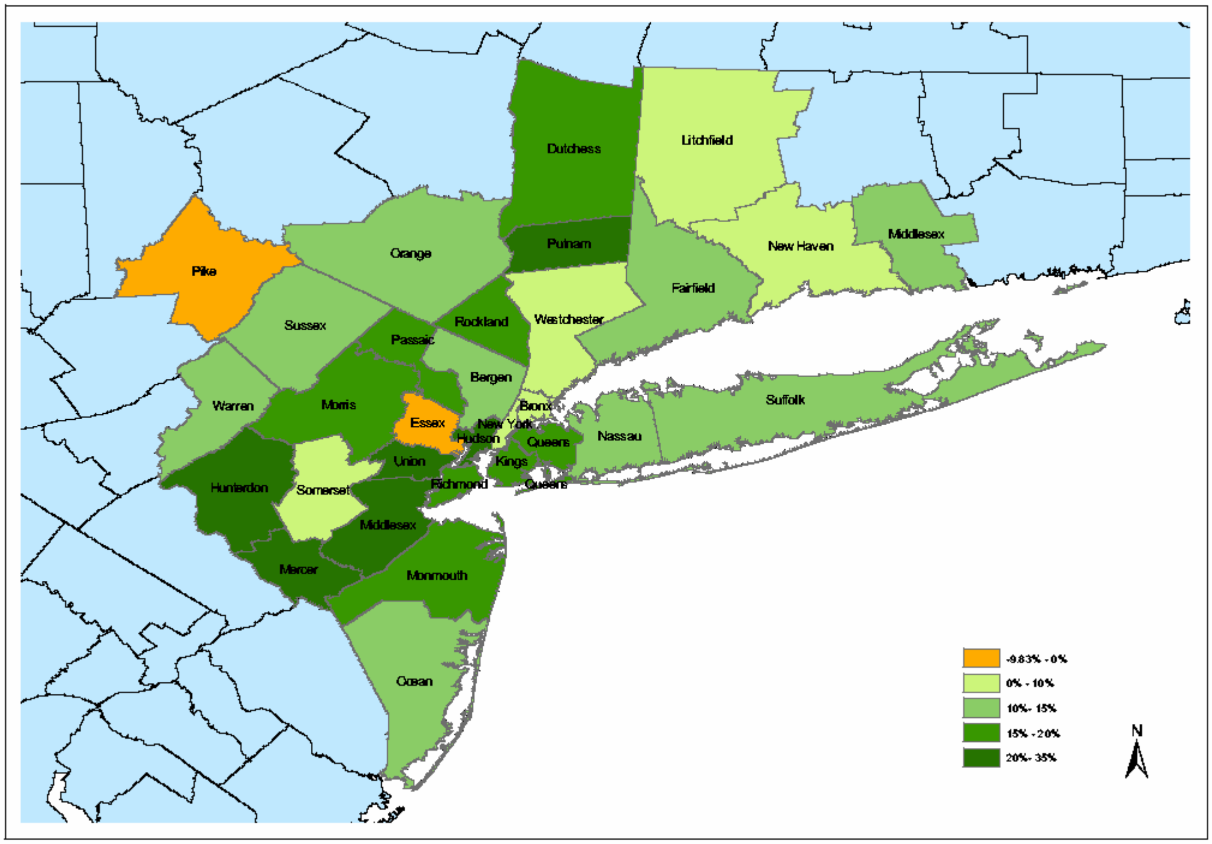


Figure 2-3: Percent change in office employment in New York CMSA counties from 1998 until 2001.

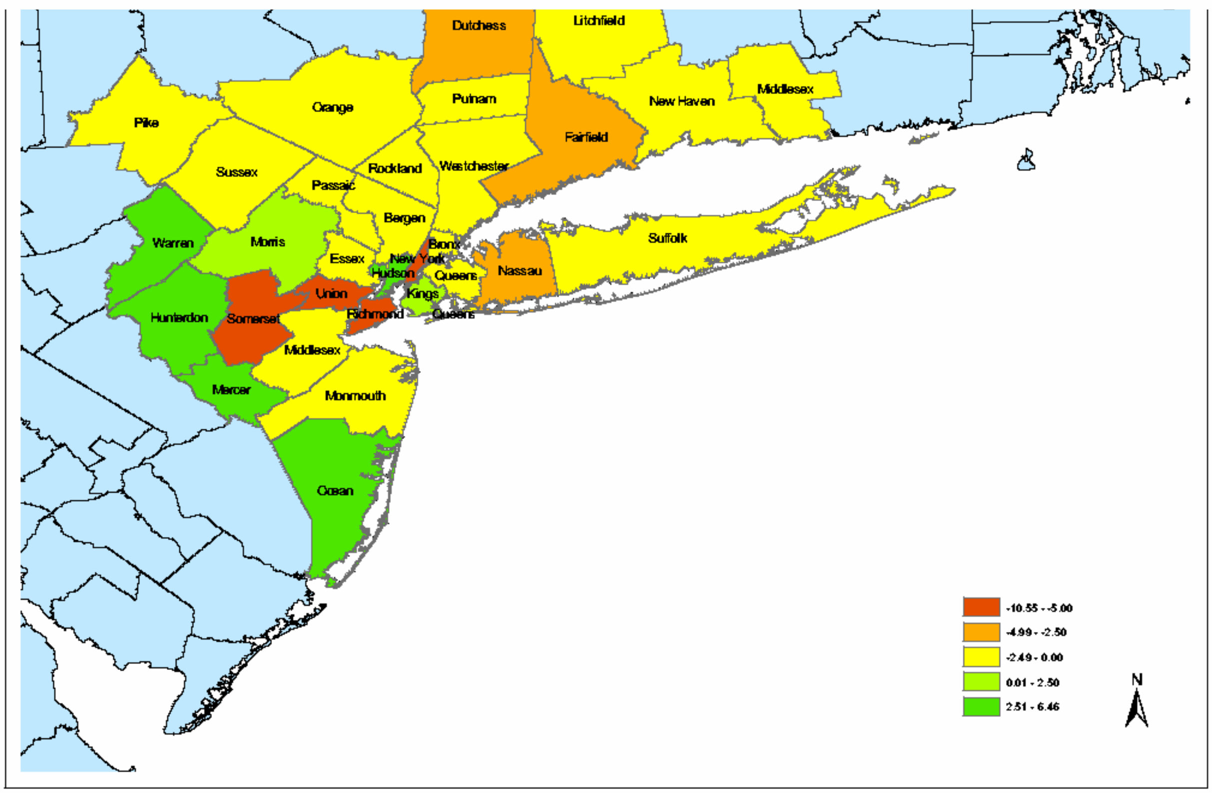


Figure 2-4: Percent change in office employment in New York CMSA counties from 2001 until 2002

Long-term trends in regional office employment

How do the trends of the short time period analyzed above fit in the longer-term employment trends of the New York region? Since consistent county-level datasets for this longer series (1983-2004) are not available, this longer-term analysis is limited to a comparison between Manhattan (New York County), and the CMSA counties at the aggregate level as well as national aggregates.[6] It is therefore not possible to calculate Gini or E-G gamma indices for the long time series. Instead, location quotients (LQs) are calculated as a measure of relative spatial concentration.

Table 2-4 presents LQs for Manhattan and separately for the CMSA counties outside of Manhattan. Overall, office industries continue to make up a significantly larger proportion of Manhattan's employment than it does in both the outer CMSA and the national level. Over the last two decades, however, the share of Manhattan's office using industries in overall employment, particularly the finance and insurance sector (NAICS 52), has been decreasing continuously. It is also noteworthy that the CMSA counties outside of Manhattan exhibit no significant overall specialization in office industries compared to the US average. Despite large gains in absolute employment numbers, no clear specialization pattern emerges in the CMSA over the last 20 years based on the analysis of LQs. The region appears to have gained somewhat from Manhattan's relative decline in the securities and commodities exchange industry (NAICS 5232) but does not exhibit any particular specialization. While a county or zip-code-level analysis reveals small-scale specialization patterns, a general regional specialization is not detectable at the CMSA level. Turning to the columns reporting the values for Manhattan it becomes obvious that the specialization in the securities industry remains one of the most striking characteristics of the Manhattan economy despite the ongoing decentralization process. A number of industries show a declining LQ in both Manhattan and the rest of the CMSA, however. This parallel decline hints at locational shifts at a higher aggregation level, in particular due to the more dynamic economic development of the southern and southwestern regions of the US.

[6] The foundation of the U.S. statistical program has been the Standard Industrial Classification (SIC) system. Since 1997, however, all economic census data is collected under the new North American Industrial Classification System (NAICS). The conversion to NAICS represents a significant change in the way economic census data are collected and reported. The data prior to 1997 reported in this study were converted from SIC to NAICS by Economy.com to allow for the construction of long-term time series data.

Table 2-4 Location quotients of predominantly office-using industries in Manhattan and the CMSA

		CMSA (excluding Manhattan)					Manhattan				
NAICS	*Industry*	*1984*	*1989*	*1994*	*1999*	*2004*	*1984*	*1989*	*1994*	*1999*	*2004*
	All office-using industries	1.01	1.08	1.10	1.07	1.06	2.51	2.39	2.23	2.09	1.99
51	Information	1.19	1.20	1.24	1.13	1.09	3.05	2.62	2.62	2.38	2.52
5111	Newspaper, Periodical, Book & Directory Publishers	1.26	1.23	1.16	1.21	1.21	3.84	3.42	3.26	3.25	3.56
5171	Wired Telecommunications Carriers	1.47	1.60	1.90	1.64	1.27	2.20	1.72	1.90	1.50	0.85
5172	Wireless Telecom. Carriers (except Satellite)	3.95	4.16	2.34	1.02	0.63	12.29	9.61	4.54	1.78	0.65
52	Finance and Insurance	1.63	1.71	1.69	1.65	1.48	3.62	3.65	3.47	3.25	2.72
5211	Monetary Authorities - Central Bank	0.36	0.45	0.42	0.35	0.39	4.23	4.32	3.92	3.38	2.41
5221	Depository Credit Intermediation	0.91	1.08	1.09	0.92	0.85	2.85	2.76	2.41	1.99	1.46
5222	Nondepository Credit Intermediation	0.90	1.07	1.06	0.99	0.87	2.26	2.33	1.88	1.36	1.07
5232	Securities and Commodity Exchanges	0.82	1.22	1.66	1.98	2.15	17.07	18.10	17.38	15.77	14.47
5239	Other Financial Investment Activities	0.62	0.68	0.94	0.91	0.87	11.58	11.91	10.91	9.59	7.40
5241	Insurance Carriers	0.90	1.01	1.00	1.14	1.13	2.10	1.77	1.60	1.40	1.29
5242	Agencies, Brokerages, and Other Insurance	1.07	1.18	1.25	1.24	1.19	2.06	1.79	1.67	1.41	1.08
53	Real estate	1.39	1.35	1.37	1.37	1.39	2.10	1.98	2.03	1.93	1.97
5311	Lessors of Real Estate	1.35	1.38	1.42	1.51	1.54	3.44	3.49	3.59	3.78	3.98
5313	Activities Related to Real Estate	0.86	0.97	0.97	1.02	0.93	2.13	1.95	1.89	1.58	1.45
54	Professional and technical services	1.46	1.50	1.50	1.47	1.33	2.44	2.48	2.42	2.38	2.17
5411	Legal Services	0.93	1.06	1.19	1.21	1.16	3.30	3.76	3.92	3.96	3.32
5412	Accounting, Tax Preparation, Payroll Services	1.01	1.11	1.17	1.23	1.31	3.26	2.67	2.73	2.63	2.49
5413	Architectural, Engineering, and Related Services	0.82	0.94	0.89	0.84	0.80	1.06	1.22	1.02	0.84	0.57
5416	Management, Scientific, and Technical Consulting	1.89	1.51	1.38	1.22	0.95	3.04	2.83	2.49	2.35	1.99
5418	Advertising and Related Services	1.13	1.02	1.19	1.21	1.15	6.83	6.13	6.21	6.96	7.16
55	Management of companies	0.94	1.01	1.15	1.21	1.31	1.26	1.37	1.55	1.59	1.85
5511	Management of Companies and Enterprises	0.82	0.90	1.02	1.09	1.15	1.28	1.38	1.55	1.58	1.84
56	Administrative and support services	1.18	1.10	0.97	0.95	1.01	1.81	1.14	0.82	0.82	0.94
5613	Employment Services	0.74	0.78	0.63	0.63	0.72	1.80	1.55	1.26	1.35	1.49
5614	Business Support Services	0.88	0.94	0.93	0.87	0.93	1.11	1.11	0.82	0.72	0.64
5617	Services to Buildings and Dwellings	1.24	1.29	1.30	1.19	1.15	1.53	1.27	0.99	1.03	1.09

Productivity comparisons of office-using industries

The analysis of employment data demonstrates that Manhattan's share of office activities in the region is declining by all accounts. Similarly, office employment has become more evenly distributed in the CMSA region in the last two decades as office firms are relocating partially or fully to suburban areas and smaller office cores in the New York region.

Apart from being an indicator for the industrial composition of regional and local economies, employment data are also subject to relative changes in productivity and capital endowment which are prone to having a distorting impact on the spatial analysis. It is therefore useful to analyze output measures such as output per worker in addition to employment data. Labor productivity is the most important indicator of the efficiency and competitiveness of local and regional economies. For the purpose of this research, it is simply defined as real output per office worker since reliable data on average working annual working hours were not available to the author. Figure 2-5 shows real output per office worker for three entities: Manhattan, the CMSA outside of Manhattan, and the national level. The results are strikingly different from the comparison of employment levels. In terms of productivity Manhattan seems to have accumulated a considerable advantage over both the CMSA and the national aggregate in the last two decades. An analysis of the components of productivity confirms that real output in the office-using industries has grown by 138 percent in Manhattan from 1983 to 2004 whereas employment in the same sectors has contracted by approximately two percent during the same period with pronounced cyclical swings as shown. It is remarkable that economic growth in Manhattan’s office-using industries is brought about almost exclusively by productivity increases and not by virtue of an expanding work.

Comparing the trajectories of employment and productivity over time reveals that the events of 9/11 and the ensuing economic recession had a profoundly negative impact on employment levels while productivity remained unscathed by the events. In fact, output per worker has been increasing throughout all phases of the business cycle in the last two decades which is particularly remarkable since labor productivity tends to stagnate or fall during a recession as companies cut production more rapidly than employment at the onset of a recession. While there were hardly any productivity gains during much of the

1990s at both the CMSA and the national level, Manhattan added productivity gains of nearly 100,000 dollars per office worker within the last decade.

How can the productivity advantage of Manhattan's office firms be explained? In principle, higher productivity in one area over another can come from two sources. The first one is the industrial composition advantage which arises when a local or regional economy has a disproportionately high share of highly productive industries. In this case, overall labor productivity in the area will be high even if productivity by industry is only average.

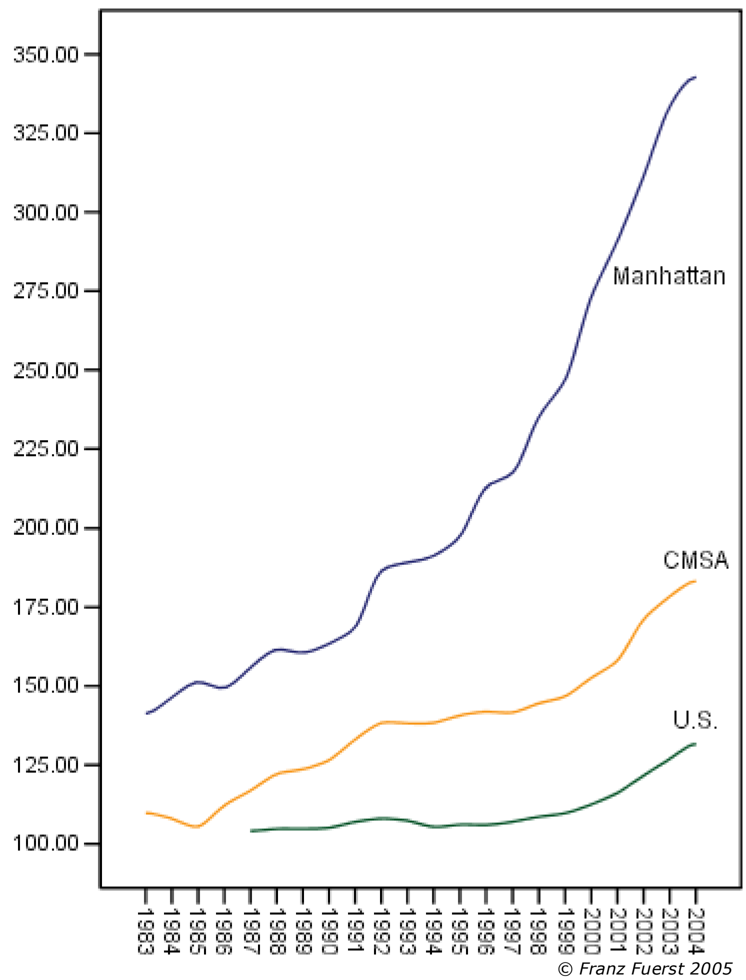


Figure 2-5: *Real output per worker in office-using industries in Manhattan, CMSA (minus Manhattan) and the US in thousands US dollars. Data: Economy.com, Department of Labor*

The second possible source is an intra-industry competitive advantage, which means that local industries achieve higher productivity levels by virtue of a more efficient use or higher quality of input capital. An ad-hoc measure that allows for distinguishing both sources is useful in this context. The so-called competitive advantage can be measured by applying the US industry mix to Manhattan at the four-digit NAICS level to correct for the effect of unequal industrial composition in both entities. The difference between the aggregated hypothetical values and the observed values is defined as the competitive advantage and the residual of the observed productivity difference is then interpreted as the industrial composition advantage. This simple method is derived from the standard shift-share framework of regional analysis, originally developed by Dunn (1960). Figure 2-6 demonstrates that Manhattan's productivity advantage over the national aggregate is based on both industry composition and competitive advantages. The share of both factors in explaining the difference has changed considerably in the last two decades, however, as has the magnitude of the difference. While the industrial composition advantage has remained largely steady around $50,000 per office worker, the competitive advantage has increased from $8000 in 1987 to $152,000 in 2004 in real terms. The preponderance of the competitive advantage over the industry mix suggests that Manhattan's office-using industries have been more adept at implementing productivity and efficiency-enhancing practices than establishments of the same industries elsewhere in the US since the 1980s.

This conclusion may not necessarily be warranted, however. Productivity advantages of Manhattan office firms vary greatly by industry and one could suspect that the productivity differential is an artifact generated by a few high-revenue companies, particularly in the financial services and securities industry. Decomposition by industry reveals, however, that 79 percent (41 out of 52) of Manhattan's office-using industries at the four-digit NAICS code level had higher output per worker in 2003 than the national aggregate. Thus, competitive advantages are not only found for high-revenue generating financial companies but also for legal, technical and a variety of business-oriented services.

One caveat in this context is that higher productivity levels may be caused by a small number of high-revenue key industries. The highest productivity differences (over $500,000 per worker) are found in the four industries Securities and Commodity Contracts Intermediation and Brokerage (5231), Securities and Commodity Exchanges (5232), Offices of Real Estate Agents and Brokers (5312), and Activities Related to Real Estate (5313). Thus, higher productivity levels may simply be explained by Wall Street's function as a global financial hub or the generally higher price volumes of Manhattan real estate.

Genuine factors that are capable of explaining differences in productivity as recognized in the research literature include higher quality of physical capital, a generally higher skill level of the local labor force, more efficient workplace practices and institutional arrangements as well as knowledge spillovers due to spatial proximity. It is virtually impossible, however, to extract the contribution of each of these factors from the general output per worker figures in the framework of this study. Regardless of these methodological and definitional difficulties, the analysis of the Manhattan data demonstrates clearly that real output and real output per worker of office firms have increased dramatically in the last two decades whereas employment has by and large stagnated.

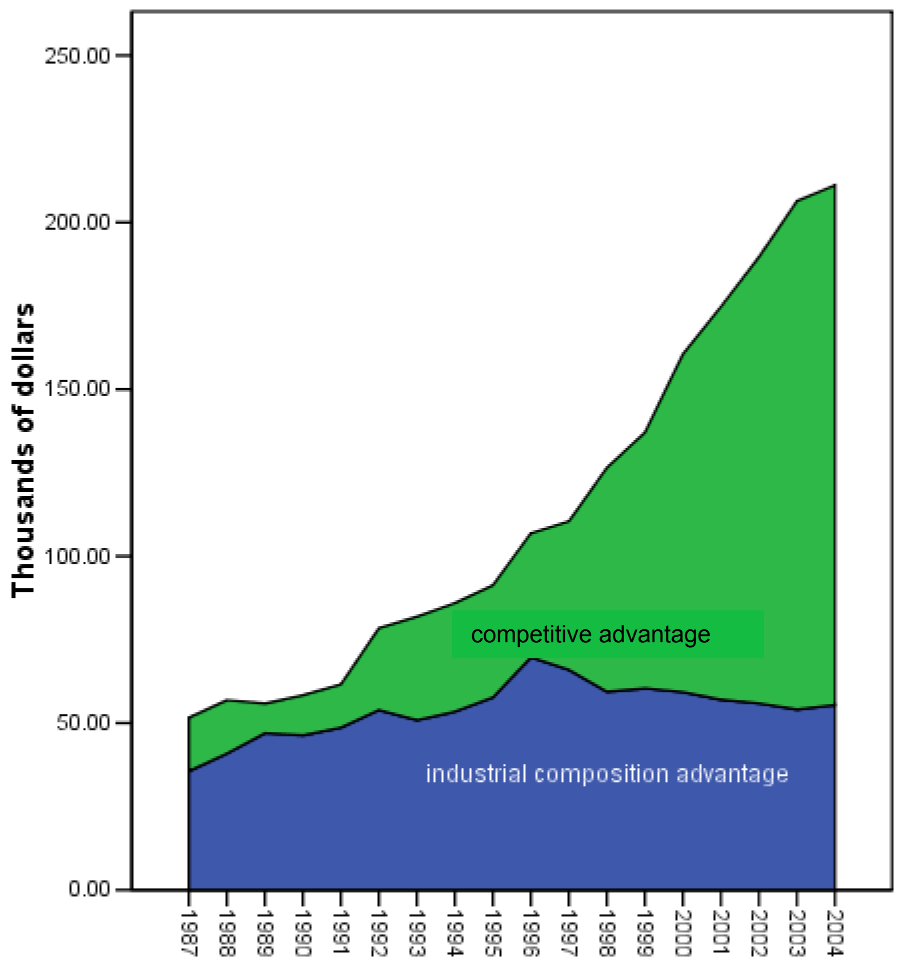


Figure 2-6: Decomposition of productivity advantages of Manhattan's office using industries over U.S. average figures. Data: Economy.com, Department of Labor

Zipcode level analysis of office employment

The analysis of county-level data of the previous section yielded some important insights into the changing dynamics of office employment in the regional context. To examine small-scale spillover effects that cannot be captured at this level of aggregation I additionally include zip-code level employment data of Manhattan in the analysis. Figure 2-7 shows the density of office employment per square mile at the zip code level. The two major office clusters of Midtown and Downtown Manhattan are clearly discernable. Some of the smaller zip code areas within these central business districts reach a density of well over 100,000 office workers per square mile. In the presence of densities of this order of magnitude, the question of micro-scale spillover effects is of particular relevance. To demonstrate the microlocational dynamics in recent years, Figure 2-8 visualizes the changes in office employment in zip code areas from 2000 to 2001 in percentage points of overall share based on ES-202 employment data. Strong losses of office employment were recorded in the area surrounding the World Trade Center site in Lower Manhattan following the 9/11 terrorist attack. Another area of disproportionate employment loss is the Midtown South area where the collapse of information technology companies in 2000 and 2001 lead to heavy losses of office employment. A large share of these IT companies was clustered in Midtown South in the area dubbed 'Silicon Alley' so that the effects of the crisis became particularly visible in this district. Figure 2-9 illustrates the changes in the following year from 2001 to 2002 with a very similar pattern. Areas with relative net gains of office employment in both years include the Midtown West area where a number of new office buildings were finished during the analyzed period and the Wall Street section of the Lower Manhattan submarket.

In order to study the question of spillover effects, a further disaggregation not only of the spatial units but also of the industries to the 4-digit level appears necessary. Table 2-5 reports Ellison-Glaeser γ values for the fifteen most important office-using industries. Surprisingly, very few industries exhibit excess concentration (γ>0.05) at this level expect Securities and Commodity Exchanges (5232) which is highly concentrated. The lack of highly concentrated industries may simply indicate that choosing Manhattan as a frame of reference leads to underestimating the concentration of industries since Manhattan itself is highly concentrated in office employment at the aggregate level. Moreover, no clear time-series pattern is detectable in the years analyzed.

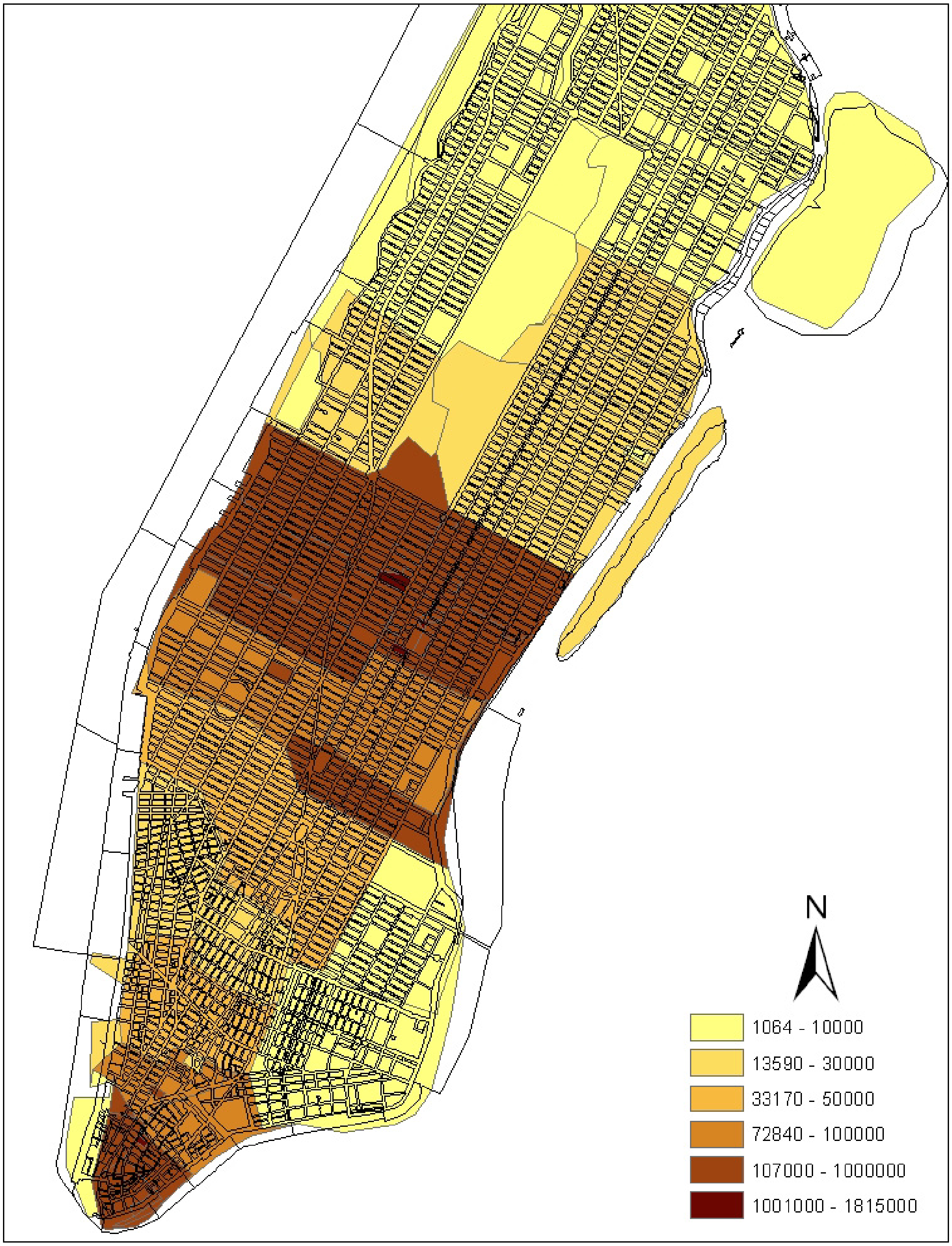


Figure 2-7 Density of office employment by zip code area (office jobs per square mile)
Data: Bureau of Labor Statistics

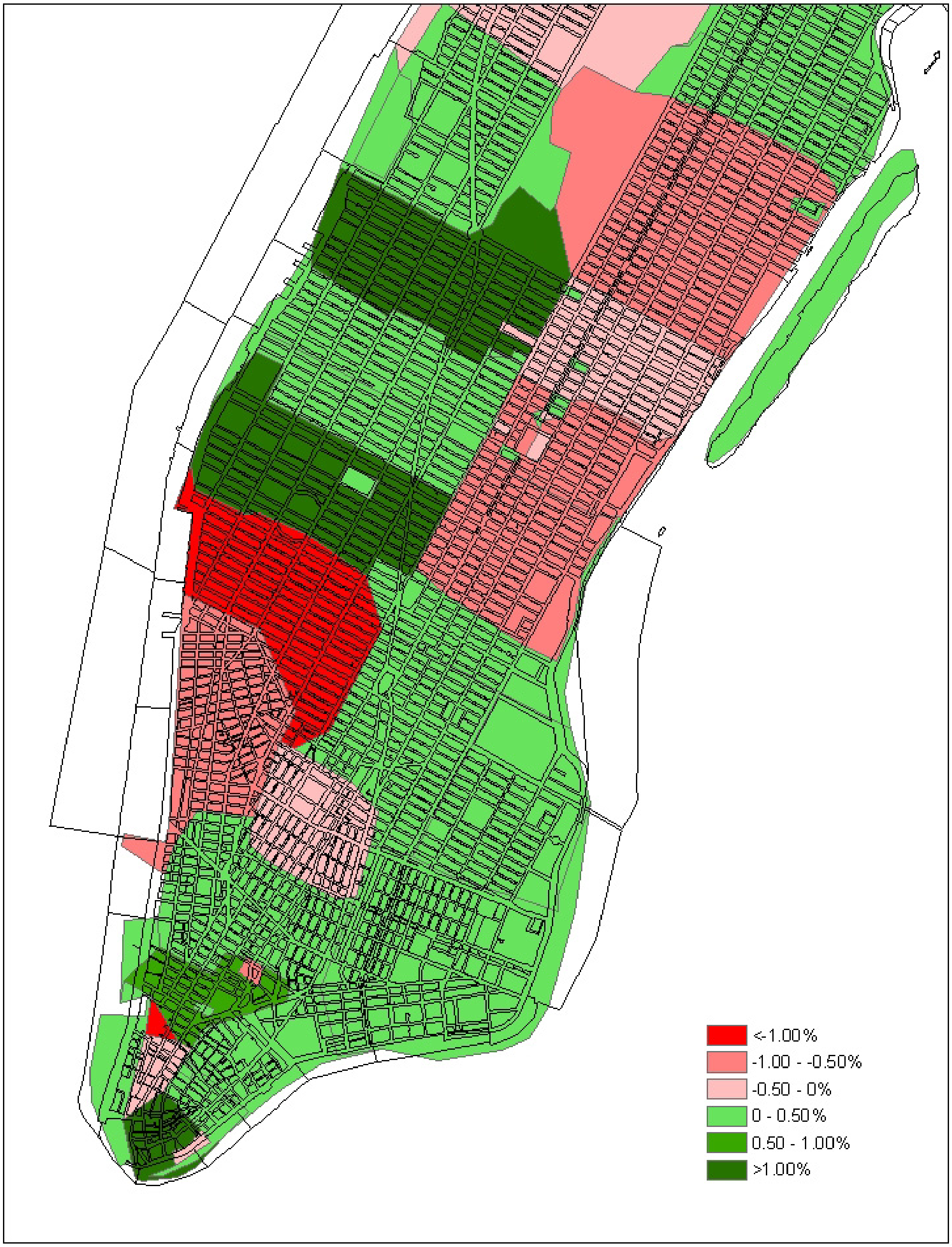


Figure 2-8: Change of share in Manhattan office employment from 2000 to 2001 for zip code areas (in percentage points of overall share). Data: Bureau of Labor Statistics

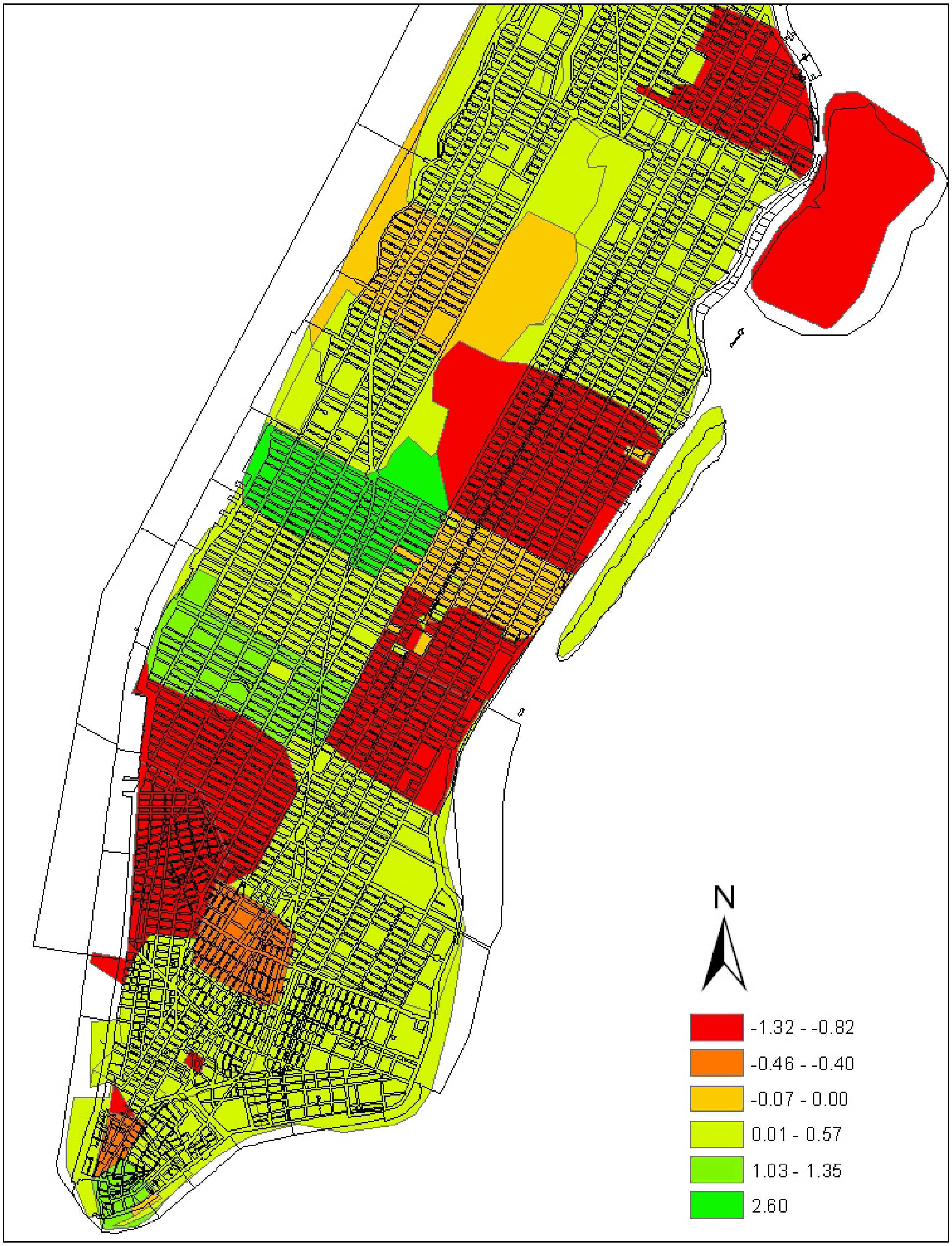


Figure 2-9: Change of share in Manhattan zip code area office employment from 2001 to 2002 (in percentage points of overall share). Data: Bureau of Labor Statistics

To further investigate the question of industry spillovers, I analyze if the agglomeration patterns of 4-digit industries are correlated. Again, the difference between a zip code area's share in total employment is calculated and compared to the share of that area in a particular industry. The resulting differences between both are then correlated over all office industries. I then sort the resulting correlation matrices according to significance levels and find that 25.6% of 1305 possible industry pairs are significant at the 5% level.

Figure 2-10 illustrates these findings in a histogram. Consequently, the industries with significant correlation coefficients above 50% can be considered coagglomerated because of spillover effects that operate at the small-scale as defined in the first section of this chapter. For instance, office administrative services (5611) show an excess agglomeration pattern that is very similar to that of the securities and commodity exchanges (5232). The same is true for management of companies and enterprises (5511) and legal services (5411). It is likely that spillovers occur simultaneously between a number of industries located in a given zip code area and not just between the pairs measures in the correlation analysis. Nevertheless, it is possible to identify industries that appear to share locational preferences due to agglomeration spillovers at these microlocations.

Table 2-5: Ellison-Glaeser γ index values for Manhattan zip-code level areas.

		2000	2001	2002	2003
5221	Depository Credit Intermediation	0.0115	0.0124	0.0112	0.0169
5222	Nondepository Credit Intermediation	0.0280	0.0258	0.0250	0.0305
5223	Credit intermediation	0.0029	0.0256	0.0254	0.2036
5231	Securities and Commodity Contracts	0.0032	0.0151	0.0106	0.0199
5232	Securities and Commodity Exchanges	0.1044	0.1582	0.1605	0.2537
5239	Other Financial Investment Activities	0.0202	0.0226	0.0226	0.0304
5241	Insurance Carriers	0.0061	0.0030	0.0019	0.0029
5411	Legal Services	0.0490	0.0262	0.0225	0.0299
5412	Accounting and payroll services	0.0185	0.0233	0.0331	0.0092
5413	Architectural, Engineering,	0.0035	0.0025	0.0112	0.0150
5415	Computer system design	0.0145	0.0114	0.0116	0.0260
5416	Management, Scientific, and Technical Consulting	0.0132	0.0101	0.0075	0.0295
5418	Advertising and Related Services	0.0432	0.0283	0.0273	0.0132
5611	Office administrative services	0.0166	0.0012	0.0002	0.0261
5614	Business Support Services	0.0195	0.0164	0.0121	0.0074

Significant at 5% level: 25.6% of 1305 industry pairs. Data: Bureau of Labor Statistics

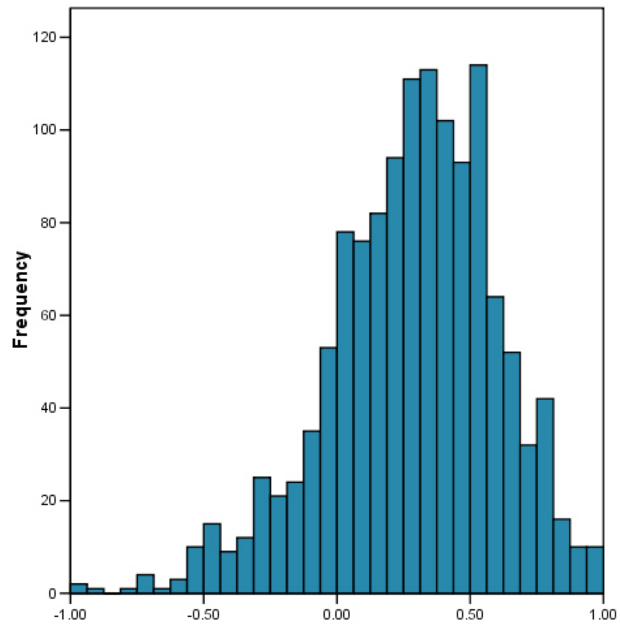


Figure 2-10: Frequency distribution of Pearson correlation coefficients of co-agglomerated industries at the 4-digit industry level

Table 2-6: Selected examples of industries with highly correlated spatial distribution patterns

Industry 1	Industry 2	R^2
Office Administrative Services (5611)	Securities and Commodity Exchanges (5232)	0.98
Facilities Support Services (5612)	Software Publishers (5112)	0.96
Facilities Support Services (5612)	Computer Systems Design Services (5415)	0.96
Legal Services (5411)	Other Financial Investment Activities (5239)	0.95
Insurance and Employee Benefit Funds (5251)	Nondepository Credit Intermediation (5222)	0.95
Facilities Support Services (5612)	Radio and Television Broadcasting (5151)	0.94
Management, Scientific/Technical Consulting (5416)	Activities Related to Real Estate (5313)	0.93
Facilities Support Services (5612)	Insurance Carriers (5241)	0.93
Offices of Real Estate Agents and Brokers (5312)	Depository Credit Intermediation (5221)	0.91
Employment Services (5613)	Insurance and Employee Benefit Funds (5251)	0.89
Management of Companies and Enterprises (5511)	Offices of Real Estate Agents and Brokers (5312)	0.88
Legal Services (5411)	Activities Related to Real Estate (5313)	0.87
Office Administrative Services (5611)	Advertising and Related Services (5418)	0.86
Management of Companies and Enterprises (5511)	Legal Services (5411)	0.85
Activities Related to Real Estate (5313)	Other Financial Investment Activities (5239)	0.83
Office Administrative Services (5611)	Management of Companies and Enterprises (5511)	0.83
Legal Services (5411)	Depository Credit Intermediation (5221)	0.83
Office Administrative Services (5611)	Insurance and Employee Benefit Funds (5251)	0.82
Activities Related to Real Estate (5313)	Offices of Real Estate Agents and Brokers (5312)	0.81
Employment Services (5613)	Office Administrative Services (5611)	0.81

2.5 Conclusions

This chapter set out to answer three basic questions. 1) How concentrated is office employment in Manhattan, the center of the New York region and what changes have occurred in the ratio between the urban core and the suburban periphery in recent years? 2) Is labor productivity in office-using industries similar in the core and periphery and how can potential differences be explained by structural features? 3) What conclusions can be reached from zip code level analysis of co-agglomeration of office industries regarding the existence of small-scale spillovers?

This work finds evidence of significant concentration of office-using industries in Manhattan despite ongoing decentralization in many of these industries over the last twenty years. Financial services tend to be highly concentrated in Manhattan whereas administrative and support services are the least concentrated of the six major office-using industry groups. Although office employment has been by and large stagnant in Manhattan for at least two decades, growth of output per worker has outpaced the CMSA as well as the national average. A shift-share type analysis reveals that the productivity differential is mainly attributable to competitive advantages of office-using industries in Manhattan and not to differences in industry composition. Although this may serve as an indication of knowledge spillovers due to spatial proximity, other reasons may account for the higher productivity of Manhattan office firms, such as higher quality of physical capital, a generally higher skill level of the labor force, more efficient workplace practices and institutional arrangements.

The zip-code level analysis of the Manhattan core area yielded further evidence of the existence of significant spillover effects at the small-scale level. Co-agglomeration of office-using industries at the micro-level is particularly strong between FIRE industries and business-oriented service industries, confirming earlier reports of extensive linkages between these industries. All in all, about one quarter of all office-using industries are coagglomerated at the zip code level.

In general, this chapter provides a number of model-based descriptive features of office employment in the New York region. Although the calculated concentration measures yielded some insights regarding potential explanatory factors, no reliable conclusion can be derived regarding the causal forces leading to the phenomena observed. Therefore, further studies are needed to explore the causal relationships of agglomeration effects and the locational behavior of office-using industries. More specifically, the empirical base of the zip-code level analysis needs to be broadened to arrive at generalizable results by including suburban zip code areas and a longer time series, an endeavor that has up to now been hampered by the transition from the SIC to the NAICS industry classification system. As time progresses, more years with NAICS data will become available for repeating the analysis conducted in this chapter. Finally, to expand the validity of the results, similar studies of office employment would need to be conducted in other metropolitan regions.

3 The impact of the 9/11 terrorist attack on the Manhattan office market

The September 11 attack obliterated 13.4 million square feet of office space in the World Trade Center (WTC) complex and seriously damaged at least another 17.8 million square feet in 23 surrounding buildings, affecting approximately 31.2 million square feet, or 10 percent of the total stock of Manhattan office space. Nearly 100,000 office workers were subsequently dispersed to over 1000 different destinations, many of them within Manhattan and a few as far away as London and Tokyo. The secondary consequences and potential economic ripple effects of the attack on Lower Manhattan and New York City as a whole are more difficult to grasp than the immediate impact. Over the years since 9/11, it has become evident that initial speculation about a mass exodus of office companies from Manhattan has been unfounded. There are concerns nevertheless that the long-term effects of 9/11 will pose a continuing threat to Lower Manhattan’s economic health. The principal objective of this chapter is to elucidate the impact of the September 11 attack on the New York office market by using exploratory data analysis and an event study methodology to analyze market mechanisms in the wake of the destruction of the World Trade Center.

In the aftermath of the September 11 attack, a number of important studies have been published, documenting the damage and giving detailed accounts of the whereabouts of displaced tenants (see, for example, Kelly 2002). This chapter presents a reevaluation of the impact of 9/11 on the New York office market more than four years after the recovery process began. The first section describes the immediate impact of 9/11 on office inventory, absorption, vacancy rates, rent and office employment by means of an exploratory data analysis. In the second section, I use an event study methodology to model the impact of 9/11 on the New York office market. Finally, these results are interpreted in the light of the discussion on rebuilding Lower Manhattan and revitalizing New York City's economy.

3.1 The immediate impact of 9/11

Beyond the tragic loss of three thousand human lives, it is the physical destruction of the World Trade Center buildings that comes to mind when we think about the impact of the 9/11 attack. The New York City comptroller estimates the property damage at $34 billion for both the destroyed World Trade Center complex and the surrounding buildings that sustained serious damage. In a more comprehensive study conducted by NYCPCC, the New York City Partnership and Chamber of Commerce (2001), a gross loss of $83 billion through 2003 is estimated as a consequence of the 9/11 attack, consisting of $30 billion in capital loss, $14 billion in cleanup costs and a compound $39 billion loss of economic output. From these gross costs we deduct insurance payments and emergency funds managed by the Federal Emergency Management Agency (FEMA) and other federal agencies to estimate the net loss to the city's economy incurred by the attack. The federal funds are intended to defray the cost of cleanup and guide the economic recovery process. Although the exact sum of all funds and compensation payments actually disbursed by insurance carriers and federal relief organizations are not fully known, the NYCPCC estimates the overall net loss due to the 9/11 attack at $16 billion (4 percent of the gross annual output of Manhattan).

Estimating the effects of 9/11 on the office market

Any attempt to measure the impact of 9/11 on the job market, on the stock market, or on fiscal revenues is faced with the difficulty of separating the effects of 9/11 from the impact of a wider economic recession and other simultaneous events influencing the market. In the case of the office market, disentangling and isolating the effects of 9/11 seems easier because of certain inherent characteristics of real estate markets. The impact on the supply of office space is clearly discernable thanks to available data on the World Trade Center buildings themselves and on the damaged buildings that were gradually returned to the market after restoration. Most of the data applied in this study were obtained from CoStar and Grubb & Ellis, two providers of real estate market intelligence. Beyond the information on displaced tenants, the analysis presented in this chapter draws on information from multiple sources at various aggregation levels.

Before we focus on assessing the observed and expected impact of the 9/11 attack on the New York office market in detail, it is helpful to review some basic mechanisms of office real estate markets relevant for understanding the reaction of the market to the exogenous shock of the 9/11 attack.

In general, the office market can be considered a system of at least three interlinked markets: a space market (also called 'user market'), a financial asset market, and a development market. The space market incorporates the demand for office space by tenants and the determination of rents. The amount of occupied space as the principal measure of demand for office space is a function of the number of office workers, the average space per office worker in a given market, and output of office firms. While employment and output are major determinants of the absolute amount of required office space, the space per office worker depends on the level of rental rates (price elasticity of demand), in the sense that higher rents entail a more efficient space use and hence less space per worker. Typically, rental rates are a lagged variable, however, since short-run demand is relatively inelastic to changes in rental rates. Most equilibrium models of the office market assume that only a certain proportion of the adjustment towards the hypothetical steady state takes place each period. The net change in occupied space from one period to the next (called space absorption) is another example of only partial adjustment to a hypothetical equilibrium value caused by imperfections inherent in the office market. Rental rates are determined in the space market as a function of the occupancy rate or its inverse, the vacancy rate. Similar to labor market economics and its concept of a 'natural unemployment rate', real estate economics defines a 'natural vacancy rate' as market equilibrium at which rents remain stable. If the actual vacancy rate falls below the natural vacancy rate, rents will rise and vice versa. Despite a number of theoretical problems associated with it, this concept proved useful in many empirical studies (Rosen 1984; Shilling, Sirmans, and Corgel 1987). It originates from the observation that real estate markets do not conform to the basic economic theorem that equilibrium is reached when supply equals demand and markets clear completely. Frictions and imperfections as well as the need for a sufficiently large fluctuation reserve are frequently cited as factors that impede complete market clearing. The magnitude of the natural vacancy rate is not fixed, however, but varies across markets - owing to local market characteristics, and within a market over time, owing to long-run changes in local market characteristics (Wheaton and Torto 1994).

The stock of office space, albeit fixed in the short run, can be expanded in response to increasing demand for office space, thus linking the space market with the development market and in turn also with the financial asset market. According to investment theory, construction of new office space at a particular site becomes feasible when the expected asset price of the building exceeds its replacement cost. The asset price of the building is a function of the net operating income (NOI) of a building, or more accurately, the present discounted value of the expected future income stream (net of tax and expenses), which is mainly a function of rental rates. The three main components to use in estimating the asset price of a building are thus rent, vacancy and the capitalization rate, which is determined by dividing the property's NOI by its purchase price. New construction is determined by all the factors making up the expected asset price as well as additional measures for estimating replacement cost. Variables used to estimate costs are typically the cost of capital (interest rates) and construction costs. Construction of new space is subject with particularly long lags, however, because assembling, financing and permitting along with actual construction are all extremely time-consuming processes.

The effects of the 9/11 attack enter into this system simultaneously at various points: first, by reducing the total stock of office space; and second, by reducing the number of office workers and the amount of occupied space through movements of displaced tenants. These changes affect in turn the long-run equilibrium rent level (through the changed vacancy rate) and the overall feasibility of new space construction (through changes in rental rates and arguably also through higher construction costs because of additional security requirements for office buildings). The following sections analyze the effects of 9/11 on the various parts of the office market in more detail.

The impact on office inventory

The total amount of office space affected by the 9/11 terrorist attack is estimated at 31.1 million square feet of which 13.4 million were completely destroyed and 17.7 million were found to be severely damaged (Table 3-1). Destroyed were the seven buildings of the World Trade Center, which included the two landmark towers with a total square footage of 4.7 million square feet of office space each, and five other buildings ranging from 600,000 to 2 million square feet in size. Also destroyed was the Deutsche Bank building at 130 Liberty Street. The building sustained damage that was eventually deemed too extensive to repair in an agreement between Deutsche Bank, four insurance carriers, and the Lower Manhattan Development Corporation (LMDC) in which the conclusion was reached to demolish and reconstruct the building. To put the numbers in perspective, the destroyed space equals roughly the entire office stock of the city of Detroit. When the comparison is limited to prime office space, the damaged and destroyed space equals the inventory of major office locations such as Atlanta and Miami (Jones Lang Lasalle 2001). In the New York City office market, however, because of its vast size, the affected space makes up approximately 10 percent of the total inventory of New York City though roughly 60 percent of Downtown's Class A space. [7]

Table 3-1: Destroyed and damaged office space by quality class. Data: Grubb & Ellis 2001

Destroyed Buildings	*Size (Square feet)*	*Occupied (Square feet)*	*Class*
1 WTC	*4.761,416*	*4.507,467*	*A*
2 WTC	*4,761,416*	*4,576,215*	*A*
7 WTC	*2,000,000*	*2,000,000*	*A*
1 Bankers Trust Plaza	*1,415,086*	*1,415,086*	*A*
5 WTC	*783,520*	*780,873*	*A*
4 WTC	*576,000*	*561,491*	*A*
6 WTC	*537,694*	*537,694*	*A*
DESTROYED TOTAL	***13,420,046***	***12,963,740***	
Damaged Buildings	*Size (Square feet)*	*Occupied (Square feet)*	*Class*
2 WFC	*2,591,244*	*2,006,577*	*A*
3 WFC	*2,263,855*	*2,167,611*	*A*
1 Liberty Plaza	*2,121,437*	*1,874,584*	*A*
4 WFC	*2,083,555*	*2,073,615*	*A*
1 WFC	*1,461,365*	*702,999*	*A*
101 Barclay	*1,226,000*	*1,226,000*	*A*
140 West	*1,171,540*	*1,171,540*	*B*
100 Church	*1,032,000*	*822,642*	*B*
90 Church	*950,000*	*950,000*	*B*
22 Cortland	*668,110*	*625,282*	*B*
90 West	*350,000*	*350,000*	*A*
125 Barclay	*273,900*	*273,900*	*C*
130 Cedar	*135,000*	*135,000*	*C*
DAMAGED TOTAL	***17,743,092***	***15,794,836***	
OVERALL TOTAL	***31,163,138***	***28,758,576***	

7 Figures of the total inventory of office space differ widely among providers of market data because of diverging definitions of geographic areas and types of buildings. Total inventory figures used in this study are based on the definition and data by Grubb & Ellis.

Figure 3-1: Map of World Trade Center area. (Source: City of New York)

Often criticized as a white elephant of an office complex whose construction was clearly not justified by the demands of the marketplace, the World Trade Center remained largely vacant and unprofitable in the first years of its existence. The largest portion of space was occupied by the Port Authority of New York and New Jersey and by various governmental institutions. Deriving its economic rationale from the principle known as Say's Law (supply creates its own demand), the World Trade Center was constructed with the intention of boosting the economic development of New York in a time of economic recession, weakening demand, and high vacancy rates. Because it was delivered to the market at an unfavorable time, however, the addition of more than 10 million square feet of office space to the existing inventory served to depress the market further. It took more than six years for the office market to adjust to the supply shock induced by the

World Trade Center. During the 1980s, when the business climate in New York City became more favorable, the WTC complex developed a reputation as an attractive location for financial services companies with a need for large floor plates. Eventually it achieved an estimated ratio of 90 percent to 10 percent of private- versus public- sector tenants. The stock market crash of 1987 initiated a protracted period of decline for the Lower Manhattan office market; vacancies soared to 25 percent and higher. By the end of the 1990s, however, the combined effect of a tech boom and exceptionally strong growth in the finance, insurance and real estate (FIRE) industries had helped Lower Manhattan to once again overcome the crisis and achieve historically high office occupancy rates and rents. At the end of 2000 the market began to soften gradually, but it was not until after September 11, 2001 that Lower Manhattan experienced large-scale job losses and a severe office market recession.

In the wake of the 9/11 attack, a number of market analysts, predicting that the reduction in space would lead to extremely low vacancy rates, saw landlords as being "in the driver's seat" (Grubb & Ellis 2001) in the lease negotiation process. To the surprise of most market observers, however, demand for office space weakened significantly despite the large-scale loss of office space. Three reasons for the unexpected drop in demand can be identified: a pronounced decline in office jobs owing to the combined effects of 9/11 and economic recession; the availability of large amounts of unused space at various locations throughout Manhattan not reported as vacant in the market statistics ("shadow space"); and reduced space per worker in higher-priced target submarkets and revised expectations for the future growth and space needs of office tenants.

The impact on leasing activity and absorption

The relocation patterns of larger private companies occupying at least 20,000 square feet of office space in the buildings destroyed or damaged on 9/11 have been recorded by the real estate services and brokerage firm Grubb & Ellis. This subset of displaced tenants accounts for roughly one third of the total occupied space of the affected buildings. The remaining two thirds of occupied space comprise large private companies with missing data, smaller private tenants and government institutions. Hugh Kelly (2002, 26) tracked the movements of displaced public-sector tenants occupying 1.7 million square feet in all affected buildings and found that only 30 percent remained downtown; the rest relocated to Midtown. Data are scarce on the approximately 500 small companies occupying less than 10,000 square feet and public tenants accounted for about 8 million square feet in the WTC. Kelly who was able to obtain and analyze a limited dataset of the smaller tenants, found that small companies displaced by the 9/11 attack were far more likely to remain in the downtown area than the large companies, thus accounting for about half of the overall space leased downtown to displaced tenants. This pattern could be explained by the fact that larger tenants typically require large floor plates and sizable amounts of contiguous space, which only a few buildings in Lower Manhattan could provide on short notice after the destruction of the World Trade Center. The search process for suitable office space was arguably shorter for smaller companies since more matching possibilities existed within a short distance from the original location.

Kelly (2002, 25-29) reports that Lower Manhattan retained about 50 percent of the large private-sector tenants. Taken together, the core markets of midtown and downtown Manhattan captured about 80 percent of the stream of displaced tenants through reoccupation of restored buildings, backfill and new leases. The nearby office agglomerations along the New Jersey waterfront, which had been developing into a back office market for Wall Street and Lower Manhattan long before 9/11, managed to attract most of the relatively few tenants who opted to leave Manhattan. It is interesting to note that none of the other four boroughs of New York City outside of Manhattan was able to capture a significant percentage of displaced tenants especially when compared to the New Jersey waterfront.

As of September 2003, a number of large tenants of the buildings that were damaged in the 9/11 attack returned to these buildings after they were restored (Newmark and Company Real Estate 2003). The remaining portion of office space damaged in the attack thus remained either vacant or was occupied by new tenants. According to a survey of Newmark and Company, more than half of the originally displaced tenants had returned to a Downtown location during the first two years following the attack and less than one fifth of the displaced tenants had decided to lease space permanently at a non-Manhattan location. These numbers are reassuring in terms of tenant retention in the restored damaged buildings and the downtown area as a whole, but it still remains to be seen whether tenants who have returned will opt to renew leases that expire in the next few years. Since some tenants were given the opportunity to break their leases after 9/11, owing to interruption-of-services clauses in their contracts, the percentage of tenants choosing to discontinue their lease later on is generally expected to be low. As far as the wider Downtown area is concerned, however, the large number of leases expiring in 2004 and 2005 (36 million square feet, or roughly one-third of the inventory) poses a potential problem, especially since the process of rebuilding the World Trade Center and restoring the economic potential of the area will continue well beyond 2010. Given the fact that more than half of the Downtown leases expire between 2004 and 2007 (Newmark & Company Real Estate 2003), around 200,000 jobs would be at risk of leaving the area. On the other hand, some factors work in favor of a recovery of Lower Manhattan. The restoration of transportation infrastructure, particularly of the PATH commuter train station, is expected to have a moderating impact on the potential job losses since it facilitates the movement of suburban workers into the city, thus enhancing Lower Manhattan's profile as an attractive location and giving the area the much-needed rapid access to a large pool of skilled labor. Moreover, an array of subsidies has been put in place to make the area more competitive. Tax deductions and accelerated depreciation benefits are available to businesses with fewer than 200 employees in the so-called Liberty Zone. Further support is available through the small firm attraction and retention grant program. Certain commercial buildings are eligible for real estate tax abatements and rent tax elimination or reduction for up to five years. The programs require that landlords to pass on any benefits received under the auspices of these revitalization incentives to tenants by reducing rents proportionally.

Besides those tenants who chose to reoccupy previously damaged buildings, a number of new leases were signed in Manhattan, and in some cases in other locations, by tenants of destroyed buildings or tenants of restored buildings who were unwilling to return. Moreover, a considerable proportion of larger tenants of the space affected by 9/11 could be accommodated in excess space available at other locations of the same company. An estimated $341 million of rental income is lost due to backfilling displaced tenants into unused space at a different location (DRI-WEFA 2002, 37). The high percentage of unused space or shadow space among the larger multi-location tenants not accounted for in any market statistics revealed that vacancy and availability rates were generally understated. Therefore, displaced tenants who were accommodated within space that was rented but previously not used by the same company did not contribute to positive absorption in the market statistics.

Shadow space is widespread in office markets and is generally attributed to inflexibilities arising from the long-term nature of office leases. Shadow space builds up when companies incorrectly estimate the number of employees and their space usage over the time of the lease term. Estimates of the amount of shadow space in Manhattan differ greatly since there are no reliable measurement methods available. Mitchell Stier, chairman of Julien Studley Inc. estimates 10 million to 14 million square feet of shadow office space in Manhattan in the fall of 2003 (quoted in Realtors Commercial Alliance 2003) while other sources claim that if shadow space were accounted for, reported vacancy rates would have to be adjusted upwards by 20 to 37 percent in some Manhattan submarkets (Holusha 2003).

Although more transparency is typically associated with a higher degree of market efficiency, some argue that the existence of shadow space generates positive effects as well. By being kept of the market, goes the argument, the vacant space does not exacerbate the downturn phase in the market cycle. Since this space is in fact excluded from the ratio of supply to demand that determines price, shadow space should work towards stabilizing the market. In other words, since shadow space is rented out and typically not offered on the market, such space –although de facto vacant, should not affect market conditions in a negative way. Two points have to be considered, however, regarding the validity of this argument. First, companies will fill up their shadow space before they lease any additional space. Consequently, shadow space does affect the office market indirectly by potentially delaying market recovery after a recession. Second, some of the unused space may indeed be available for sublease, even though it is not officially listed. Transactions of this kind are typically made when brokers possess insider knowledge of unofficially vacant space and approach the main tenant to find out whether the vacant space would be suitable for sublease to other companies.

More recently, changes to the generally accepted accounting principles (GAAP) adopted in 2003 strictly require companies to record the write-off of unused space once a company has formally acknowledged that a certain percentage of its leased space is not being used. The unintended consequence of this change is that office tenants have an additional incentive to keep unoccupied space off the market. Under previous regulations, office tenants were flexible with regard to both the definition of what constitutes unused space and the timing of the write-off in their accounting reports. While the previous accounting principles stipulated that companies do not have to take a charge against their earnings for rent payments made for unused space unless they adopt a formal 'facility exit plan', the new regulations require a company to write off the cost of unused or underutilized office space as soon as the company terminates the lease or physically 'ceases using' the space (Rich 2003). Offering space for sublease on the market is a clear indication of unused space in the definition of the GAAP. It is thus expected that many companies will avoid recording the write-offs thereby aggravating the general problem of understated vacancy in office market space accounting. A quantitative analysis of the expected effect of the new GAAP is not, however, available to date.

Since there are no direct measures of the volume of shadow space, estimates must be inferred from other indicators. Typically, a large percentage of sublet space in a market is indicative of a related amount of shadow space, even though it is not possible to quantify the relationship accurately. Figure 3-2 illustrates that the share of sublet space rose dramatically in the second half of 2000 at a time when the direct vacancy rate was relatively low and asking rents still growing, indicating an impending shift in overall vacancy and rents. The progression of the indicators over time reveals that sublet space is a leading market indicator that captures the turning point in the market cycle three to four quarters prior to a change in rental rates.

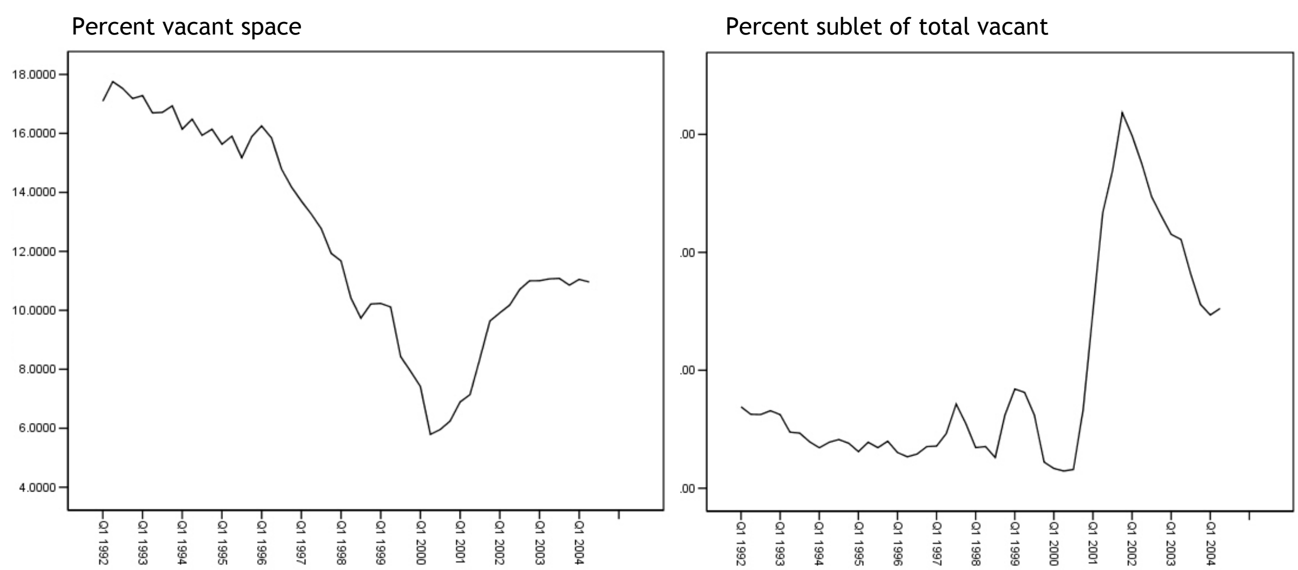


Figure 3-2: Vacant space as a percentage of overall office space inventory (left) and sublet space as a percentage of overall vacant space (right). Data: Grubb & Ellis

The relationship between direct vacant space and sublet space is of particular relevance for understanding the market mechanisms of commercial real estate. It is noteworthy that the share of sublet space in total vacant space more than tripled within one year (from the third quarter of 2000 to the third quarter of 2001). In general, the more sudden and unexpected a recession is, the higher the amount of sublet space put on the market will be. This phenomenon became evident in the Manhattan office market at the end of a prolonged growth period. When the market unexpectedly started to soften at the end of 2000, many tenants realized that some of the space they had leased would not be required in the near future, and they made a large proportion of the excess space available for sublease. The third quarter of 2001 marks a peak in the percentage of sublet space. The additional amount of sublet space, however, not only is an indicator of weakened demand but also reflects the expectations of tenants with excess space tohat they would sublet some of it to displaced World Trade Center tenants. Thus, tenants with unused space in their portfolio were more apt to offer sublet space on the market in the wake of the 9/11 attack than would have otherwise been the case. In the following quarters, the percentage of sublet space decreased as leases expired, direct vacancies increased, and tenants withdrew some of the available sublet space from the market.

Apart from the fact that displaced tenants were accommodated in a firm's existing space portfolio, the strongly negative absorption in the aftermath of 9/11 has also been caused by the fact that displaced companies rented less space than they had occupied in the damaged or destroyed buildings. Table 3-2 demonstrates this phenomenon for a subset of 6.4 million square feet for which both tenant and building information was available (Grubb & Ellis 2002). Backfill is not considered in this subset. Grouped by submarkets, the data show on average that companies rented only about 15 percent less space in the new buildings than they originally held in the affected buildings.

A further reason for reduced space usage by displaced tenants at their new locations is price elasticity of demand. The observed reduction in newly leased space by displaced tenants was particularly strong in high-priced buildings and submarkets, such as the Plaza District or Grand Central (Table 3-2). Relatively high rents in some submarkets had an additional dampening effect on the amount of space leased by displaced companies. In turn, the reduced space usage contributed to higher vacancy rates and declining asking rents in the following quarters. The aggregated demand elasticity of the World Trade Center tenants in the destination submarkets is -1.12. The aggregate price elasticity of demand is calculated here as the quotient of the percentage change in rented space and the percentage change in average rental rates. The basis of the comparison are the average rents paid at the original WTC location versus rental rates at new locations weighted by the amount of space that the tenant held in the WTC. Typically, demand for space is considered rather inelastic in the short run. For example, Wheaton, Torto and Evans (1995) and Wheaton (1999) assume a general price elasticity of demand of -0,4 in the office market. Owing to the particular circumstances of the 9/11 attack, displaced tenants were forced to sign new leases in the various submarkets during a macroeconomic recession, when price sensitivity is particularly high. While it is difficult to separate the contribution to reduced space demand of recession-related employment layoffs from a ‘true’ price elasticity effect, the cross-sectional data presented in Table 3-2 suggest an inverse relationship between submarket prices and space reduction.

Table 3-2: Former WTC/WFC tenants by destination submarket (new leases only)

Submarket	Occupied space old (sq.ft.)	Occupied space new (sq.ft.)	Difference (%)	Average rent ($)	Typical floorplate (sq.f.)
Plaza District	817,496	355,724	-56.49	39.87	22,294
Grand Central	619,470	481,733	-22.23	38.44	23,190
Hudson Square/Tribeca	60,000	80,000	33.33	33.00	65,828
Madison Square	1,142,482	923,911	-19.13	19.17	18,705
Midtown West	2,351,352	2,299,163	-2.22	19.75	19,578
Penn Station	578,800	472,000	-18.45	22.30	67,308
Wall Street	843,404	793,500	-5.92	25.38	10,881
Total	6,413,004	5,406,031	-15.70	32.22	25,981

Data: Grubb & Ellis (2002), CoStar (2001)

In summary, the most unanticipated effect in the aftermath of 9/11 has been the fact that the expected surge in additional space consumption attributable to the leasing activities of displaced tenants did not occur. Backfill of displaced tenants into existing leased space, employee layoffs, and reduced space usage per worker as evidenced by a relatively elastic demand for surrogate space are the three most important reasons for this. As a consequence, predictions of increasing rents and extreme space shortages did not come true because they were based on the simplistic calculation that constant demand after a 10 percent reduction in supply would bring the vacancy rate to almost zero. On balance, however, absorption in the Manhattan market was overall negative because the wider economic recession and the indirect effects of 9/11 more than offset the positive absorption of space induced by displaced WTC tenants.

The impact on office employment and locational behavior

The employment dynamics of office-based service industries are a main determinant of the demand for office space and an integral part of contemporary metropolitan economies. This is particularly true for Manhattan, where FIRE (finance, insurance and real estate) and other office-using industries account for over 40 percent of the total employment. In Lower Manhattan, office jobs make up approximately 75 percent of all jobs. The importance of these jobs for the local economy, however, is even greater than the primary employment statistics suggest. When taking into account local multiplier linkages of the FIRE sector, one employee in the financial industry supports two further jobs in various types of economic activities, such as business services and restaurants (NYC Partnership and Chamber of Commerce 2001, 11).

To assess the dynamics of office employment in the context of 9/11 adequately, empirical datasets are analyzed at three levels. First, I examine the regional context of office employment dynamics for spatial shifts of agglomeration economies. The second step is analyzing Manhattan office industries at the zip code level to determine which submarkets were hit hardest by the attack. Third, I trace the relocation patterns of the displaced World Trade Center tenants. The observed relocation patterns of the displaced companies can provide valuable clues in our attempt to estimate the longer-term reverberations of the attack on the locational behavior of office companies. If the companies that were immediately affected by the attack chose to remain within the office districts of Manhattan, there is reason to assume that the long-term negative impact of the 9/11 attack was not as powerful as it would be when displaced companies choose to disperse to peripheral locations.

Other analysts have disagreed on the implications of the attack for the future of Manhattan and particularly Lower Manhattan. Some authors claim that 9/11 has had no significant lasting impact on the city (for example Harrigan and Martin 2002), but others envisage a downward spiral that will eventually lead the demise of Lower Manhattan and some of the older inner-city office clusters. Those who take the latter view claim that even before the catastrophic events of September 11, 2001, New York's financial district was an 'anachronism' whose economic viability could only be artificially maintained by massive government subsidies (Glaeser and Shapiro 2001). Arguing that the direct and indirect damage caused by the 9/11 attack created a need for even more subsidies to keep Lower Manhattan alive, they conclude that it might not be justified to attempt saving the area at all because the public funds needed for this endeavor might be spent more efficiently elsewhere. On the other hand, Lower Manhattan has experienced considerable economic growth in the years preceding the attack, thereby demonstrating that the area’s structural problems are in principle curable. Before reliable conclusions on this highly controversial topic can be drawn, however, it is necessary to provide some background on the long-term locational behavior of service industries and office employment in various parts of the New York metropolitan area in which the effects of the 9/11 attack are embedded.

Spatially disaggregated analysis of employment impacts

Estimates of the total number of jobs lost because of the catastrophic events of September 11 differ considerably depending on research methodology and time frame of the analysis. Jason Bram, James Orr and Carol Rapaport (2002) applied an autoregressive forecasting model and arrived at an estimate of initial job losses in the amount of 38,000 to 46,000 in October 2001. Although the exact number of lost jobs is difficult to assess, it is clear that office-using industries were hit particularly hard by the attack.

This section explores the dynamics of office employment after September 11 in various Manhattan submarkets. While almost all areas of Manhattan have been affected by the economic recession and subsequent declines in the number of office jobs, Lower Manhattan has sustained particularly great losses because of the double impact of the 9/11 attack and the macroeconomic recession. The attack of September 11 ended a period of sustained strong job growth in Lower Manhattan, turning the overall balance from 2000 until 2003 negative. Besides the World Trade Center area, the sharpest relative decline in office employment occurred in the neighborhoods formerly dubbed 'Silicon Alley' – in particular Chelsea – as a consequence of the collapse of the dot-com boom. More surprisingly, the submarkets in the eastern section of the Midtown market –including the Plaza District, which is the highest priced area of Manhattan– saw their shares in Manhattan office employment diminish to varying degrees. In contrast, the western areas of Midtown exhibit relative growth in office employment; a large part of Manhattan's new office space was built in the Times Square and Columbus Circle areas. In the Downtown area, sharp losses in the World Trade Center area are juxtaposed with relative gains in the eastern financial district and north of the World Trade Center area in Tribeca. Although these areas have not been major recipients of displaced WTC tenants, it seems likely that temporary locational shifts of office companies away from the western area of Lower Manhattan to the east and north contributed to their relative increase. Nevertheless, almost all areas of Manhattan lost office jobs in absolute numbers. Since this happened to varying degrees, however, relative shares in overall office employment increased even if office employment in absolute numbers decreases.

The loss to Lower Manhattan's economy as outlined in the previous sections becomes even clearer when considering the displaced tenants of the World Trade Center attack. DRI-WEFA (2002, 36) estimates that approximately seventy thousand jobs were lost as a consequence of the attack, whereof thirty thousand are estimated to be displaced permanently. Taking into account that each of these jobs supports other jobs, for example in the financial sector through economic linkages to the business and hospitality services sector, a complete economic recovery of Lower Manhattan is bound to be a difficult long-term endeavor. The overall employment prospects may be more positive as these initial job loss assessments suggest, simply because new companies are attracted by the positive locational profile of Lower Manhattan. Additional business incentives and tax benefits are available through a number of government programs, which enhance lower Manhattan's reputation as an attractive business location. Incoming new tenants attracted by lower rents and government incentives are bound to fill the vacancies created by those displaced tenants who are not returning to their original locations in Lower Manhattan. It remains unclear, however, how long it will take to achieve a new market balance in the Downtown area.

In the wake of the September 11 attack, some have argued that the collapse of the twin towers was definite proof that skyscrapers are 'an experimental building topology that has failed' (Peirce 2001) and have prophesied the eventual demise of dense Central Business Districts characterized by office high-rises. Contrary to these predictions, the relocation patterns of displaced World Trade Center firms and other developments after 9/11 demonstrated that agglomeration economies, the underlying invisible forces that created and sustain dense urban environments like Manhattan's, are surprisingly resilient. Outside of Lower Manhattan, companies displaced by the 9/11 attack relocated mainly in other high-density office submarkets in Manhattan. As outlined in the previous section, Midtown Manhattan captured the majority of displaced tenants who moved away from Lower Manhattan.

Relocation patterns of displaced WTC tenants

The data presented in the preceding section suggest that urbanization economies were relevant in the location decision of companies displaced by the 9/11 attack since the share of displaced tenants in a particular area corresponds roughly with the overall size of the respective target area. Comparing GINI values of the overall distribution of office firms and the displaced WTC tenants shows that they are more concentrated in Manhattan than office employment in general (GINI of 0.48 versus 0.33 for overall office employment). This finding runs contrary to the notion that WTC tenants spread out to low-profile locations after the 9/11 attack to escape possible future attack and adds further evidence to the relevance of urbanization economies in the dispersal process after September 11.

To further explore the relevance of localization economies, the destinations of the former World Trade Center tenants who left the Lower Manhattan area are broken down by both industry and submarket in Figure 3-3. The charts demonstrate that most companies chose to relocate to the largest existing cluster of their respective industry, thereby roughly mirroring the overall distribution of their industry sector across the submarkets. This is in part corroborated by the correlation coefficients (Spearman's rho) which compare the rank order of submarkets for an industry with the rank order of submarkets for just the displaced WTC tenants of the same industry. While the distribution is far from perfect it lends sufficient support to the claim that localization economies have also played an important role in the relocation decisions of displaced WTC tenants. A further complication is that urbanization economies and localization economies cannot be separated sufficiently in this analysis since the core of Midtown is not only the largest overall office submarket within Manhattan but also hosts the largest share of many office-using industries, thus making it difficult to distinguish between the overall size effect and the industry-specific effect. In this respect, it is interesting to focus on some of the industries that are concentrated in smaller submarkets such as architects or communication services. The data on these industries reveal that the WTC companies displaced by the 9/11 attack were more likely to move to submarkets with an existing cluster of the respective industry as opposed to moving to the largest overall office cluster (Midtown Core). These findings give some preliminary clues about the relevance of both urbanization and localization economies in the wake of the September 11 attack.

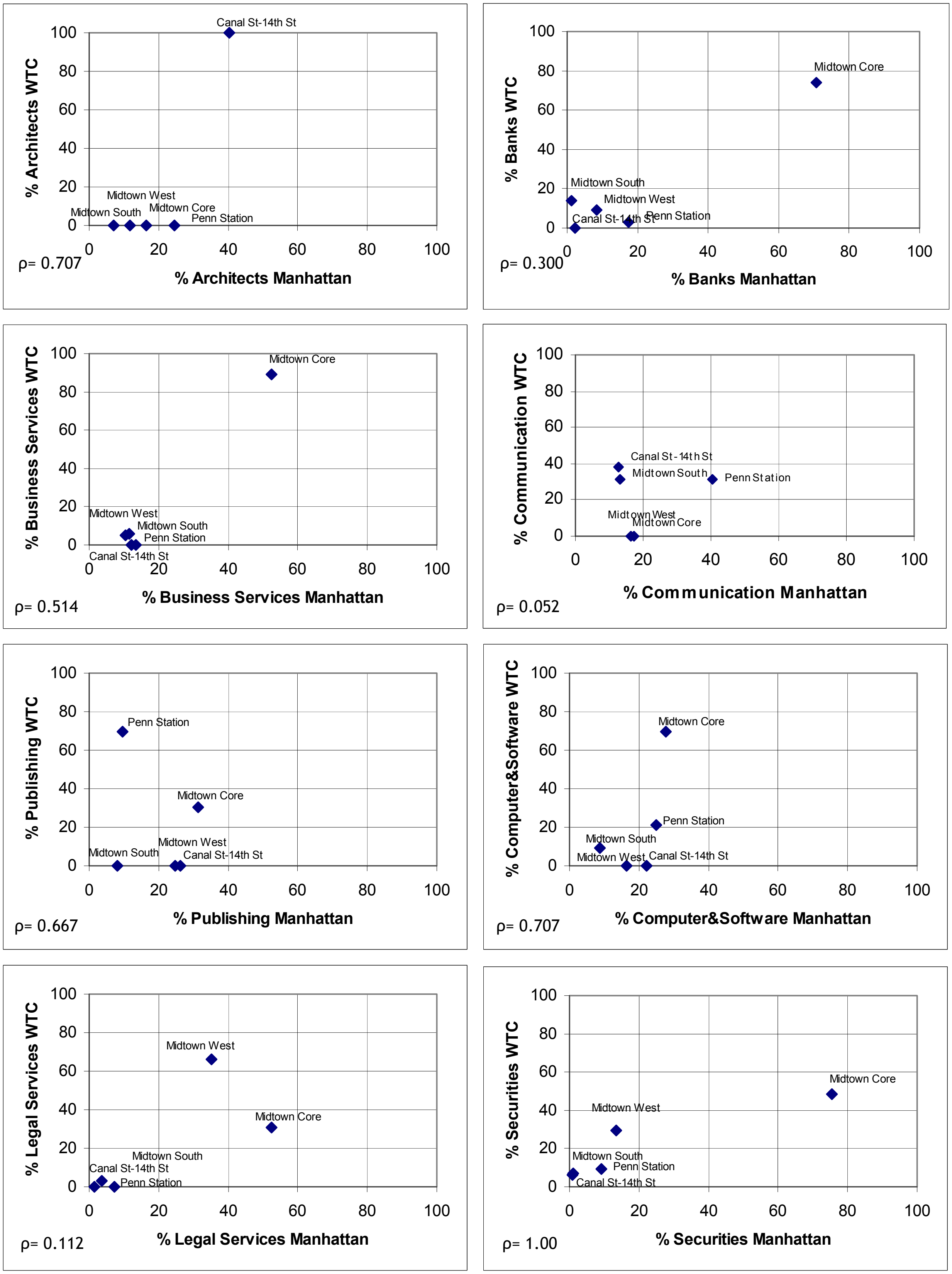


Figure 3-3: General distribution of selected industries in Manhattan submarkets and destinations of displaced World Trade Center tenants (Spearman's ρ indicated in lower left corner). Data: Kelly (2002), Grubb & Elllis (2002)

The impact on rents

As demonstrated by the data presented in the previous section, displaced tenants were not led merely by cost considerations in their relocation decisions. The aggregated dataset as well as anecdotal evidence suggest that companies did not simply migrate to areas where office space was readily available at the cheapest prices but gravitated towards existing agglomerations of the respective industry. The resiliency of agglomeration effects in the face of the 9/11 attack which had nurtured concerns of a catalyzed dispersion of office firms to remote locations, bodes well for the ability of New York City to retain the industries that form its economic base.

Before estimating the impact of 9/11 on overall market rents and subsets of office buildings, we examine the spatial differentiation of Manhattan's submarkets over time. Being by far the largest office market in the United States, and arguably the second largest office market in the world (after Tokyo), Manhattan's wide range of specialized business and financial services as well as the array of building types and locations, generate effects in the submarkets that reflect the particular industry mix of tenants and the building characteristics. Figure 3-4 shows a boxplot of the rental rates of the fifteen Manhattan submarkets in relation to overall aggregate market rents over a period of about twelve years. The horizontal reference line represents the average Manhattan rent and the vertical reference lines delineate the areas of Midtown (left), Midtown South (center), and Downtown (right). The boxplot shows the quartiles of the distribution for each submarket. The length of the box represents the difference between the 25th and 75th percentiles of the rent distribution relative to the Manhattan aggregate. It may seem surprising at first sight that the median values of all but three submarkets are below the Manhattan average. This can be explained, however, by the fact that about half of Manhattan's office space is concentrated in just three Midtown submarkets with above average values.

The height distribution of the columns in the boxplot resembles a longitudinal cross-section of Manhattan's built environment. This pattern is in line with urban economic theory, which states that the physical density of the built environment is a function of the bid rents in the area. Apart from the differences in median rent, the submarkets also differ in the volatility of rents over time, as illustrated by the spread of the quartiles. In general, the established Midtown and Downtown office core locations exhibit less variability in office rent over time than the more peripheral locations of Midtown-South. The greater volatility of rents in Gramercy Park, Chelsea, Soho or Tribeca can be attributed to the 'dotcom' boom of the late 1990s when more than one thousand technology-related start-up companies settled in these hitherto peripheral office locations. Soon after the precipitous fall of technology share prices and the subsequent demise of many start-up companies in the district in the year 2000, rents also began to decline to previous levels and few areas were able to retain a significant share of office companies.

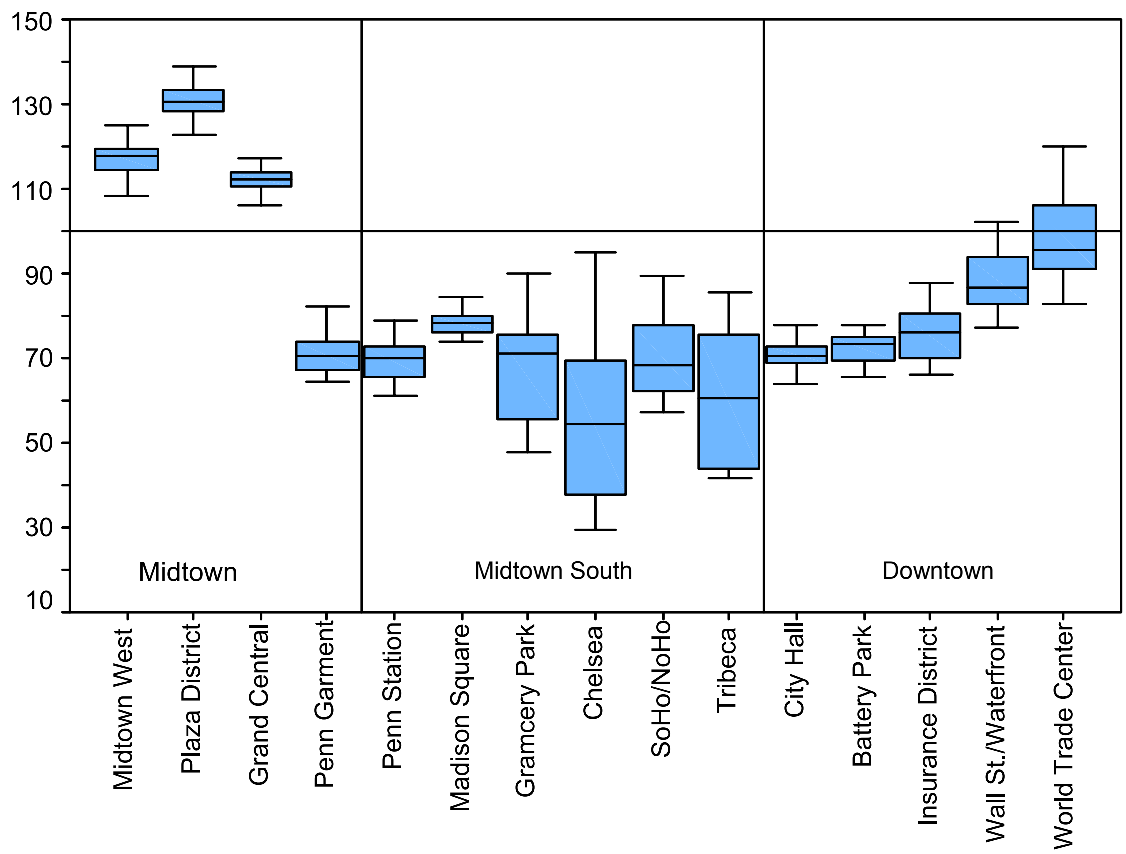


Figure 3-4: Boxplot of submarket rents relative to the overall Manhattan office market from Q1-1992 through Q1-2004 (index, Manhattan=100). Data: Grubb & Ellis.

Among the submarkets in the established office cores of Midtown and Downtown, the World Trade Center area (which today comprises about seventeen million square feet of office space in the World Financial Center and a number of other office buildings in the vicinity of the World Trade Center site) shows the greatest volatility. An analysis of the rent time series reveals that this volatility is attributable to a particularly steep decline in rents in the first half of the 1990s, possibly exacerbated by the first terrorist attack on the WTC building complex, a subsequent sharp increase in rents in the second half of the 1990s; and a dramatic decline in the wake of 9/11, with a partial recovery in the more recent quarters.

Afraid of heights? Tall buildings before and after 9/11

The 9/11 attack had a unequal impact on various spatial submarkets, as the preceding section demonstrates. A further assumption to be investigated is that tenants would shun prominent skyscrapers in response to the 9/11 attack. The susceptability of famous buildings and very tall buildings to terrorist attack in the future might lead tenants in search of office space to move to low-height and 'low-profile' buildings instead of the most prestigious and conspicuous buildings, which were favored locations before 9/11. Norman Miller and his colleagues (2003), along with Torto Wheaton Research (2002), postulate, however, that these so-called trophy buildings are still coveted by both tenants and investors and that there is no flight from tall buildings due to psychological reasons and fear of new attack. By analyzing a set of seven high-profile trophy buildings, Torto Wheaton Research shows that these buildings exhibited below-average vacancy rates one year after the attack. Miller et al. (2003) envision, however, that adverse affects will harm the marketability of a few truly famous office buildings such as the Empire State Building.

To test this assumption, it is important to distinguish between 'trophy' buildings and 'tall' buildings (despite a large overlap of both categories). There are several buildings in Manhattan that are considered 'trophy' or 'top-tier' but not all of these buildings are in the group of the thirty or even fifty tallest buildings in Manhattan. Conversely, not all of the thirty tallest office buildings in Manhattan are considered trophy. As far as a discounting of market values for fear of future terrorist attack is concerned, it is simply the height of an office building that evokes concerns about being the target of another terrorist attack rather than the rating of a building by brokerage professionals or any measures of value and rental income. Figure 3-5 compares the vacancy rates of two sets of buildings (forty or more stories and fifty or more stories) extracted from the CoStar (2001) building database. The samples are weighted by rentable building area. The vacancy rate which is a leading indicator and thus more appropriate to reveal trends than rental rates, shows that the tallest buildings (fifty or more stories) in particular recorded a sharp hike in vacancies after 9/11.

Despite the fact that vacancy rates declined and approached the values of the average market in the following quarters, they still remain above market average and significantly above rates for buildings forty or more stories high. The difference becomes even more pronounced when fifty-story-or-higher buildings are eliminated from the forty-story-plus subset of buildings. The category of buildings between forty and forty-nine stories high shows significantly lower vacancies for these buildings. In general, it is evident that the expected flight of tenants from tall office buildings did not occur in the first three years following the attack. The data point to a potential problem for the tallest office buildings (fifty stories or higher), at least in the first three years following the attack. This might be attributed to a psychological effect among office tenants perceiving some of the tallest structures in the city as potential targets of terrorist attack and seeking to avoid them, but the impact of this effect on overall vacancy in the affected buildings appears to be small and is likely to dissipate barring another incidence involving tall office buildings.

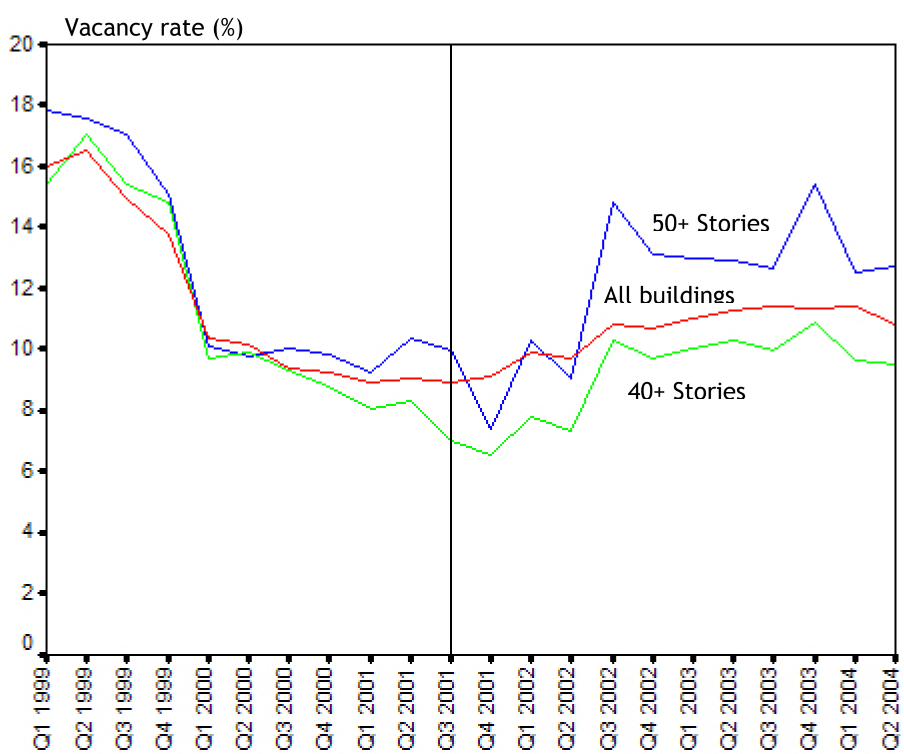


Figure 3-5: Vacancy rates in office buildings of various heights. Data: CoStar

A list of the destinations of displaced tenants published by Grubb & Ellis (2002) reveals that most tenants in the database moved to buildings with more than twenty, but fewer than forty stories. A smaller percentage moved to buildings with forty to forty-nine stories, and a few large tenants decided to move to buildings with fifty or more stories. Overall, only a small share of the displaced tenants contained in the subsample moved to non-skyscraper buildings (i.e. buildings with fewer than twenty stories). These findings underline the conclusion that there is no clear evidence of an aversion effect for either tenants in general or the group that was immediately affected by the attack.

The impact on building values and sales transactions

Beyond the destruction of human lives, the September 11 attack also resulted in a massive destruction of capital values. The market value of the destroyed World Trade Center was assessed at $4 billion and the replacement cost estimated at $6 billion (not including excavation, infrastructure repair, environmental costs, internal finish, telecommunication and other technological equipment). The total cost for restoring the damaged space in the World Trade Center is estimated at $2.2 billion (New York City Partnership and Chamber of Commerce 2001, 74).

One of the most remarkable and unexpected phenomena in the wake of 9/11 was the significant increase in sales prices per square foot, despite widespread speculations that falling rents, rising vacancies, and a growing aversion to working in high-rise office buildings would drive prices down dramatically. Simultaneously, average capitalization rates of Central Business District (CBD) office buildings (closed rates) continuously declined from about 9 percent in the third quarter of 2001 to 7.57 percent in the third quarter of 2004. Figure 3-6 shows the increase in sales prices after September 11, despite worsening market fundamentals and the overall economic recession. One particularly notable case is the sale of the General Motors Building in Manhattan in September 2003 for $1.4 billion ($764 per square foot), the highest price ever paid for an office building.
The rise in property values has been attributed to historically low interest rates and the fact that real estate is still considered a "safe haven" in times of economic and political uncertainty (Reis 2003). Large capital flows into office real estate and the sizable portion of international and domestic investors looking to purchase class A office buildings in prime locations put additional upward pressure on prices in the high-quality segment of

inner city office markets. It appears that the downward pressure on capitalization rates exerted by the extremely low level of interest rates was stronger than the upward pressure induced by weak market fundamentals (Torto Wheaton Research 2002). Although the complex interaction of interest rates, sales prices, and capitalization rates in the wake of 9/11 cannot be adequately considered in this chapter, the apparent disconnect between market fundamentals and sales prices deserve further investigation in order to arrive at a more comprehensive understanding of these effects.

Figure 3-6: Average sales price per square foot for office properties in Manhattan (n=183). Data: Real Capital Analytics

3.2 Event study of the 9/11 attack

Following the exploratory analysis of the previous section, I will investigate the impact of the 9/11 attack in more detail by utilizing an event study methodology. The event study approach was first laid out by Eugene Fama and his colleagues (1969) in a seminal paper and has since been applied to a wide variety of topics in economics and finance, typically with the objective of examining the impact of past occurrences on financial markets or particular industries and companies.

The basic assumption of the event study methodology is that markets are information-efficient so that any new information about changes in market conditions will be reflected in changing asset prices of the affected industries. The portion of the price change attributable to this specific event (for example, the announcement of a merger) is measured as an 'abnormal return'. In other words, the abnormal return is the difference between the expected future price of an asset prior to the event and the observed price including the event. The expected price can be derived by estimating the parameters of the statistical relationship between Manhattan and the overall national office market with OLS regression. Since the number of independently estimated cross-sectional data is very limited in contrast to firm-level event studies, no further measures are taken in this study to account for cross-sectional heteroskedasticity and covariability.

The Definition of the event window

The first step of an event study is to define an estimation window and an event window. The estimation window is a sufficiently long time series of data before the onset of the event required to estimate the expected price of the asset. The occurrence of the event itself marks the end of the estimation window and the beginning of the event window. The sequence of data points that constitute the event window is determined either by a significance measure of abnormal changes for a specific event window or simply by the most recent available observation. In most event studies, the precise definition of the event window is plagued by the fact that information about an impending event - for example a merger - can become available before the actual event; owing to news leaks. However, since the September 11 attack was a truly unpredictable event, the earliest possible beginning of the event window can be determined with great certainty. We therefore define the third quarter of 2001 as the first observation (T_1) and the fourth quarter of 2003 as the last observation (T_2) in the event window. The estimation window is specified as the quarterly time series from the first quarter of 1990 (T_0) through the second quarter of 2001, as shown in Figure 3-7.

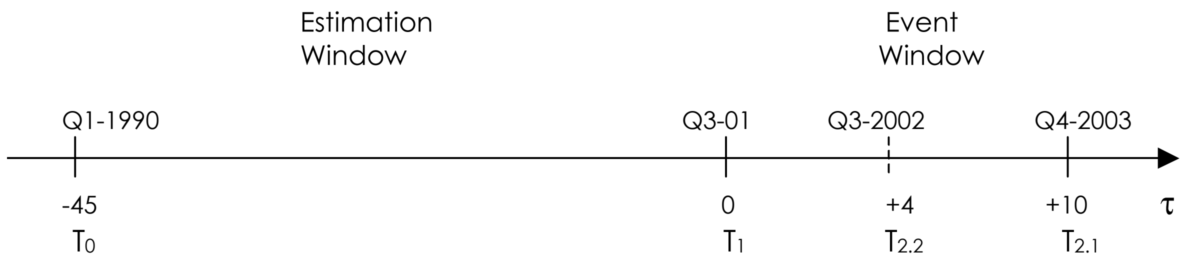


Figure 3-7: Timeline for the event study of September 11 attack

Estimation of abnormal changes and cumulative abnormal changes

There are several ways to estimate the expected and abnormal changes of an asset (see MacKinlay 1997). To test the impact of the September 11 attack on the New York office market, we adopt here the market model approach because it is more accurate than a long-run mean measure or approaches based on assumed identical change rates in submarkets and aggregated markets. The expected return or change rate is expressed as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad (1)$$

where R_{it} is the total return of asset i in period t, t, α_i is the base-line return of the asset in question, β_i is the coefficient for asset *i* in relation to R_{mt}, the overall market return, and ε_{it} is white noise, which is assumed to have a constant mean of zero and zero covariance. Conditional on the standard assumptions of OLS regression models, α_i and β_i are efficient estimators. In the context of this research, the market return rate R_{it} is proxied by the rental or vacancy rate of the Manhattan market or other submarkets, and R_{mt} is the corresponding rental or vacancy change rate of the overall U.S. office market. The abnormal change rate A_{it} is thus defined as:

$$A_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \qquad (2)$$

The abnormal change rate is the difference between the actual observed ex post return minus the expected return, as calculated in equation 1 with estimation window data. Patell (1976) suggested that the values obtained for the event window period should be adjusted because they are bound to have a higher variance than the residuals of the estimation window. For the purpose of the present study, however, the values of abnormal returns are not standardized since this would not change the results significantly (see Brown and Warner 1985). In the present study, the abnormal change due to the 9/11 attack can be calculated through out-of-sample forecasting of the market model for all the periods constituting the event window (whose limits are denoted by T_1 and $T_{2.n}$). Assuming efficient markets, the null hypothesis is consequently:

$$H_0 = CA(T_1, T_{2.n}.) = 0 \tag{3}$$

If the 9/11 attack have generated no abnormal changes over the defined event window, the mean abnormal change rate and the cumulative abnormal change rate should be insignificantly different from zero. To test this hypothesis we define the average abnormal return as:

$$\overline{A}_i = \sum_{i=1}^{N} \hat{A}_{it} = \sum_{i=1}^{N} \left(R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \right) \tag{4}$$

The total estimated impact or cumulative abnormal change over the defined period is calculated in the following manner:

$$CA(\tau_1, \tau_n) = \sum_{t=\tau_1}^{\tau_n} A_{it} \tag{5}$$

where τ_n are the time units (quarters) in the event window that are summed up to yield the cumulative abnormal change of the event. The variance of the cumulative abnormal change is calculated as:

$$\sigma^2_{CA_{it}} = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2 (T_1, T_{2.n}) \tag{6}$$

To test the null hypothesis, we apply a Z-test in the following form:

$$Z = \frac{CA(T_1, T_2)}{\sqrt{\overline{\sigma}^2_{CA}}} \sim N(0,1) \qquad (7)$$

If Z is significantly greater than zero, we reject the null hypothesis that the 9/11 attack had no significant effect on rents and vacancies in favor of the alternative hypothesis that the attack did have a significant impact. Since both A and CA are assumed to follow a normal distribution with zero mean and constant variance, the critical absolute test value for Z is 1.96 (for $p<.05$). If the absolute value of Z exceeds 2.58 the difference is also significant at the $p<.01$ level.

The measurement of abnormal changes in event studies is typically based on monetary units. In the case of the office market, however, using data on asking rents in the office market may not give an entirely accurate representation of the temporal reaction to the 9/11 effect, since asking rents are known to be 'sticky' and do not adjust to new information with the same speed as, for example, stock prices. Therefore, we also examine vacancy levels (including sublet) which respond to market shocks with shorter delays.

It may be argued that the U.S. office market data utilized to estimate the expected values for the New York market was also subject to effects from the September 11 attack, thus introducing a possible bias into the estimators that could lead to underestimating the true impact of 9/11 on the New York office market. Although the overall direct impact of the attack on the aggregated US market was considerably lower than their impact on the New York market, it is nevertheless important to keep in mind that any effects and abnormal changes reported here are specific local effects and in excess of the broader and indirect 9/11 impact on the U.S. market.

Empirical results

The results of the analysis for the event window (T_1 and $T_{2.1}$) are reported in Table 3-3. The average abnormal changes ($\bar{A}$) and the cumulative abnormal changes (CA) demonstrate clear differences among the analyzed areas in the calculated impact of the 9/11 attack. As indicated by the R square and F statistics, significance values of the regressions decrease generally with the size of the geographic unit, giving rise to the assumption that smaller areas are more prone to idiosyncratic behavior over time than larger, aggregated markets. In the case of the World Trade Center submarket (which also comprises the World Financial Center and a number of other office buildings in the area), the regression is not significant at the 5 percent level and therefore the reported abnormal changes have to be interpreted with caution.

In general, all the reported abnormal changes show the expected sign, a lower than predicted rent level and a higher than predicted vacancy rate. An intuitive assumption would be that the Downtown and especially the World Trade Center submarkets exhibit higher abnormal changes than Midtown or the overall Manhattan market. This is not unequivocally confirmed, however, by the results for the defined event window. Regarding rental values, the Downtown market is indeed more strongly affected by the attack and is the only market where the null hypothesis of a non-significant impact can be rejected. In terms of vacancy rates, the opposite is the case. All markets exhibit a significant impact except Downtown. Since the relationship between rents and vacancy rates is marked by significant lags, it seems advisable to inspect the quarterly changes after September 11, 2001, for both variables in more detail before re-defining the event window.

Table 3-3: Model results and abnormal changes due to the September 11 attack for event window Q3-2001 through Q4-2003

		average abnormal changes $\bar{A}$	cumulative abnormal changes *CA*	*Z statistic*	*R square*	*T of* β_i	*F*	*Durbin-Watson*
Rent	Manhattan	-0.64%	-6.94%	-1.81	0.517	7.023	37.41***	2.10
	Midtown	-0.68%	-6.81%	-1.78	0.462	6.116	30.024**	2.15
	Downtown	-1.15%	-13.53%	-3.89***	0.323	4.147	17.19***	1.65
	WTC submarket	-0.35%	-3.46%	-0.33	0.144	2.391	5.71*	1.40
Vacancy	Manhattan	0.080%	0.42%	3.53***	0.291	3.606	13.00***	1.75
	Midtown	0.18%	1.77%	2.63***	0.258	3.955	15.64***	2.10
	Downtown	0.07%	0.73%	1.05	0.363	4.462	19.91***	1.94
	WTC submarket	0.49%	4.93%	2.46***	0.145	2.432	5.91*	1.42

*** significant at 1% level, ** significant at 5% level, * significant at 10% level. Data: Grubb & Ellis

Table 3-4 shows the quarterly abnormal changes for vacancy rates in the four examined areas. As expected, the initial impact in the third quarter of 2001 is highest in the Downtown and WTC submarkets. The abnormal change data suggests, however, that the pattern was reversed about one year after the attack when changes in the vacancy rate exhibited a more positive pattern than expected, which continued throughout the period. The reason for the unexpectedly positive developments downtown might be the effect of the massive subsidies and revitalization efforts of multiple levels of government. An alternative explanation would be that this is simply a mean reversion effect, a counter movement to the jump in vacancy rates in the wake of September 11, 2001. The assumption underlying such an explanation is that markets tend to return to long-run equilibrium prices after a one-time, non-persisting shock event.

Table 3-4: Quarterly abnormal changes in vacancy rates due to the September 11 attack

	Manhattan	Midtown	Downtown	WTC
Q3 2001	0.59	0.16	0.95	2.76
Q4 2001	-0.38	-0.09	-0.49	1.67
Q1 2002	-0.25	-0.18	0.00	2.96
Q2 2002	0.48	0.05	1.47	2.22
Q3 2002	-0.01	-0.07	0.44	-1.51
Q4 2002	-0.15	0.30	-1.09	-0.66
Q1 2003	0.07	0.63	-0.47	0.05
Q2 2003	0.13	0.37	-0.31	-0.40
Q3 2003	-0.10	0.00	-0.20	-0.96
Q4 2003	0.41	0.59	0.42	-1.21

Data: Grubb & Ellis

The rent data reported in Table 3-5 appear to support this argument. While rents fell precipitously in the Downtown and WTC submarkets in the first quarter following the September 11 attack (see Figure 3-8), these submarkets achieved higher than predicted positive change rates as conditions in Lower Manhattan gradually improved and buildings and critical infrastructure links were restored. This phenomenon is especially pronounced in the WTC market in Q4 2001, when rental rates trended up towards previous levels as a result of the efforts to clean up the area and to restore damaged buildings. The effect, however, dissipated in the medium run, hinting at a possible structural problem in the World Trade Center submarket that may not be completely remedied until the area has been fully rebuilt as a major office cluster and transportation hub.

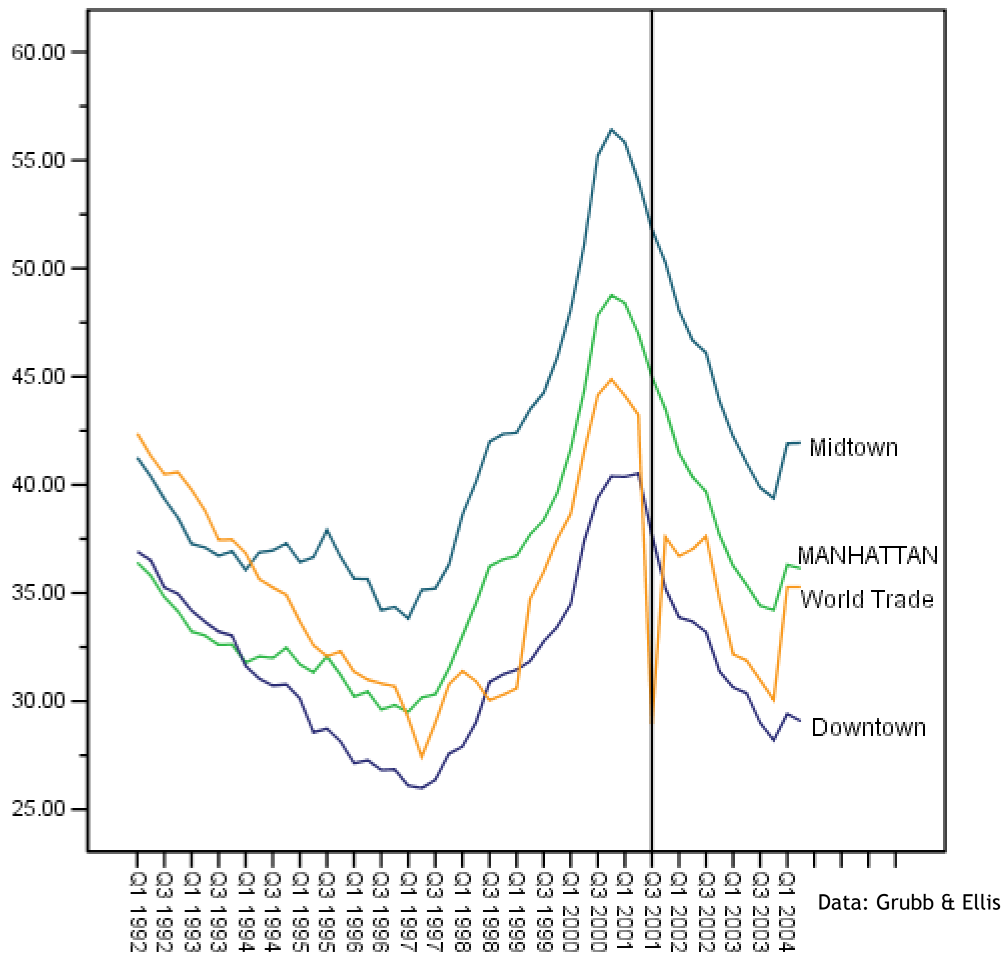


Figure 3-8: Rental rates of the submarkets analyzed in the event study (constant dollars).

Table 3-5: Quarterly abnormal changes in rental rates due to the September 11 attack

	Manhattan	Midtown	Downtown	WTC
Q3 2001	0.36%	0.39%	-3.16%	-29.44%
Q4 2001	-1.32%	-1.01%	-4.81%	31.69%
Q1 2002	-1.01%	-0.82%	-0.68%	0.58%
Q2 2002	-1.65%	-1.87%	0.51%	2.00%
Q3 2002	0.94%	1.31%	0.86%	3.81%
Q4 2002	-1.72%	-1.53%	-2.62%	-5.00%
Q1 2003	-3.77%	-3.78%	-2.11%	-6.93%
Q2 2003	-1.48%	-2.01%	0.13%	0.17%
Q3 2003	-1.29%	-1.41%	-3.17%	-1.48%
Q4 2003	4.00%	3.92%	1.54%	1.13%

To test the null hypothesis of insignificant cumulative abnormal changes from the September 11 attack for a shorter period, we redefine the event window. Table 3-6 shows the results for the event window ranging from the third quarter of 2001 through the third quarter of 2002 (T_1 and $T_{2.2}$ in Figure 3-7). This time we find a more consistent pattern in the combination of rental and vacancy rates. Based on the statistical evidence for this event window, we reject the null hypothesis for the overall Manhattan and Midtown markets but find a significant impact on the Downtown market. The World Trade Center submarket exhibits highly significant results in terms of vacancies, but these results are not significant in terms of rents, this may be due to attempts by landlords to restore the previous levels of asking rents soon after 9/11 when in fact market conditions as reflected by vacancy rates were less favorable.

Table 3-6: Quarterly abnormal changes in vacancy rates due to the September 11 attack

		average abnormal changes $\bar{A}$	cumulative abnormal changes CA	*Z statistic*
Rent	Manhattan	-0.53%	-2.67%	-1.533
	Midtown	-0.40%	-2.00%	-1.78
	Downtown	-1.46%	-7.29%	-3.77***
	WTC submarket	-0.35%	-3.46%	0.56
Vacancy	Manhattan	0.09%	0.42%	1.725
	Midtown	-0.02%	-0.12%	-0.96
	Downtown	0.48%	2.37%	3.100***
	WTC submarket	1.62%	8.11%	2.896***

*** significant at 1% level

In summary, we find evidence of significant effects of the September 11 attack in the New York office market. These effects seem to be limited, however, in terms of their spatial and temporal impact, however. While the Manhattan office market as a whole has demonstrated remarkable resiliency in the wake of the attack (measured in reported rents and vacancy rates), the Downtown market and particularly the World Trade Center submarket have been affected more clearly. Therefore, it is not surprising that rent levels are lower than expected and vacancy levels are higher than expected in these markets when compared to estimates derived from historic time-series data. Measured two years after the attack, however, cumulative abnormal changes in vacancy rates are moderate in the Downtown submarket, indicating a much weaker medium-term impact of the attack than expected in its aftermath.

3.3 Conclusions and further work

More than three years after 9/11, there is scant evidence that the attack will have a long-lasting impact on the Manhattan office market. Particularly in the submarkets of Midtown Manhattan, no significant impact could be detected beyond the market adjustment process that took place in the two quarters following 9/11. Lower Manhattan, however, was more deeply affected by the attack and its various consequences.

The Manhattan office market as a whole does not show any signs of lasting economic damage. Of the companies that decided not to return to Lower Manhattan after 9/11, the majority relocated to Midtown Manhattan. An industry analysis demonstrated that both urbanization and localization economies were at play in the relocation process and that companies preferred to settle in preexisting large industry clusters in Manhattan. Taken together, the core markets of Midtown and Downtown Manhattan captured about 80 percent of the stream of displaced tenants after 9/11, while areas outside of these two core clusters captured only 20 percent, which bodes well for Manhattan's ability to remain a prime office location even in the face of a severe crisis.

To be sure, a more decentralized development of office space and a more dynamic increase in office workers in the wider CMSA region outside of Manhattan – a process that has been evolving for at least two decades – is likely to continue over the next years. Although security concerns are likely to accelerate this development at least temporarily as firms seek to create backup facilities and distribute key functions across various locations to protect their operations, preliminary analysis of the period after 9/11 shows that agglomeration economies and firm efficiency criteria are restraining and mitigating such dispersion tendencies in Manhattan. Moreover, Manhattan has clearly been able to retain a competitive productivity advantage in the office-using industries. In fact, Manhattan's productivity differential in the office-using industries over both the national and the regional average has continued to increase even since 9/11.

More than four years after the attack, Lower Manhattan has demonstrated considerable progress in overcoming this crisis both physically and economically. A total of 31.1 million square feet of office space were affected in Lower Manhattan, of which 14.8 were destroyed and 19.6 million damaged and eventually restored. The affected space makes up less than 10 percent of the total inventory of New York City but accounts for roughly 60 percent of Downtown's Class A space. The sudden loss of more than 100,000 jobs and of a large portion of its office inventory sent Lower Manhattan, which had been struggling for much of the last three decades, into a severe economic crisis.

However, the majority of businesses directly affected by the attack have opted to remain in the Downtown area or have returned there after the damaged buildings were restored. The rebuilding process is well under way, and the first office tower to be rebuilt on the World Trade Center site, Building 7, with 52 stories and 1.7 million square feet of office space, is expected to open in early 2006. Rental rates and building vacancies seem to have stabilized after the Lower Manhattan market weakened dramatically in the quarters following 9/11.

Despite the progress made to date, the Lower Manhattan office market faces some serious challenges for the next few years. Office employment in the area is considerably lower than it was before the 9/11 attack, and it remains to be seen whether the losses can be fully recovered before the completion of the rebuilding process around 2015. Considering that the area has traditionally been more volatile due to the dominance of finance and technology industries, a full recovery is possible once these key sectors demonstrate sustained job growth again. In the long run, however, it is critical that for Lower Manhattan diversify its economy and attract a broader cross-section of office-using industries to the area.

Both the exploratory data analysis and the event analysis demonstrate that markets reacted efficiently and predictably to the 9/11 attack. Among the most notable phenomena are the downward corrections in occupied space across Manhattan when displaced tenants had the choice of leasing new space after 9/11. On the aggregate, companies rented about 15 percent less space than they had occupied in the World Trade Center. Space reduction was particularly pronounced in high-priced buildings and submarkets, such as Park Avenue or Grand Central. Moreover, the set of so-called "trophy" buildings proved to be less affected by the recession than the general market, a finding that runs counter to initial assumptions about the future of office high-rises. Only the tallest buildings in the city (fifty or more stories) exhibited slightly higher vacancies after 9/11, arguably because of an aversion to the very tallest and most famous structures in the city as potential targets of further terrorist attack.

In addition to a drastic reduction in leased space, accommodation of displaced tenants within the existing office space portfolio of large companies contributed further to lower occupancy rates than had been expected after the destruction of 10 percent of the inventory. This phenomenon, also known as backfill, caused overall absorption to be negative in the quarters following 9/11, since the positive demand created by displaced tenants was more than offset by losses incurred in the accelerated recession. Positive absorption of approximately 7 million square feet of office space in various submarkets of Manhattan can be attributed to tenants who were displaced by the 9/11 attack. This figure is much lower than expected given the square footage of the destroyed buildings. Approximately half of the anticipated demand dissipated trough backfill into existing space, reduced staff, subleasing, and more economical space usage per office worker.
The full impact of the September 11 attack is still unknown after more than four years. The rent implications of 9/11-related factors such as increased security and insurance costs as well as government subsidies to New York City are not entirely clear at this point. Moreover, the recovery trajectory of the Lower Manhattan market needs to be explored in detail with an econometric model, which is able to take into account a number of factors that influence supply and demand. Further research is required to answer these questions as longer time series of data become available to separate short-term adjustment processes from long-term impacts.

4 Forecasting the aggregate Manhattan market with a simultaneous equation model

The Manhattan office market is unique not only because of its size – it is more than twice as large as Chicago, which ranks second in terms of square feet of office space in the United States - but also because of its maturity of its inventory and market structure. The singular market shock brought about by the destruction of 14.5 million square feet of office space on September 11, 2001 is yet another distinctive feature that sets Manhattan apart from other office markets. Hence, it appears reasonable to ask whether standard econometric market models are apt to successfully predict the Manhattan market. Pertaining to its size, it can be argued that the use of change rates to capture market dynamics over time is problematic in a market of the size and maturity of Manhattan because these rates will naturally be low despite potentially large absolute numbers underlying these rates. Pertaining to 9/11, it may be expected that the exogenous shock of a terrorist attack of this magnitude renders all the calculations of econometric models invalid.

To explore the predictability of the Manhattan office market, a three-stage system of simultaneous equations is utilized in this chapter. The first stage incorporates the office space market in terms of occupied space and absorption of new space. The second stage captures the adjustment of office rents to changing market conditions and the third stage specifies the supply response to market signals in terms of construction of new office space. The standard simultaneous equation model as laid out by Wheaton et al. (1997) is modified to account for the specific characteristics of the Manhattan office market.

4.1 The model

The overall model structure and underlying theoretical principles have been utilized and refined in a number of earlier studies. One of the first researchers to use a three-component framework was Rosen (1984) who estimated demand (proxied by the amount of occupied space), supply (new construction), and rents for the San Francisco office market. At the core of this model is the assumption that the deviation of the actual vacancy rate from equilibrium or 'natural' vacancy rate determines the level of office rents. Hekman (1985) specified rent and supply equations for a panel of 14 cities. While his estimation results exhibited some problems with statistical significance levels, Hekman was among the first to introduce a measure of capital availability (ten year treasury bond rate minus three month T-bill rate) which has been used in subsequent econometric studies of the supply of office space (Viezer 1999) and is also used in this study. Wheaton (1987) developed a structural model of demand for and supply of office space. Demand (proxied by net absorption of space was specified as a function of real rents, the level of office employment and the rate of employment growth. In the absence of data on rents, vacancy rates were used and proved to be a significant determinant of absorption rates with a lag of three years. Wheaton's office construction equation incorporated the variables rents, vacancy, employment growth rates, inventory size, construction cost and nominal interest rates. The latter two variables, however, turned out to be insignificant in the empirical estimation. Pollakowski, Wachter and Lynford (1992) applied a similar modeling framework with an emphasis on the relevance of market size using pooled data from 21 cities across the US. The empirical estimation examined a number of different specifications with dummy variables capturing unobserved city-specific factors. This strand of models has been subject to criticism because of their failure to link rent to the capital markets. Hendershott et al (1999) specify a model for London which provides this link by incorporating the real gross redemption yield on 20 year government stocks as well as operating expense ratios and the replacement cost as independent variables in the rent equation. The performance of the model is enhanced by the use of time dummy variables for years with values not well explained by the OLS model. While the model adopted for this study is more similar to the specifications of the first strand of models as used by Wheaton (1987) and Wheaton, Torto and Evans (1997) in an application to the London market, the significance of the capital markets in determining rent as contained in the Hendershott model, have been tested but have not been found to enhance the explanatory power of the model for the New York case. While the attempt to link capital markets to rent levels failed in the empirical estimation of the New York model, dummy variables turned out to be helpful in capturing some of the effects in the immediate aftermath of the 9/11 attack. The theoretical framework of the three components is described in more detail below followed by the results of the empirical estimation of the model for the Manhattan market.

Demand for Office Space: Estimating absorption and occupied office space

The main determinants of the total demand for office space in a given city are assumed to be the level of office employment and a measure of the intensity of space usage expressed as the average amount of square feet per office worker. Thus, the hypothetical level of occupied space is:

$$OS_t^* = \alpha_0 + E_t(\alpha_1 + \phi_1 \frac{(E_t - E_{t-1})}{E_t} - \phi_2 R_{t-1}) + Z_1 \tag{1.1}$$

where E_t is the current total number of office workers in a city and R_{t-1} is the rent level of the previous period. The coefficient ϕ_1 denotes the degree to which dynamic growth in office employment translates into additional space consumption in excess of the space required to accommodate the employees of a firm. The inclusion of this dynamic aspect of office employment besides the variable representing the overall employment level is based on the empirical observation that firms tend to rent more space than needed based on their current operational needs. This phenomenon is analogous to purchasing an option in the financial markets whereby a buyer acquires the right to trade at a fixed price regardless of the actual future price of the asset in question. In the real estate market, office firms acquire an 'option' by leasing additional space in anticipation of further expansion in terms of employment and office space as well as further increases in rental rates in the overall marketplace. This phenomenon is key to understanding the reaction of the office market after the 9/11 attack on New York City. The coefficient ϕ_2 is a measure of the price elasticity of demand, i.e. the proportionate change in office space per worker that occurs in response to changes in rents. The underlying assumption is that firms will choose to consume less space per worker in times of high rents and more space in times of low rents. Z_1 is a 9/11 dummy variable that takes on the value of 1 in the period immediately following the 9/11 attack and 0 otherwise to account for the sharp decline in occupied space after 9/11 that would not be fully accounted for in an estimation of the standard model (for parameter values see the following section).

The hypothetical consumption of office space in Equation 1, however, does not equal the observed consumption. The discrepancy is due to the sluggish adjustment of demand levels towards hypothetical consumption brought about by the long-term nature of office leases (typically 10 years), information asymmetries and the cost of searching for adequate office space. Adjustment towards hypothetical aggregate space consumption is only gradual because only a fraction of leases expires every year. Moreover, finding adequate office space incurs considerable search cost and the lease negotiation process is complex and typically requires a long time. OS* reflects the amount of occupied office space in a market under conditions of perfect rationality, no lease restrictions, no information asymmetries and no adjustment costs. The following equation takes these friction costs into account:

$$OS_t - OS_{t-1} = A_t = \delta(OS_t^* - OS_{t-1}) \qquad \text{where} \quad 0 < \delta \le 1 \tag{1.2}$$

At is absorption of office space in period t and δ is a coefficient indicating the rate of adjustment from the occupied space of the previous period towards the hypothetical aggregate space demand in the current period. For the purpose of the present study, two additional correction terms are included to account for the massive negative absorption that occurred on September 11, 2001 (Z_1) and for the exceptionally high positive absorption that occurred as a consequence of the re-opening of damaged buildings in the subsequent two quarters (Z_2, Z_3). The final equation for absorption is thus:

$$A_t = \delta_0(\alpha_0 + E_t(\alpha_1 + \phi_2 \frac{(E_t - E_{t-1})}{E_t} - \phi_3 R_t + Z_1) - \delta_0 OS_{t-1} + \delta_1 Z_2 + \delta_2 Z_3 \tag{1.3}$$

Thus, if office employment and rents remain stable over an extended period of time, actual occupied space will eventually equal hypothetical occupied space, absorption will be zero and the market is considered to be in equilibrium.

Rental rate adjustment and vacancy rates

The technical definition of the vacancy rate is that it is the residual of supplied space and demanded space in the following form:

$$V_t = \frac{S_t - OC_t}{S_t} \tag{2}$$

In order to arrive at a model of what drives vacancy rates and, more specifically, to capture the inverse relationship between rents and vacancies, most simultaneous equation models assume either an equilibrium rental rate or an equilibrium vacancy rate as a starting point with the latter option typically being specified in the following form:

$$\Delta R_t \div R_{t-1} = \lambda(V^* - V_{t-1}) \tag{3}$$

where ΔR_t denotes the change in rent from the previous observed period t-1 and R_{t-1} is the actual rent in period t-1. The coefficient λ indicates the extent to which the actual vacancy rate of the previous period V_{t-1} adjusts towards the hypothetical equilibrium or 'natural' vacancy rate V^*.

While this approach is theoretically sound, researchers attempting to estimate the natural vacancy rate of a given metropolitan market have faced numerous difficulties and the calculated rate is subject to great fluctuation both cross-sectionally and longitudinally. Shilling et al (1987) estimated individual natural vacancy rates for the most important office markets in the US based on the above equation and arrived at values ranging from 1% to 21% with most cities clustering in a corridor between 5% and 15%. This variance of natural vacancy rates is due to a series of diverging factors in the individual cities, such as market size, geographic shape, building inventory, institutional arrangements all of which make it difficult to arrive at a an accurate and reliable estimate of the natural vacancy rate.

The concept of an equilibrium state inherent in the real estate market is, however, not necessarily an integral part of an office market model. For example, Key et al. (1994) specified the following rent equation:

$$R_t = \beta_0 + \beta_1 R_{t-n} + \beta_2 D_{t-n} + \beta_3 I_{t-n} + \beta_4 C_{t-n} + \beta_5 Q_t \tag{4}$$

The explanatory variables in this equation include average rent (R_{t-n}), a proxy for demand (D_{t-1}) which is typically either the number of office workers or an aggregate economic output measure, total inventory development (I_{t-1}), the rate of new construction (C_{t-1}) as well as interest rate levels (Q_{t-1}). Similar to the equilibrium model, it is assumed that rents do not react instantaneously to changes in the dependent variables because of long-term contracts and other status-quo conserving factors but will adjust with a time lag which is to be determined individually for each variable in the estimation process.

A micro-economic approach, however, is required to explain the relationship between demand for office space (proxied either by positive demand, office workers or negatively by vacant space). Since office space is a heterogeneous good and tenants typically have rather specific requirements as to the ideal location and attributes of an office building, the real estate market is generally characterized by high search costs. Arnott und Igarashi (2000) formulated the matching process of tenants to suitable space in the following way:

$$\Omega_S = (V / S)^{1/2} \tag{5.1}$$

and

$$\Omega_V = (S / V)^{1/2} \tag{5.2}$$

where Ω_s and Ω_V denote each the individual opportunities to match for a prospective tenant searching for space (*S*) and a landlord with rentable vacant units of space (*V*). Both the tenant match rate and the vacant unit match rate are a function of the quantitative relationship between offered space to the aggregate demand for space. Hence, the respective uncertainty of the tenant and the landlord are necessarily inversely related. In principle, landlords and tenants are both faced with a trade-off process between the cost of continued uncertainty on one hand and potentially suboptimal occupancy on the other. This also implies that a lower risk of vacancy for landlords necessitates higher search and uncertainty costs for tenants. For instance, in an office market characterized by a high vacancy rate, there is a relatively high probability for prospective tenants to find office space that matches their specific preferences while landlords in the same market condition face a low probability of finding a matching tenant willing to pay the desired rental rate.

Instead of calculating the hypothetical natural vacancy rate which marks the threshold above which rents are bound to react to further increases in vacancy, the approach chosen in this chapter expresses the state of a market in relation to a equilibrium rent which in turn is a function of the vacancy rate and absorption rate. Similar to the gradual adjustment in occupied space, observed rental rates will move towards equilibrium in the following linear form:

$$R_t - R_{t-1} = \mu_3 (R^* - R_{t-1}) \tag{6.1}$$

where μ_3 is the degree of adjustment of observed rents towards equilibrium between two periods and equilibrium rent is determined by

$$R^* = \alpha_0 - \alpha_2 V_{t-1} + \alpha_3 (A_{t-1} \div I_{t-1}) \tag{6.2}$$

It is assumed that the observed rental rates converge towards a steady state from one period to the next with an adjustment rate of α_1. The equilibrium rent R* is again largely determined by the vacancy rate and the absorption rate which is a proxy for the dynamics of a market. The absorption rate is simply the quotient of the quarterly absorption in square feet (A_{t-1}) and the total inventory of the market (I_{t-1}) and α_0, α_2 and α_3 are coefficients to be determined endogenously. Again, all dependent variables which determine R* are lagged at least one quarter due to the sluggish adjustment of rents to changing market conditions. As a consequence of the lag relationships, some markets may never reach equilibrium since they are in a constant state of adjusting to past shocks and disturbances but the underlying assumption is that the rental rate tends to adjust towards this equilibrium point at a certain rate.

Since supply is fixed in the short run, any change in occupied space is also a change in vacant space which in turn exerts upward or downward pressure on rents. The final equation developed for empirically modeling the New York office market reads as follows:

$$R^* = \mu_0 - \mu_1 V_{t-n} + \mu_2 \frac{A_{t-n}}{S_{t-n}} + \mu_3 B_{t-n} + \mu_4 U_{t-n} \tag{6.3}$$

In this specification, two additional explanatory variables are included: the differential between Class A and Class B rents (B_{t-n}) and the amount of sublet space (U_{t-n}). Based on theoretical and empirical considerations, the differential is assumed to narrow in times of high rents and occupancy levels and widens as market conditions deteriorate. The rationale behind this assumption is that availability of Class A space is typically very low during the boom phase of the market, so that tenants with smaller rent budgets are pushed off to the Class B and C markets where they fill up space more quickly than would be the case if Class A rents were low. As soon as market conditions deteriorate again and vacancy rates rise, more firms perform a 'flight to quality', i.e. to Class A space, thus disproportionately driving down Class B rents. The oscillation of the spread between Class A and Class B rents serves thus as an indicator of changes in rent and position in the market cycle.

Sublet space variable is included because it provides an additional measure for short-term corrections of the space needs of office firms that are not reflected in the overall vacancy rate due to the long-term nature of office leases. Overall, fluctuations in sublet space demonstrate that office firms do not have perfect foresight of the development of the market or their own future space needs. Therefore, sublet space can be thought of as the margin of error in a tenant's expectation of future space needs at the time of signing the lease. This phenomenon is caused by the long-term nature of the leases which forces tenants to estimate their space needs for about ten years in advance and creates a lock-in situation which can only partially be resolved by subletting some of the leased office space. In the aggregate, the amount of sublet space (or alternatively, the share of sublet space in total vacant space) is therefore a leading indicator of future demand for office space (see Figure A-2 in the appendix).

Modeling supply of office space and new construction

The third stage of the model links the existing framework to supply and new construction of office space. The stock of office space is updated between two periods in the following way:

$$S_t = S_{t-1} - T_t + C_t \tag{7}$$

where S_t is the total stock of office space, T_t is the amount of space that is demolished or permanently withdrawn from the market and C_t is the level of new construction.[8]

According to investment theory, construction of new office space at a particular site becomes feasible when the expected asset price of the building exceeds its replacement cost (Viezer 1999). The asset price of the building is a function of the net operating income (NOI) of a building, or more accurately, the present discounted value of the expected future income stream (net of tax and expenses). The three main components to estimate the asset price of a building are thus rent, vacancy and the capitalization rate. Since the simultaneous use of both rent and vacancy as independent variables is bound to introduce multicollinearity because of the mentioned strong statistical relationship between both only rent is included in lieu of a full NOI estimation. At the aggregate market level, the relationship can be specified in the following form:

$$C_t^* = \beta_0 + \beta_1 R_{t-n} + \beta_2 A_{t-n} + \beta_3 CC_t + \beta_4 (CA_{t-n}) \qquad (8.1)$$

where C_t^* is hypothetical construction determined by appropriately lagged rent levels, CC_t is a construction cost index and CA_{t-n} is a measure of capital availability. There are several possible proxies for capital availability to be found in the modeling literature. Hekman (1985) specifies it as the difference between the ten-year treasury bond rate and the three-month-treasury bill rates whereas Viezer (1999) includes additional variables for inflation and the differential between the corporate Baa bond rate and the ten-year treasury bill rate in line with the pre-specified Arbitrage Pricing Theory by Chen et al (1983). Replacement cost is not included in the above specification since there are no reliable data available to estimate the empirical model.

Parallel to the equations for occupied space and rent, the actual construction is a fraction of hypothetical construction in the following form:

[8] Because of a lack of reliable data on the actual rate of buildings demolished or permanently taken off the market for the New York market, it is assumed that the change in supply is net of a depreciation rate which is probably below 0.1% of the total stock.

$$C_t - C_{t-n}\psi_3(C^* - C_{t-n}) \tag{8.2}$$

The appropriate lag structure between changes suggested in the equilibrium equation and delivery of space is to be estimated with measures of cross-correlation of equilibrium and observed delivery.

The three stage model is now complete and the datasets and results of the empirical estimation for the Manhattan market will be presented in the following section.

4.2 Empirical database of the Manhattan office market model

The empirical estimation of the model draws on two distinct databases: A longer time series on rents, vacancy and absorption ranging from 1979 until 2004 based on market research by Insignia/ESG and reviewed by the Real Estate Board of New York (REBNY) as well as a shorter but more comprehensive database covering the period from 1992 until 2004. The shorter series was produced by Grubb & Ellis combining the firm's own market research with aggregated individual property data compiled by the CoStar Group. The parameters reported in the following section were obtained using the short series because it does not contain any data gaps. The longer time series was mainly used as an auxiliary dataset for testing purposes with the aim of ensuring the relative applicability and stability of parameter estimates of the shorter series. The shorter series might also be considered favorable from a theoretical viewpoint, since one of the underlying assumptions of the linear regression model is that no fundamental changes in the underlying economic conditions of a city take place throughout the modeled period which is more likely in the case of a series spanning 11 years (one full office market cycle) than with a series spanning 24 years. Considering the manifold changes in the economic and regulatory framework that have taken place since the late 1970s in New York City, makes it seem more appropriate to use the 11-year series. A further reason for the selection of the shorter data series is the fact that it is based on and consistent with submarket and individual building data used in subsequent steps of this research. The time increment used in this model is one quarter, which is different from most other modeling studies which use either annual or semi-annual data. Quarterly data are typically subject to greater fluctuations than annual or semi-annual averages, which eliminates a large part of the variation of more fine-grained data. Some datasets, such as employment exhibit seasonal bias when a quarterly model is used. Despite the fact that some of the datasets have to be deseasonalized and smoothed prior to being used in the model estimation, a quarterly time increment is being applied here to provide a more accurate picture of the workings of the market, especially in the wake of the 9/11 attack. The model was estimated with quarterly data as well but this did not yield a significantly better fit.

Inventory, occupancy and vacancy data

Figures on total inventory size differ widely among the providers of office market data. The appendix contains a comparison table of total inventory figures for different sources. A comparison of the ratio of office employment to office space shows that the applied dataset matches roughly the space per worker figures determined in research surveys.

The Grubb & Ellis data aggregate from a set of 680 office buildings comprising about 350 million square feet of office space. A possible bias of modeling results due to the construction of new buildings and change of sample composition should not be a serious concern in this case because new buildings from 1992-2004 constitute less than 1 percent of the pre-existing Manhattan inventory. A potentially more serious issue is the fact that Grubb & Ellis have changed the underlying sample size in 2002 by including more buildings (circa 10% of the original sample size). To correct for a possible bias in the aggregate totals resulting from this, the original sample size has been retained for the purpose of this study and quarter-to-quarter percentage changes have been applied to the original sample. A heuristic check both longitudinally and cross-sectionally and an additional comparison with market data from other major researchers yielded that no distortions were detectable in the various market indicators.

As far as space accounting of the 9/11 attack is concerned, all destroyed and damaged buildings (31.2 million square feet) have been removed from the inventory data in the third quarter and re-inserted as buildings were gradually repaired and returned to their tenants. The construction variable which is usually the net change of inventory between two periods has been adjusted for this effect so that the re-opened buildings are not counted as new construction.

Rental data

The data on rent used in this study are asking rents per square foot aggregated from a large sample of buildings in the CoStar property information system. A known limitation of using asking rents is, of course that they are not as accurate as actual rents derived from lease transactions. Asking rent information is still sufficiently accurate provided that the inherent error is systematic. In practice, the difference between asking rents and actual rents varies according to the position in the market cycle. This difference will be highest at the outset of a recession. This occurs because landlords are initially reluctant to lower asking rents after a prolonged period of growth but will instead concede free rent periods and other incentives to prospective tenants. Only when market conditions have deteriorated considerably and vacant space becomes a serious problem, landlords will adaptively discount asking rents in order to attract tenants. While rents based on actual leases would be preferable, they are generally not available to researchers and pose additional problems, such as the adequate incorporation of non-monetary or non-rent-related incentives in the lease. In the absence of actual rents, asking rents are being used in this study despite their known inaccuracies and shortcomings. The asking rents and all other monetary variables are adjusted for inflation with the implicit price deflator as applied in the National Income and Product Accounts (NIPA).

Employment data

An office employment series is constructed using datasets compiled by Economy.com and the New Bureau of Labor Statistics of the New York State Department of Labor. The definition used to identify office-using industries is adopted from the New York City Office of Management and Budget and is used widely by researchers. It comprises the sectors financial activities, information, professional and business services, management of companies and administrative and support services. The classification of these industries is based on NAICS codes. While the bulk of office workers is included in this definition, the total number does probably not contain all employees working in an office-type establishment. There are a number of employees in other branches such as manufacturing not considered in this definition who are partially or fully classify as office users in practice. There exist no reliable figures on the proportion of office-using occupations within generally non-office using industries, so the aggregate figure of office workers in

New York City is an approximation in the absence of data on the actual figure. Office space per worker as calculated from the independent data sources used in this study yields on average 300 square feet which is on the upper end of counts on space use by industry (CoStar 2001) which usually report averages of around 250 square feet for New York City. It can thus be concluded that a number of office workers are excluded from the above definition, however, in the absence of a precise definition of office workers in the current County Business Pattern employment statistics, it can be assumed that the margin of error and bias introduced by this circumstance is tolerable and does not invalidate the model estimation and projections as a whole.

Study area

The geographical reference area for all data applied in this study is the borough of Manhattan which contains most of the office space of New York City. In fact, the Manhattan office market can be considered as almost synonymous with New York City since only a small percentage of competitive office space is located in the boroughs outside of Manhattan. Spatial competition of the Manhattan market with office space in the wider metropolitan area, particularly along the New Jersey waterfront, on Long Island and in Connecticut are not explicitly modeled here but are the subject of follow-up research work. The eventual goal of this research is to arrive at a comprehensive cross-section time-series model that is able to capture the effects of suburbanization of office space and intra-regional competition. Table 4-1 contains an overview of all variables and data sources applied in the empirical estimation process.

Table 4-1: Overview of datasets used in the empirical estimation of the office market model

Data	Source
Inventory of office space (in sq. ft.)	Grubb & Ellis (1992-2004) Insignia ESG, Real Estate Board of NY (1979-2004)
Asking rents (in $ per sq. ft.), Class A/B/C	
Net absorption	
Vacancy (in sq.ft.), sublet and direct	
Employment data by zip-code area and NAICS code (ES 202)	Bureau of Labor Statistics
Current Employment Statistics (CES) survey	Economy.com, Bureau of Labor Statistics
Employment projections for New York City (2004-2007)	New York City Office of Management and Budget
Economic output by NAICS code	New York City or submarkets
Floor area per employee (by branch)	CoStar
Sales transactions in Manhattan (2000-2004	REAlert, Real Capital Analytics
Construction cost index	Turner building cost index, OECD building cost index
"Pipeline projects", proposed developments	Grubb & Ellis, Real Estate Board of NY
Baa bond ratings	Moody's Investor's Services
Three month treasury constant maturity rate	Federal Reserve Bank of Saint Louis
Ten-year treasury constant maturity rate	
New York business conditions index	National Association of Purchasing Management

4.3 Results of the empirical estimation

The model outlined earlier was estimated empirically using an OLS regression framework. Additional dummy variables have been included where the model was unable to capture the full magnitude of the effects of 9/11. Modifications and refinements of the basic structure are explained in more detail below. Table 4-2 reports some descriptive statistics of the most important variables of the model for the time period 1992-2004[9]. The descriptives underline the fact that Manhattan is a large and mature office market, as reflected in large absolute numbers of existing stock, employment and occupied space and relatively small first order differences compared to the total stock.

Table 4-2 Descriptive statistics of basic variables for the period 1992-2004

Variables	Mean	Standard Deviation
E (office employment in thousands)	929.566	64.890
E_t - E_{t-1} (change in office employment in percent)	0.169	1.431
S (inventory in million sq.ft.)	317.087	6.118
OS (occupied space in million sq.ft.)	283.688	13.165
S/W (space per worker in sq.ft.)	302.887	10.965
U sublet as % of total vacant	18.711	9.100
R (asking rent per sq.ft. in constant 1996 dollars)	35.625	6.516
B (Class B rents as a percentage of Class A rents)	68.892	4.213
A (absorption rate as a percentage of total stock)	0.134	1.533
C (annual delivery of new space in million sq.ft.)	0.835	1.045

Estimation of occupied space and absorption

As a first step, the demand for office space was estimated. Table 4-3 shows the results of the OLS estimation of hypothetically occupied total space. First order differences of employment as an indicator of the dynamics of office demand was tested but excluded in the final specification because the variable did not reach the required significance level. The estimated square footage per worker was multiplied by centered moving average values of office employment to eliminate seasonal bias in the estimation of the equilibrium level of occupied space OS*. Raw values of office employees have also been tested and significance levels have been found to be slightly higher. In order to minimize bias induced by the usage of quarterly data in the model estimation, however, deseasonalized data is preferable. A visual examination of the values of the dependent variable shows that the data is non-stationary. To control for the secular increase in occupied space, a time trend variable is included. Moreover, early estimations of the

9 A longer time series (1983-2004) has also been used to estimate the model. Significance levels have been higher for the shorter time series which also meets the longitudinal homogeneity assumption of time series models better than the longer series.

model were not able to fully capture the combined supply and demand shock of the 9/11 attack. The estimation was particularly complicated by the fact that total inventory was abruptly reduced by 34.5 million square feet in the third quarter of 2001. Inventory rose in the following two quarters when more than 20 million square feet of damaged office space in the vicinity of the World Trade Center were restored and tenants moved back into the restored buildings. To control for these exogenous events, three dummy variables were included. In the final form of the specification, all variables are significant and show the expected sign (Table 4-3).

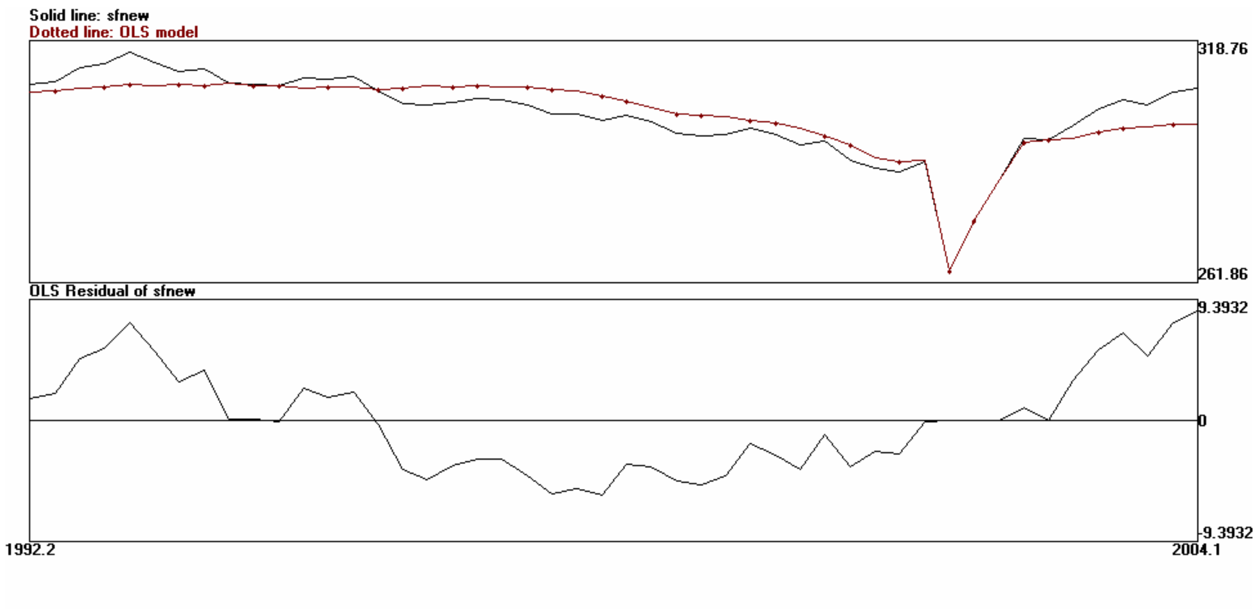
Table 4-3: Estimation of occupied space

Dependent variable OS*				
Variable	Coefficient	t-value	H.C. t-value[10]	Probability
α_0 (intercept of OS^*-OS_{t-1})	-2,200,000	-11.212	-14.435	.000
α_1 (basic sq.ft./worker)	339.54245	64.042	71.242	.000
R_{t-1}	-0.83845	-5.141	-5.039	.000
Z_1	-29.62176	-5.915	-24.840	.000
Z_2	-18.02937	-3.663	-16.911	.000
Z_3	-8.18453	-1.769	-7.651	.000
T (time trend)	-0.22253	-3.721	-2.713(	.000

Adjusted R^2 = 0.815
F test: F(5,42) = 42.62
Standard error = 4.564
Jarque-Bera/Salmon-Kiefer test[11] = 3.038184 (accept at 5%)
Breusch-Pagan test = 7.381228, p-value = 0.19380 (accept at 5%)
Information criteria:
Akaike: 3.20288E+00
Hannan-Quinn: 3.29127E+00
Schwarz: 3.43678E+00
Collinearity: highest VIF = 1.1, lowest eigenvalue = .907
n=49

10 H.C. = Heteroskedasticity consistent t-value. These t-values and standard errors are based on White's heteroskedasticity consistent variance matrix.

11 The Jarque-Bera/Salmon-Kiefer test of the null hypothesis that the model errors u_j are $N(0,\sigma^2)$ distributed. This test actually tests the joint null hypothesis that the skewness $E[u_j^3]$ is equal to zero and the kurtosis $E[u_j^4]$ is equal to $3\sigma^4$, which hold if the u_j's are $N(0,\sigma^2)$ distributed. Under the null hypothesis the test statistic involved has (for large n) a χ^2 distribution with 2 degrees of freedom. Of course, this is a right-sided test: The null hypothesis is rejected if the value of the test statistic is larger than the critical value.

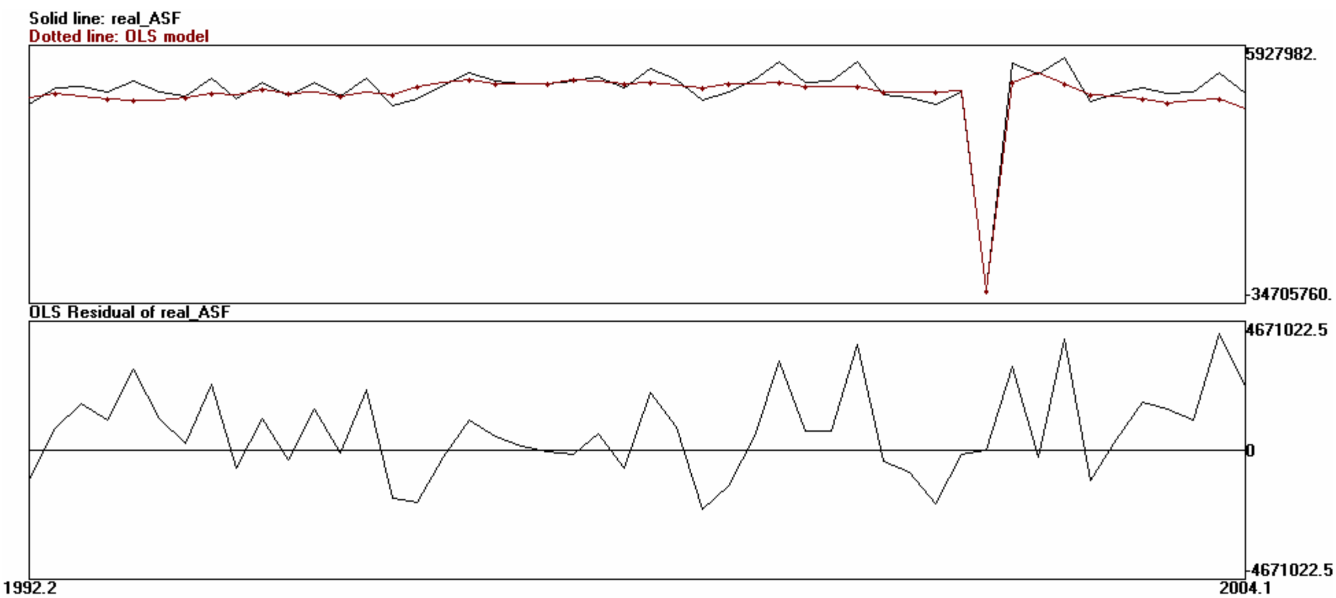


The parameter α_1 is a baseline amount of square feet per office employee that is inversely related to the rent level. At a long-term average rent of 36 dollars per sq.ft., this elasticity measure yields about 340 square feet per office worker. During periods of low rents (such as the early 1990's) space use rises to 360 square feet and is found to fall to approximately 285 square feet per worker during periods of high rents (1999-2001).

In the next step, quarter-to-quarter absorption is estimated as a function of the difference between desired and observed occupied space (Table 4-4). The coefficient of OS^*-OS_{t-1} shows the adjustment speed of occupied space to the hypothetically demand for space. The adjustment rate is 0.2803 which means that 28% of the change in hypothetical demand for space is actually implemented from one period to the next. For the purpose of this estimation, two dummy variables have been included to account for the effects of 9/11. While Z_2 is intended to capture the negative absorption of 34 million square feet of office space that occurred in the third quarter of 2001 resulting from the attack, Z_3 accounts for the contrary effect of high positive absorption in the first two quarters of 2002 resulting from the re-opening of damaged buildings after restoration.

Table 4-4: Estimation of space absorption

Dependent variable A				
Variable	Coefficient	t-value (S.E.)	H.C. (S.E.)	probability
$OS^{*}-OS_{t-1}$	0.28023	4.727	4.567	.000
Z1 (3/11 dummy)	-25478610.68028 (1,753,875)	-9.298 (2,740,121)	-12.611 (2,020,390)	.000
Adjusted R^2 = . 0.918 F test = 164.299 Standard error = 1.640.000 Jarque-Bera/Salmon-Kiefer test = 14.874 (reject at 5%) Information criteria: Akaike: 2.89796E+01 Hannan-Quinn: 2.90091E+01 Schwarz: 2.90576E+01 Collinearity: highest VIF = 2.001, lowest eigenvalue = .286 n=49				



with regard to the discussion of the efficient market hypothesis within real estate markets that there is a significant lag for rents to adapt to changes in vacancy rates - despite the universal availability of timely market data. With the help of cross-correlation the optimal lag structure of vacancy was determined to be three quarters. This means that it takes landlords on the average three quarters before they effectively lower the rents to a level that is in line with prevailing vacancy rates. One reason for this is that landlords are reluctant to lower the rent at the onset of a recession. Only when vacancy rates become so manifest that landlords are faced with the decision to either lower the rents or accept large vacancies, they eventually start lowering the rent. It is surprising though that a lag can also be detected at the beginning of a market recovery when landlords would be expected to be more inclined to reacting to news about changing market conditions. This shows that market sentiment as established in the previous quarters prevails in the bargaining process and imperfect information is likely to contribute to persisting prices. Table 4-5 shows the specification of the rent equation.

Table 4-5 Estimation of the equilibrium rent

Dependent variable R*			
Variable	Coefficient	t-value (VIF)	probability
Constant	50.201	2.659	.012
B_{t-2}	0.092	0.399 (8.159)	.692
V_{t-3}	-1.551	-5.476 (10.136)	.000
A_{t-2}	0.328	1.278 (1.625)	.210
U_{t-2}	-0.969	-1.454 (1.822)	.155
Adjusted R^2 = .908 F = 94.55 Durbin-Watson 0.795 Collinearity, largest VIF = 10.136, lowest eigenvalue = .000 Standard error = 2.063 n=47			

All variables show the expected sign but the Class A/B rent spread variable (B) as well as the absorption rate does not reach the desired significance levels. Moreover, the diagnostic tests indicate serious multicollinearity problems for this variable. Despite the fact that each of the included variables is theoretically and empirically sound as a single predictor, the above specification is not viable, probably because of the high degree of variance explained by one variable, the lagged vacancy rate. The rent spread variable Bt-1 for instance is highly correlated with vacancy rates (R^2 =.91). Table 4-6 shows a re-estimation of the rent equation with only the vacancy rate and an additional dummy variable to capture the effects of 9/11 and the first differences modeled rather than absolute rent levels.

In this reduced specification collinearity remains within tolerable boundaries. Despite the fact that three variables have been discarded the model performs better overall and shows a slightly higher adjusted R^2 than the original specification. This version of the equation is therefore used for the estimation of the model. The test for ARCH confirms that this specification is also preferable because it does not exhibit significant autocorrelation of the residuals.

Table 4-6: Alternative estimation of the equilibrium rent

Dependent variable R^*-R_{t-1}				
Variable	Coefficient	t-value (S.E.)	H.C. (S.E.)	probability
V_{t-3}	0.05352	3.768 (0.01420)	4.125 (0.01298)	.000
U_{t-2}	-0.14813	-8.583 (0.01726)	-7.631 (0.01941)	.000
T(time trend)	0.08091	7.169 (0.01129)	6.061 (0.01335)	.000
Adjusted R^2 = 0.6155 F test = 22.39 Standard error = 0.750195 Jarque-Bera/Salmon-Kiefer test = 0.257 (critical 5.99, accept at 5%) Information criteria: Akaike: -5.11851E-01 Hannan-Quinn: -4.67176E-01 Schwarz: -3.92592E-01 Collinearity: highest VIF = 1.567, lowest eigenvalue = .730 n=47 Test for ARCH u(t) is Gaussian white noise (accepted)[12]				

[12] Test for ARCH(p) of u(t) = True value of
OLS Residual of r_diff1
Null hypothesis: u(t) is Gausssian white noise
Alternative hypothesis: V(t) = a(0) + a(1)u(t-1)^2 +.. +a(p)u(t-p)^2,
where V(t) is the conditional variance of u(t).
The ARCH test is the LM test of the joint hypothesis
a(1) =..= a(p) = 0
p = 1
Test statistic = 0.05
Null distribution: Chi-square with 1 degrees of freedom
p-value = 0.83022
Significance levels: 10% 5%
Critical values: 2.71 3.84
Conclusions: accept accept

According to the specified model, the rent calculated from this equation is the equilibrium rent and the residuals of this regression can be interpreted as the deviation of the observed rent from the hypothetical equilibrium. In the next step, the lagged partial adjustment of actual rents to the equilibrium rent is estimated (Table 4-7):

Table 4-7: Estimation of change in rental rates

Specification 2: Dependent variable ΔR*				
Variable	Coefficient	t-value		probability
R* Rt-1	0.68487	7.893 (0.08676)	7.692 (0.08903)	.000
Adjusted R^2 = 0.5753 F test = 22.39 Standard error = 0.7824220.750195 Jarque-Bera/Salmon-Kiefer test = 0.267 (critical 5.99, accept at 5%) Information criteria: Akaike: -4.69676E-01 Hannan-Quinn: -4.54863E-01 Schwarz: -4.30311E-01 Collinearity: highest VIF = 1.56, lowest eigenvalue = .730 n=47 Test for ARCH u(t) is Gaussian white noise (accepted)[13]				

The R^2 of this specification is slightly lower than comparable values obtained in model runs done for other cities. An alternative specification which estimated absolute rent levels rather than changes in rent obtained a much higher R^2 (0.91) but the estimators were biased because of heteroskedasticity and autocorrelation of errors. Therefore, the partial adjustment change rate specification is used for the market forecast. Figure 4-1

[13] Test for ARCH(p) of u(t) = True value of
OLS Residual of r_diff1
Null hypothesis: u(t) is Gausssian white noise
Alternative hypothesis: V(t) = a(0) + a(1)u(t-1)^2 +.. +a(p)u(t-p)^2,
where V(t) is the conditional variance of u(t).
The ARCH test is the LM test of the joint hypothesis
a(1) =..= a(p) = 0
p = 1
Test statistic = 0.05
Null distribution: Chi-square with 1 degrees of freedom
p-value = 0.83022
Significance levels: 10% 5%
Critical values: 2.71 3.84
Conclusions: accept accept

illustrates that the predicted rents do not fully capture the peak of the rental rates but perform reasonably well during other phases of the market cycle.

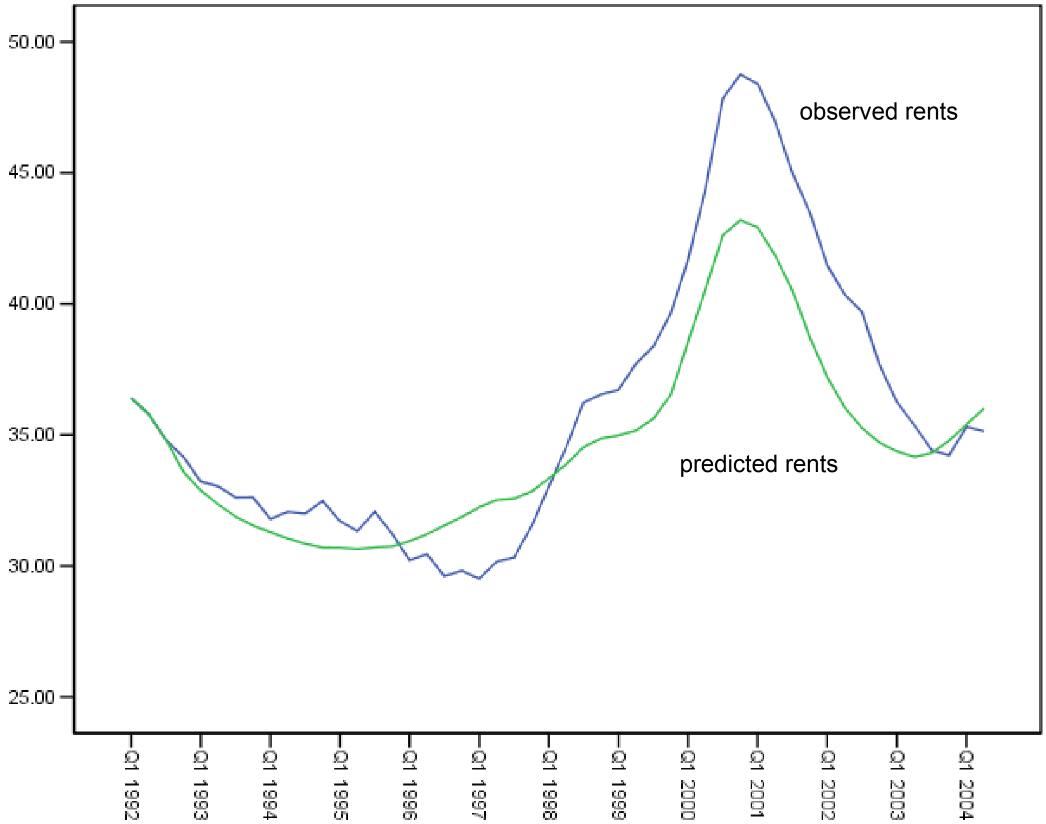


Figure 4-1: Fitted versus observed rents

Supply of office space: Estimating construction and total market inventory

Finding a model specification which yields a good fit for new construction of office space is more challenging than the estimations of the other two components. This is due to the fact that the delivery of new office space follows a somewhat erratic pattern in New York City with some periods exhibiting very high activity of new space delivery and virtually no activity in the next period. To account for these oscillations, a moving average value of space deliveries and new construction as a percentage of the total inventory rather than absolute values in square feet were used to estimate the equation. The model fit is further limited by the fact that almost no construction occurred in New York City during the 1990s even though the model would suggest some level of construction activity. The lack of construction is usually attributed to heightened risk-aversion by lenders after the real estate crash of the late 1980's. Table 4-8 shows a summary of the coefficient estimates using the variables lagged vacancy rate, rental rate, absorption and capital availability (proxied by the difference between the 10-year treasury bond rate and the 3-month treasury bill rate).

Table 4-8: Estimation of new space construction

Dependent variable C				
Variable	Coefficient	t-value	H.C. (S.E.)	probability
V_{t-7}	-0.87920	-3.471 (0.25328)	-2.998 (0.29324)	.001
R_{t-4}	0.00604	8.550 (0.00071)	5.678 (0.00106)	.000
A_{t-4}	-0.01465	-2.581 (0.00568)	-2.297 (0.00638)	.001
CA_{t-6}	-0.01702	-1.777 (0.01118)	-1.494 (0.01139)	.120

Adjusted R^2 = 0.600844
F test: F(5,42) = 42.62
Standard error = 4.564
Jarque-Bera/Salmon-Kiefer test = 0.257 (critical 5.99, accept at 5%)
Information criteria:
Akaike: -5.23513E+00
Hannan-Quinn: -5.17472E+00
Schwarz: -5.07130E+00
Standard error = 0.069824
n=45
Test for ARCH u(t) is Gaussian white noise (accepted p-value = 0.58447[14]

Results of scenario model runs

The simultaneous equation model is now set up to generate forecasts for the Manhattan office market. A general difficulty with using simultaneous equation models for forecasting purposes is that some of the explanatory variables are not modeled endogenously in the system and have to be obtained from extraneous sources whose

[14] The ARCH test is the LM test of the joint hypothesis
a(1) =..= a(p) = 0
p = 1
Test statistic = 0.30
Null distribution: Chi-square with 1 degrees of freedom
Significance levels: 10% 5%
Critical values: 2.71 3.84
Conclusions: accept accept

quality can sometimes not be fully verified. The model presented in this study contains three such variables: the number of office workers (E) in the occupied space equation, the amount of sublet space (U) in the rent equation as well as capital availability (CA). Since sublet space and capital availability were mainly incorporated into the model for analytical purposes and cannot be forecasted reliably, the long run mean of these variables is assumed for the forecast period. Thus, only the office employment variable needs to be specified exogenously. This is done by constructing three scenarios based on various professional forecasts. The base scenario is derived from the New York City Office of Management and Budget. In addition to this, an optimistic and a pessimistic variant was constructed and its plausibility checked with other employment projections (Partnership for New York City 2003). Figure 4-2 illustrates the employment scenarios of the various scenarios. The spread between the optimistic and pessimistic scenario represents the bounds of possible developments for the Manhattan office market. The three scenarios are characterized as follows:

(A) Base Scenario

The base scenario assumes that office employment will recover only gradually with a growth rate of 0.6% in 2004 and approximately 1% from 2005 until 2007. These assumptions are based on the projections of the NYC Office of Management and Budget (2003). Beyond the time horizon of the OMB projections, continued modest growth rate of 1% p.a. is assumed from 2007-2010. When these conservative growth rates are applied, pre-9/11 levels will not be reached until the end of the decade and will still be around 10% lower than they were at the height of the boom in 2000. This cautious scenario can thus be considered a "middle-of-the-road" baseline scenario for the purpose of the modeling exercise.

(B) Pessimistic Scenario

The pessimistic scenario assumes that New York will not regain its pre-9/11 employment levels in the office-using industries and will continue to lose office jobs due to a centrifugal movement of office firms away from Manhattan into the broader catalyzed by the ongoing technological advances. Office employment in Manhattan is thus assumed to decline by 1% p.a. through 2006 and to remain flat from 2007-2010. This scenario constitutes the lower bound within the set of conceivable office employment trajectories.

(C) Optimistic Scenario

The optimistic scenario envisions a recovery process of office employment with above average growth rates of the office-using service industry sectors of about 3.5% p.a. until 2007. According to this growth scenario, pre-9/11 office employment levels will be reached by the end of 2007. After the year 2007, office employment is assumed to continue growing at a slower rate of 1 percent p.a. until 2010. The assumed growth rate is derived from historical rates during similar phases (from 1998-2001 the average annual growth rate was 4% p.a.) and the employment assumptions of pre-9/11 forecasts corrected for the effects of 9/11. This scenario presupposes that New York City will remain the prime location for advanced financial services in the region and nationwide and that no significant movement from Manhattan to suburban areas or other regions will take place. The high growth rates are brought about by a preponderance of growth industries in the city's industrial composition and a continued secular shift in employment towards higher overall shares of service and office-using industries. This scenario constitutes the upper bound within the set of conceivable office employment trajectories.

Interpretation of the model runs

The most important output variables of the forecasting model comprise vacancy rates (Figure 4-3), rental rates (Figure 4-4), and office space inventory (Figure 4-5). The projected values of all three of the tested scenarios underline the robustness and plausibility of the model. As expected, the optimistic employment growth scenario yields the lowest vacancy rates and highest levels of occupied space whereas the pessimistic scenario generates higher vacancy. Interestingly, absorption turns positive for a period of time after 2007 even though there is no positive growth in office employment throughout the forecast period in this scenario. The model correctly reflects the effect that even under zero employment growth, absorption would temporarily turn positive as firms are choosing to consume more space per employee in their lagged adaptation to low office rents. Eventually, absorption becomes zero as employment is assumed to stagnate from 2007 onwards which is in line with the implications of the equilibrium model. Because of the more steady assumptions in employment growth, all projected absorption values exhibit lower oscillations than observed past values.

Regarding vacancy rates and rents (Figure 4-3 and Figure 4-4), the scenarios differ as expected from the optimistic scenario yielding the lowest vacancy rates and the highest rents but even this scenario does not reach the high-rent and low-vacancy pattern of the peak around the turn of the century. This is mainly due to the fact that the last office boom occurred after a period of virtually no new additions to the existing inventory in almost a decade whereas a considerable amount of office space was delivered from 2000 onwards.

The optimistic scenario triggers construction of new office space in the amount of nearly 36 million square feet in the period of 2004-2010 (whereof 3.2 million square feet are 'known' deliveries of buildings currently under construction in 2004 and the rest is predicted by the model). Interestingly, the base scenario and even the pessimistic scenario generate new construction of office space. The base scenario yields new construction of about 12.4 million square feet which is roughly the amount of space destroyed in the 9/11 attack and the pessimistic scenario suggests new construction of 6.9 million square feet over the next six years. These findings are in line with the assumptions made in a recent rebuilding study carried out by Appleseed Consulting for the Lower Manhattan Development Corporation (Appleseed 2003). It is evident, however, that new office construction in the pessimistic variant would have to constrained to the World Trade Center site almost exclusively to balance supply and demand in New York City. To compare the obtained values with actually planned pipeline projects in New York City, lists of planned and proposed construction projects throughout Manhattan, as maintained by Grubb & Ellis and the Real Estate Board of New York are reviewed.

The pipeline projects amount to a total of 33.4 million square feet of new office space in Manhattan until 2010 (not including space already under construction). It is unlikely, however, that all the proposed projects will be implemented and only in the optimistic scenario would the construction of this amount of office space be justified by market conditions. Based on the model results, it seems reasonable to assume that there will be moderate growth of demand for office space until the end of the decade and unless a large amount of competing new office space will be built in Midtown Manhattan, the rebuilding of most of the space that has been destroyed during 9/11 in Lower Manhattan is feasible under the assumed scenarios.

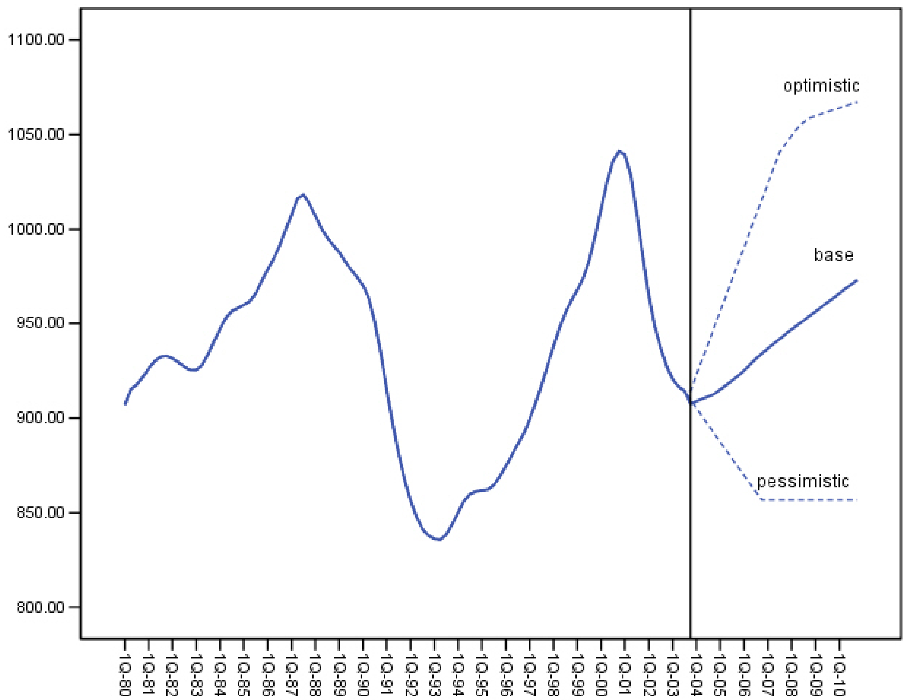


Figure 4-2: Office employment scenarios (in thousands of employees)

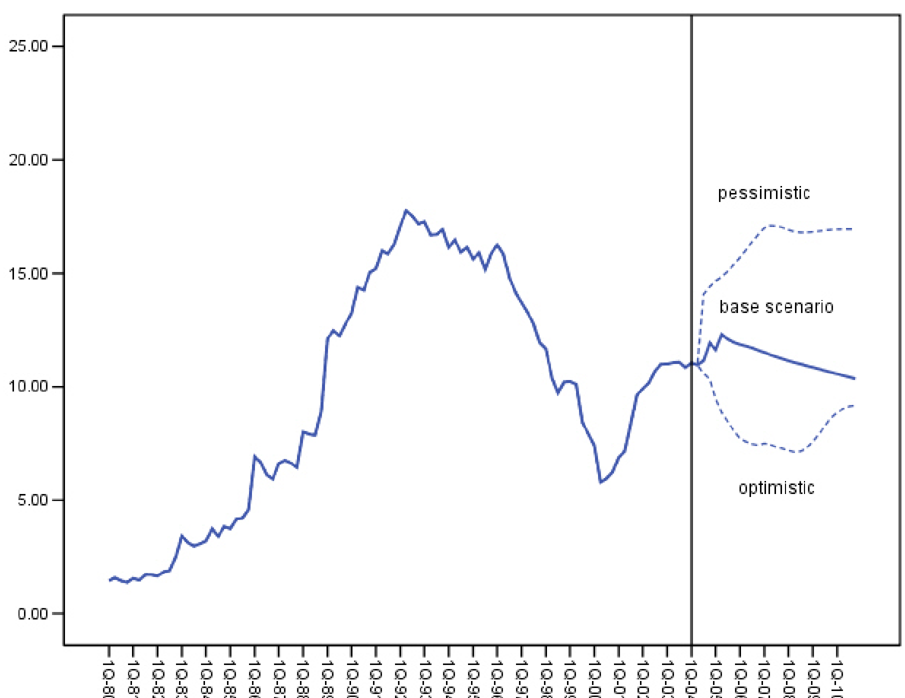


Figure 4-3: Vacancy rates (in percent)

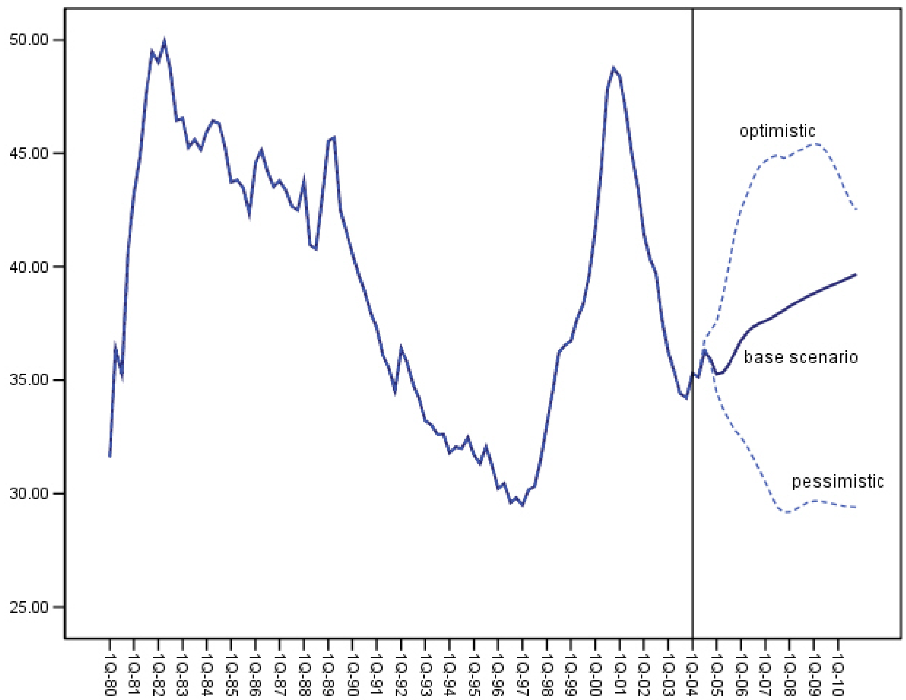


Figure 4-4: Rent per sq.ft. (in constant dollars)

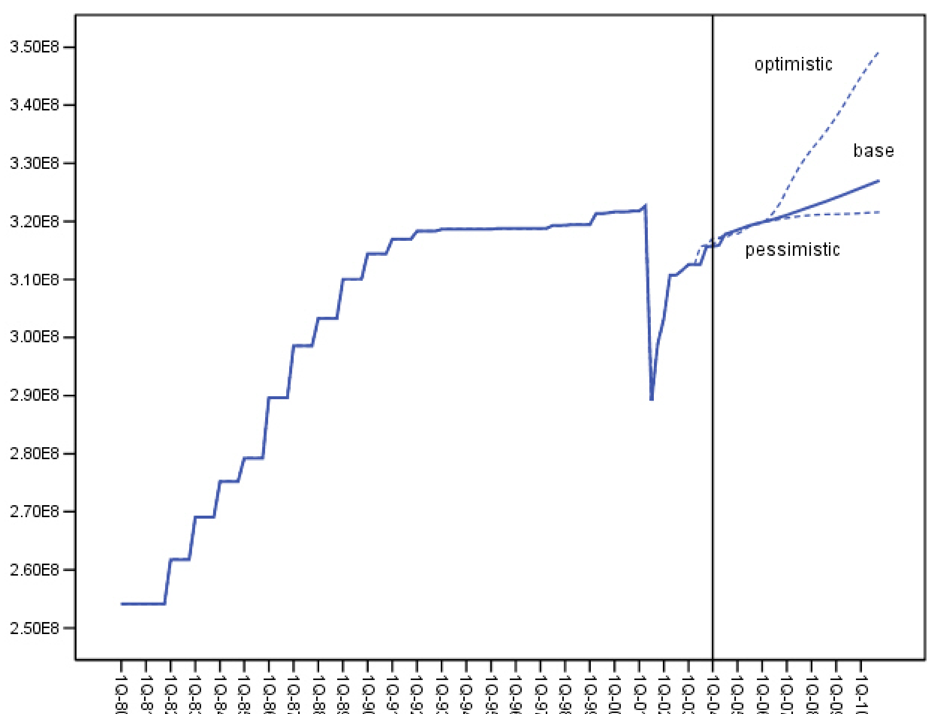


Figure 4-5 Inventory of office space (in sq.ft.)

4.4 Conclusions and further work

To explore the predictability of the Manhattan office market, a three-stage system of simultaneous equations was applied in this chapter, where the first stage incorporates the office space market in terms of occupied space and absorption of new space, the second stage captures the adjustment of office rents to changing market conditions and the third stage specifies the supply response to market signals in terms of construction of new office space.

The model demonstrates that the Manhattan markets reacts efficiently and predictably to changes in market conditions, especially to the economic shock generated by the 9/11 attack. The significance of the estimated parameters underscores the general validity and robustness of the simultaneous equation approach. The modifications of the standard model, notably the inclusion of sublet space in the rent equation, contributed considerably to improving the explanatory power of the model.

A number of further refinements are possible, however. First, a more comprehensive integration of capital markets would be desirable to capture the impact of these markets on investment in and construction of office real estate. In this context, the integration of urban land markets could enhance the model considerably. Moreover, it would be preferable if office employment were endogenized by modeling structural changes in the composition and trends in the spatial organization of office employment. This would require a module capable of forecasting the dynamics of individual office-using industries over a number of years. Lastly, it remains to be explored if a model specification can be found that fully captures the oscillations of the market cycle. All in all, there is clear potential for the simultaneous equation model to evolve further because of its relatively open structure which allows for a flexible integration of theoretical advances and local market specifications.

5 Office submarkets and intracity portfolio diversification

This chapter examines the heterogeneity and volatility of submarket rental rates in the context of portfolio diversification strategies. In contrast to most real estate portfolio studies, however, I investigate whether diversification is possible within a single city and property type (office) or even within the core of an urban area using Manhattan submarkets as an empirical base. This research aims in particular at answering the following questions: First, do changes in rental rates vary significantly among submarkets or do they generally follow the larger urban area trend? Second, are changes in rental rates an autoregressive function of vacancy rates and/or office employment? Thirdly, is the rent volatility of all submarkets the same or do submarkets differ regarding risk-reward relationships? Finally, do the empirical data support the possibility of intracity portfolio diversification or are submarket rental rates too highly correlated to achieve diversification within a single city?

In order to explore the first question, I apply a one-way ANOVA as well as a series of cointegration tests using the Johansen approach. The second question is addressed by conducting tests for Granger causality and impulse response analyses to detect dynamic relationships between the variables. The third question implicates the use of various risk-reward indicators, such as the beta measure and the Sharpe ratio. Finally, I use of synopsis of the results of cointegration tests, impulse response analyses and tests for Granger causality to answer the question of intracity diversification.

The remainder of the chapter is organized as follows. The first section reviews previous studies on portfolio risk diversification, submarket differentiation and the volatility of commercial real estate rental and vacancy rates. Next, the methodology of the chapter is laid out, datasets are explained and research hypotheses are presented. In a further section, the results of the empirical analysis are explained. Finally, I draw conclusions from the results of the methods applied and discuss the implications for portfolio selection strategies.

5.1 Relevant background

The fundamental principle of modern portfolio theory states that risk and rates of return can be traded off in a portfolio including assets whose performance is less than perfectly correlated (Markowitz 1952). Given a specific risk/return preference structure, an investor can combine assets in an optimal portfolio, where investment risk is reduced through various forms of diversification. In a real estate context, diversification is typically achieved by investing in different geographic markets and/or property types.[15] Most of these previous studies, however, investigate interregional diversification and do not provide any insights on the possibility of achieving sufficient diversification by simply investing in different distinct submarkets within a city. This research is seeking to fill this gap.

The potential benefits of diversification have received considerable attention in commercial real estate portfolio analysis. There are two basic strategies: geographic and economic diversification. While the former is exclusively based on a selection of administrative or geographic regions, the latter considers areas that have structural similarities and are thus subject to the same underlying economic fundamentals. A main feature of geographic regions is that they are spatially contiguous whereas this is not a necessarily the case in economic regions whose elements can be located far from one another as long as they satisfy the requirement of structural similarity in economic terms. In this research, I use economic (micro-)regions in the form of submarket areas as defined by commercial market researchers, albeit without applying market delineation algorithms to construct new submarkets since it seems more appropriate to examine intracity diversification with market area definitions that are known to and accepted by those who are in charge of making portfolio investment decisions.

The majority of existing studies focuses on far more aggregate regional units than this dissertation, however. Working with a basic geographic division of the United States into four regions, the majority of early studies on the subject did not find substantial benefits of geographic diversification compared to naïve portfolio selection (Miles and McCue 1982; Hartzell, Hekman and Miles 1986). Further disaggregation into a greater number of regions and urban agglomerations did not yield significantly better results either (Hartzell, Shulman and Wurtzebach 1987; Giliberto and Hopkins 1990). The majority of early studies ignored the problem of economic heterogeneity within administrative regions. As a consequence of this, the effectiveness of geographic diversification strategies was distorted and potentially underestimated in these studies because of insufficiently defined regions. In an effort to overcome this shortcoming, Mueller and Ziering (1992) removed the arbitrary geographic restriction and looked at the local economic drivers of individual metropolitan areas as the key determinant for more efficient diversification. Although

[15] For comprehensive overview of studies on returns and risk of real estate compared to other investment types, see Benjamin, Sirmans and Zietz (2001).

their comparison of geographic versus economic regions did not yield consistent results in all cases, economic classifications of regions proved to be superior to purely geographic definitions. In follow-up research, Mueller (1993) confirmed the advantage of economically defined regions and Ziering and Hess (1995) found that the analysis can be enhanced by including socio-economic criteria in the definition of regions.

Apart from analyzing interregional diversification, some studies focused specifically on the potential of intracity submarkets to produce diversification benefits similar to interregional diversification. This question is of considerable practical relevance given the large proportion of property owners whose portfolios are limited to a single metropolitan area. Moreover, if intrametropolitan diversification yielded benefits similar to interregional or international diversification strategies, diversification at the intrametropolitan level would be preferable because it entails lower transaction costs than a more dispersed portfolio (Shilton and Stanley 1995).

A number of studies support the hypothesis of intrametropolitan diversification. Grissom, Hartzell and Liu (1987) applied the Arbitrage Pricing Theory (APT) to investigate real estate market segmentation and confirm the relevance of submarkets in predicting returns on industrial properties. In a later study, Grissom, Wang and Webb (1991) found significantly different rates of return both at the inter-city and intra-city level in their study of Texan cities. Rabianski and Cheng (1997) found low and in some cases negative correlations between office and industrial vacancy rates in intracity submarkets in Atlanta, Boston, Chicago and Denver. The authors conclude that portfolio risk can be reduced by diversification within a city's submarkets and that treating metropolitan areas as homogenous real estate markets may result in misdirected investment strategy. In a similar study of intrametropolitan diversification, Wolverton, Cheng and Hardin (1999) applied cluster analysis and bootstrapping techniques to divide the Seattle market into a number of relatively homogenous submarkets based on effective rents. The study blends geographic and economic concepts by reducing fifteen geographically defined submarkets to five submarkets based on similarities in effective rental rates. Three options are compared: 1) an efficient frontier portfolio, i.e. a combination of properties that yields the highest return given a specific risk-level, 2) naïve portfolio selection and 3) concentration of properties in the submarket with the lowest overall risk. The authors conclude that the efficient frontier strategy yields superior results. In a more recent study, Brown, Li and Lusht (2000) compare intracity submarket diversification to a selection strategy over geographic regions. The authors construct a number of model portfolios with the aim of comparing them to the efficient frontier portfolio and find that intracity geographic diversification produces marginally improved portfolio performance. However, a number of naïve diversification strategies are also found to be efficient. In summary, all of the studies investigating intrametropolitan diversification reach the conclusion that it effectively mitigates investment risk, albeit with varying degrees of statistical significance.

In view of the conclusions reached in previous studies, it appears promising to examine the question of intracity portfolio diversification with additional methods of econometric time-series analysis, such as cointegration tests, Granger causality and impulse response analysis. Most earlier studies of intracity portfolio diversification fail to incorporate rental rates as part of a cointegrated system of individually nonstationary series. The cointegration of rental rate series has implications that go beyond pure diversification issues, for example in price discovery or the predictability of returns (Tuluca et al 2000).

5.2 Research strategy and hypotheses

As outlined in the previous section, the concept of an efficient and spatially unified metropolitan office market with an underlying single pricing scheme rests on several assumptions which will be tested in the empirical part of this chapter.

Testing for differences in rent and vacancy levels

The first hypothesis (***H1***) tests the market homogeneity assumption. It states that average rental and vacancy rates of any given submarket are not significantly different from the values of all other intra-city submarkets. This hypothesis is tested using a one-way analysis of variance (ANOVA). The null and alternative hypotheses can then be formulated for the set of 15 submarkets as:

$$H_0 = \mu_1 = \mu_2 = \ldots = \mu_{15}$$

where μ_i are the mean rental or vacancy rates of the respective submarkets.

$$H_a = \mu_1 \neq \mu_2 \neq \ldots \neq \mu_{15}$$

Correlation and cointegration patterns

Having tested for significant differences in submarket levels, we proceed to examine dynamic changes over time. First, the time series properties of the variables are analyzed using standard Augmented Dickey-Fuller (ADF) tests for unit roots on all variables with the following specification:

$$z_t - z_{t-1} = \alpha_0 z_{t-1} + \beta_1 (z_{t-1} - z_{t-2}) + \ldots + \beta_p (z_{t-p} - z_{t-p-1}) + \beta_{p+1} + \beta_{p+2}.t + \mu_t \quad (1)$$

where t = p+2,...,n and μ_t is a white noise error term. By comparing the t-statistic of α_0 to a table of critical values, the null hypothesis of a unit root process is either accepted or rejected (see Said and Dickey 1984, Fuller 1996). The null and alternative hypotheses of ***H2*** are then:

$H_0 : \alpha_0 = 0$ (-> a unit root with drift exists)

$H_a : \alpha_0 < 0$ (->data are trend stationary)

If the null hypothesis of a unit root with drift process is accepted, the dataset has to be differenced to avoid spurious regression results. As noted by Engle and Granger (1987), however, important information regarding equilibrium relationships of price levels is lost in the differencing step.

The rejection of the unit root null hypothesis is interpreted as evidence that the time-series fluctuates around zero and is therefore trend-stationary. If the existence of a unit root is accepted in some submarkets and rejected in others, this can be interpreted as a further indication that the examined market area is less than perfectly integrated.

If united root tests yield that the series are integrated of order one, the number of significant cointegration vectors is determined following the procedure introduced by Johansen (1988, 1991, 1994). The model uses the maximum likelihood-based, maximum eigenvalue and trace test statistics as follows.

$$\Delta X_t = \beta + \eta_1 \Delta X_{t-1} + \eta_2 \Delta X_{t-2} + \ldots + \eta_{k-1} \Delta X_{t-k+1} + \pi X_{t-1} + V_t \quad (2)$$

where X_t is an m-dimensional vector of variables, k is the number of lags and β is a vector of constants. The error vector V_t is multivariate normal and independent across observations, and t=1,2,…,T is the number of observations. The number of cointegrating vectors is derived from the rank of π. According to the Engle-Granger representation theorem, if the rank of π is *r*, with *r*<*m*, then there exist *m*×*r* matrices α and ϕ , each with rank so that $\pi = \alpha\phi'$ and $\phi' X$ are trend stationary (Engle and Granger 1987). The implication of this is that the existence of one or several co-integrating vectors implies an error correction model and vice versa. The hypotheses (***H3***) are formally presented as:

$H_0 : \pi = r$ (-> no cointegrating vector exists)

$H_a : \pi = k$ (->at least one cointegrating vector exists)

Regarding the relevance of this hypothesis for the question of intracity diversification benefits, cointegrated markets can be assumed to be high or perfect substitutes since they share the same set of fundamentals and hence the same set of systematic risks. Lack of cointegration would imply that a different set of fundamentals drives the submarkets. Thus, portfolio managers may achieve intracity diversification benefits in these non-cointegrated markets.

Exploring causality and lag structures

Recalling the discussion of economic theory in the previous section, the next hypothesis (***H4***) implies that institutional and informational impediments do not have any significant distorting effects on the market so that all submarkets respond simultaneously to changes in market conditions without any systematic lag or lead relationships. This hypothesis will be tested by applying the concept of Granger causality. I test three different pairs of dependent and independent variables to assess the impact: 1) rent on rent, 2) vacancy on rent, and 3) employment on occupancy. The first test sets out to determine whether shifts in prices are transmitted across all submarkets with any significant lags. Thus, the rental rates of a submarket (R_{st}) are said to be Granger caused by overall market rents (R_{mt}) if lagged values of R_{mt} are able to explain current values of (R_{st}) in the functional form:

$$R_{st} = y_0 + \sum_{i=1}^{p} \alpha_i R_{st-i} + \sum_{i=1}^{p} \beta_i R_{mt-i} + \mu_t \tag{3}$$

The second equation tests if vacancy rates have an impact on submarket rental rates as suggested by the theory of real estate markets. Equivalently to Equation 3, I test the impact of both submarket vacancy rates (V_{st}) and overall market vacancy rates (V_{mt}) on rental rates and compare the results. This equation takes the form:

$$R_{st} = y_0 + \sum_{i=1}^{p} \alpha_i V_{st-i} + \sum_{i=1}^{p} \beta_i V_{mt-i} + \mu_t \tag{4}$$

Occupancy rates are a further major parameter of income streams from real estate. Occupancy levels (OS_{st}) in turn depend on changes in demand as proxied by the variable office employment in this specification. The impact of submarket office employment (E_{st}) levels is then compared to the impact of overall market office employment (E_{mt})

$$OS_{st} = y_0 + \sum_{i=1}^{p} \alpha_i E_{st-i} + \sum_{i=1}^{p} \beta_i E_{mt-i} + \mu_t \tag{5}$$

Estimating the causal relationship is more intricate than the first two equations, however, because the assumed linear relationship between office employment and occupancy rates is complicated by the fact that the intensity of space usage per worker fluctuates in response to rent changes. In general, companies tend to consume less space per worker in times of high rents and more space in times of low rents, thereby distorting the effect that changes in office employment have on occupied space. To control for this price elasticity of demand, I set square foot per worker by submarket as an exogenous variable in the Granger causality tests.

In order to more fully grasp the impact of changes in overall market versus submarket indicators, I formulate a vector autoregressive (VAR) model and conduct impulse response analyses (also called innovation response analyses) as proposed in Sims (1980, 1992). The impulse response analysis illustrates the response of the dependent variable to a hypothetical unit shock in the independent variable. This response is then projected with a dynamic multiplier over several periods following the unit shock. The operationalization of Bierens (2004) for computation with an econometric software package is based on a k-variate Gaussian VAR(p) model of the following form:

$$X_t = C_0 + C_1 X_{t-1} + \ldots + C_p X_{t-p} + U_t \tag{6}$$

where X_t = ($X_{1,t}$, ... ,$X_{k,t}$)' is a vector time series of the variable in question, C_0 is a k-vector of intercept parameters, C_j represents k´k parameter matrices, and U_t is an error vector, which is assumed to be k-variate normally distributed. The components of the impulse vector U_t = (U_1,t, ... ,U_k,t)' are taken to represent market shocks. Sims (1980) solves the problem of correlated error components by rewriting the equation so that individual components can be interpreted as the actual impulses of sequential market shocks.

Exploring risk-return measures

In addition to the time-series analysis of the previous sections, an explicit analysis of risk-return relationship is needed to answer the question whether intracity portfolio diversification is feasible or not. To this aim, I first calculate simple Beta measures, which are defined as:

$$\beta_s = \frac{Cov[r_s, r_{mt}]}{Cov[r_{mt}, r_{mt}]} = \frac{Cov[r_s, r_{mt}]}{Var[r_{mt}]} \qquad (7)$$

where rs_s and rmt are the random returns of the submarket s and on the overall Manhattan office market, respectively. In equilibrium, all assets and portfolios in a submarkets will have the same return after adjustment for risk. Ihus, the hypothesis (***H5***) reads:

$H_0 = \beta_1 = \beta_2 = ... = \beta_{15}$ (-> betas are equal across submarkets)

$H_a = \beta_1 \neq \beta_2 \neq ... \neq \beta_{15}$ (-> betas are not equal across submarkets)

In addition to the Beta measures, I calculate Sharpe Ratios. Compared to the Beta, the Sharpe ratio calculates the expected return per unit of standard deviation of return for a zero-investment strategy (Sharpe 1966). While the expected return and standard deviation of such a strategy depends on the scale, their ratio will not. Consequently, the Sharpe Ratio is not distorted by different scales. The Sharpe Ratio follows Markowitz' mean-variance paradigm in that it assumes the mean and standard deviation of the distribution of one-period return to be sufficient statistics for evaluating the prospects of an investment portfolio. The common definition is as follows (Sharpe 1994):

$$D_t = R_{Ft} - R_{Bt} \qquad (8)$$

where R_{Ft} is the return on an asset in period t, R_{Bt} the return on the benchmark portfolio or market index in period t, and D_t the differential return in period t:

Next, the average value ($\overline{D}$) of D_t over the historic period from t=1 through T is calculated as:

$$\overline{D} = \frac{1}{T}\sum_{t=1}^{T} D_t \tag{9}$$

The standard deviation over the entire period is defined as:

$$\sigma_D = \sqrt{\frac{\sum_{t=1}^{T}(D_t - \overline{D})^2}{T-1}} \tag{10}$$

Finally, the ex post, or historic Sharpe Ratio (S_h) used in this research is:

$$S_h = \frac{\overline{D}}{\sigma_D} \tag{11}$$

The Sharpe ratio is an important tool in determining the differential between two portfolios. The differential return represents the outcome of a zero investment strategy, which is defined as a zero outlay of assets in the present and positive, negative or zero returns in the future. The generally accepted rule of thumb in interpreting it is that the higher the Sharpe ratio, the higher the risk-adjusted return. Therefore, the Sharpe ratio is a proxy for the risk-adjusted return. In the context of this chapter, the Sharpe ratio is useful for comparing the risk-return profiles of the Manhattan submarkets during the analyzed periods. The corresponding hypothesis (***H6***) is

$H_0 = S_1 = S_2 = ... = S_{15}$ (-> Sharpe ratios are equal across submarkets)

$H_a = S_1 \neq S_2 \neq ... \neq S_{15}$ (-> Sharpe ratios are not equal across submarkets)

Both ***H5*** and ***H6*** are tested using a one sample t-test, which tests whether the mean absolute percentage error of submarkets from Manhattan is significantly different from zero. We expect a zero value in a market with efficient asset pricing.

It may be argued that the Sharpe Ratio is not applicable to aggregate measures of the office rental market since these measures do not exhibit the volatility typical of financial markets and publicly traded securities. Furthermore, rental rates are typically predetermined over a longer period through long-term leases. Although investors' rental income streams are usually defined by these fixed lease terms, the Sharpe Ratio conveys useful information for submarkets because a) leases expiring into a weakening rental market are a definite risk which becomes measurable through Sharpe Ratios, b) at the submarket level, leases are constantly expiring so the comparison to a risk-free investment seems justified.

Study area

For the purpose of in-depth real estate market studies, Manhattan is commonly divided into three subareas (Midtown Core, Midtown South, and Downtown). Each of these subareas can be further subdivided into submarket areas. The submarket delineation used in this study is based on the definition by Grubb & Ellis. Some of the smaller submarkets have been aggregated to obtain submarkets that are comparable in size and to be able to match the office market zones to employment zones (ES-202 data) which are available at the zip code level.[16]

Data issues

The time-series cross-sectional database was produced by Grubb & Ellis based on individual property data collected by the CoStar Group. The time increment used in this model is one quarter, which is different from most other modeling studies which use either annual or semi-annual data. Quarterly data are typically subject to greater fluctuations than annual or semi-annual averages which eliminate a large part of the variation of more fine-grained data. Some datasets, such as employment exhibit seasonal bias when a quarterly model is used and have been smoothed prior to being used in the regression analysis. For the purpose of testing for Granger-causality, cointegration and for calculating portfolio risk measures, quarterly intervals can be considered superior to longer intervals. We reiterate at this point that all price and rental data used in this dissertation are inflation-adjusted by applying the standard chain-weighted NIPA (National Income and Product Account) index as proposed by Whelan (2000).

An office employment series is constructed using county business pattern data. This New York State Department of Labor (DOL) Covered Employment and Wages data series (also known as ES202) provides a time series of the number of workers and aggregate wages by detailed industry by zip code of firm location. ES202 data cover approximately 97 percent of New York's nonfarm employment, providing a virtual census of employees and their

[16] The following submarkets were merged to match the boundaries of zip-code level employment data: 1) Midtown West and Avenue of the Americas, 2) Fifth Avenue, Madison Avenue, Park Avenue and East Side, and 3) Broadway/Battery Park, Wall Street and Waterfront. The number of submarkets was thus reduced from 19 to 15.

wages as well as the most complete universe of employment and wage data, by industry, at the State, regional, county, and zip code levels. The definition used to identify office-using industries is adopted from the New York City Office of Management and Budget and is used widely by researchers. It comprises the sectors, financial activities, information, professional and business services, management of companies and administrative and support services. The classification of these industries is based on NAICS codes (with all of the industries designated as office employment start with the number '5' in the six digit numbering system). While the total number probably does not contain all employees working in an office-type environment, the bulk of office workers is included in this definition.

5.3 Empirical Results

Prior to reporting the results of the hypothesis tests, some descriptives are useful for illustrating the general dynamics and economic framework of the case study market. Figure 5-1 shows the trajectories of quarterly rental rates of Manhattan submarkets since 1992. The time series data seem to suggest prima facie that distinct submarket patterns do exist.

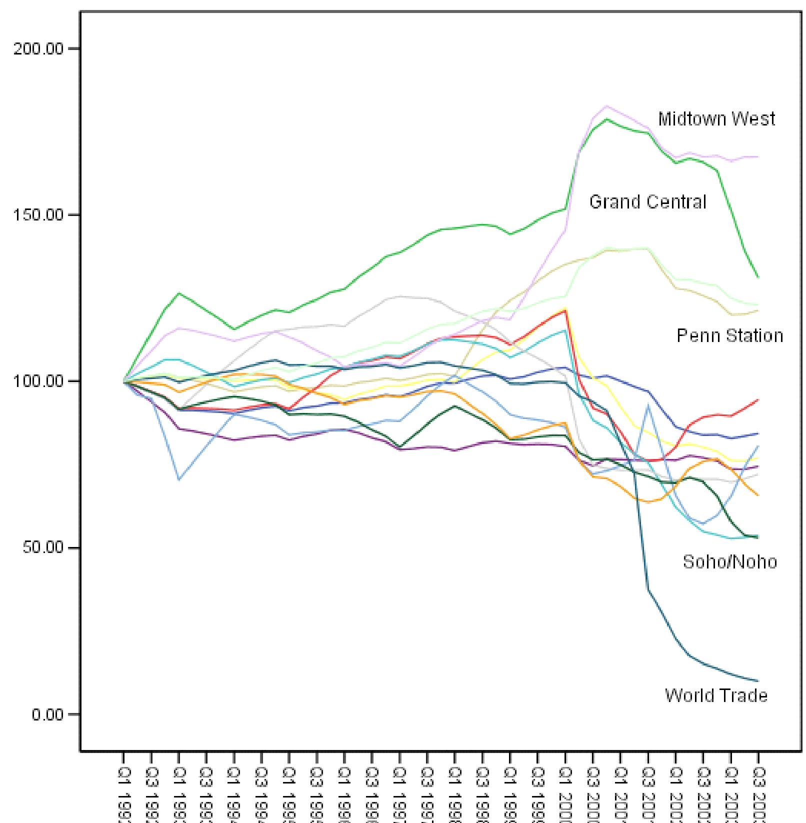


Figure 5-1: Rental rate indices in Manhattan submarkets from 1992 until 2004 (Q1 1992=100)

Figure 5-2 shows the basic risk-return tradeoff pattern of Manhattan submarkets by plotting the volatility of rental rates (standard deviations) against their average quarterly growth rates. The resulting pattern suggests the existence of a tradeoff relationship between risk and return. Moreover, to illustrate the spatial arrangement of submarkets, Figure 5-3 maps the distribution of volatility in rental rates as measured by standard deviations in quarterly rental rates over a period of 13 years. It is remarkable that the high-priced Midtown submarkets exhibit relatively small variation over time whereas the submarkets of Midtown South show a much more volatile pattern. One possible explanation for this is the highly volatile development of the technology sector in the study period. Since the submarkets of Midtown South provided the type of office space and locational amenities that innovative technology startup companies were typically looking for, many companies chose to locate in these areas (also known as Silicon Alley) thus driving up rental rates. This trend was reversed, however, after the crisis of the technology sector became apparent in 2000 causing rental rates in these submarkets to drop precipitously as occupancy levels declined due to massive layoffs and firm closures.

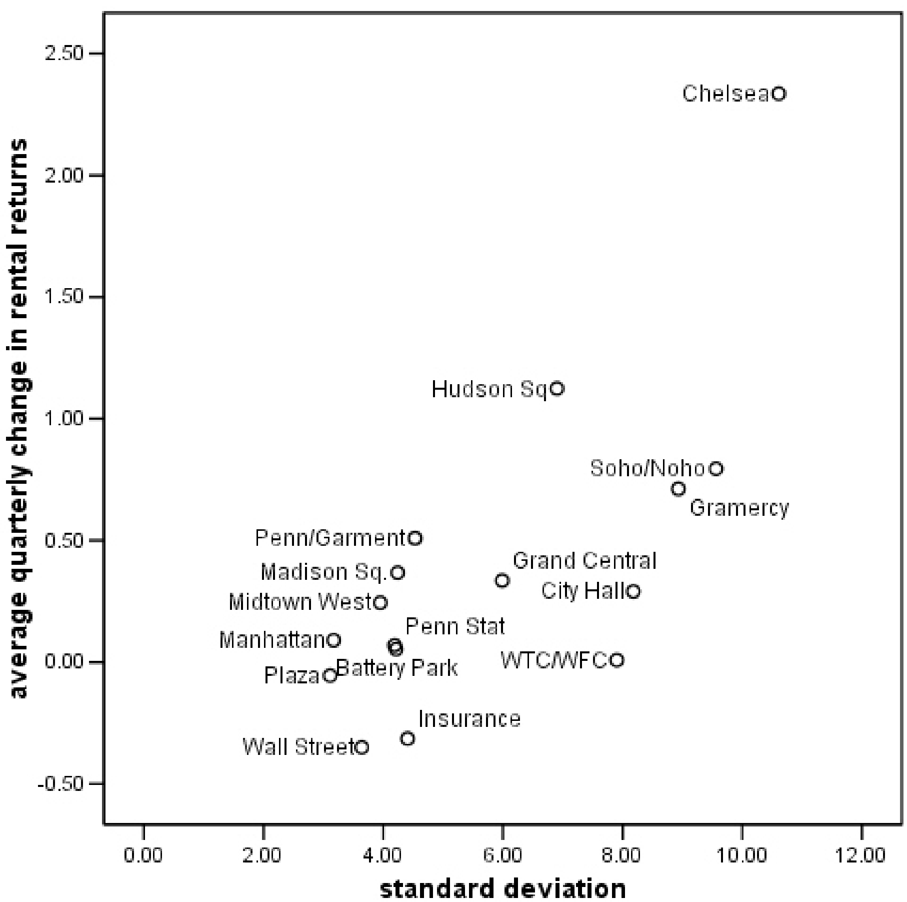


Figure 5-2: Risk-return tradeoff for Manhattan office submarkets

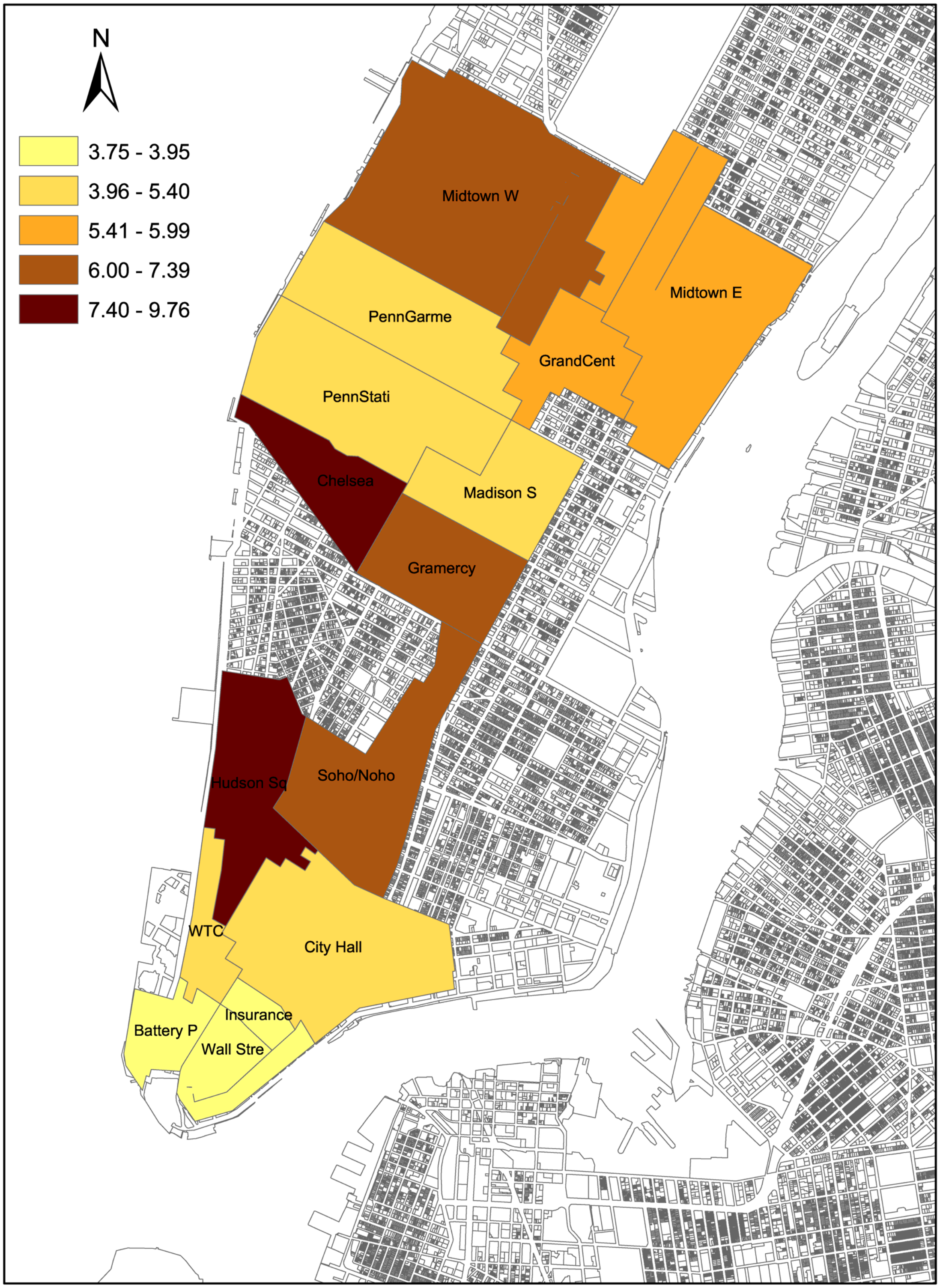


Figure 5-3: Standard deviations of submarket rents (1992-2004)

The results of the ANOVA tests of the first hypothesis (H1) are presented in Table 5-1 and Table 5-2. Since the values of the standard F-test are sensitive to potential non-equal variances in the submarkets, additional robust measures such as the Welch and Brown-

Forsythe tests are presented. All three test measures support unequivocally the rejection of the null hypothesis of equal rents across submarkets. Similarly, the null hypothesis is also rejected for vacancy rates. It is interesting to note that the variation in vacancy rates within submarkets over time is larger than the cross-sectional variation between submarkets (within group versus between group in Table 5-2) whereas the opposite is the case for rental rates. Put differently, vacancy rates in individual submarkets tend to fluctuate more strongly over time than across space and rental rates vary considerably across submarkets but are relatively more stable over time in the analyzed case study. The overall conclusion from this test is that both rental and vacancy rates are significantly different in the analyzed submarkets. This result seems to suggest that intracity diversification may in principle be a feasible strategy.

Table 5-1: ANOVA, Rents

	Sum of Squares	df	Mean Square	F (Sig.)	Welch (Sig.)	Brown-Forsythe (Sig.)
Between Groups	42475.94	14	3033.99	80.994 (.000)	76.018 (.000)	80.994 (.000)
Within Groups	27532.79	735	37.46			
Total	70008.73	749				

Table 5-2: ANOVA, Vacancy

	Sum of Squares	df	Mean Square	F (Sig.)	Welch (Sig.)	Brown-Forsythe (Sig.)
Between Groups	10894.33	14	778.16	37.633 (.000)	44.718 (.000)	37.633 (.000)
Within Groups	14888.07	720	20.67			
Total	25782.41	734				

Nevertheless, the differences in submarket means of the ANOVA are not sufficient to make any valid inferences about intracity diversification at this point. One potentially serious problem is that while levels of rental and vacancy rates are significantly different in submarkets, their first-order differences are not. This would be in line with the previously mentioned theory of fixed relative differences, which states that the relative differences in submarket rents and vacancy rates are preserved regardless of cyclical fluctuations. An ANOVA of first differences would not reveal, however, to what extent submarkets exhibit such similar dynamics since it is only capable of measuring differences in mean values.

Therefore, correlation matrices of first-order differences in rental rates and vacancy rates are more suitable to explore this issue. The empirical evidence presented in Table 5-3 and Table 5-4 is mixed. While the changes in rental rates of some submarkets are significantly correlated at the 1% level with more than 75% of all other submarkets, about half of the submarkets exhibit correlations with 50% or fewer of the other submarkets. Despite this, changes in rental rates can be considered highly correlated, especially when compared to correlations in vacancy rates which fail to demonstrate significant correlation of any submarket with more than a third of all other submarkets. Thus, we may conclude that changes in rental rates are more synchronized and highly correlated across all submarket areas whereas vacancy dynamics are more localized.

Table 5-3: Correlation matrix of percentage changes in rental rates

	Midtown West	Midtown /Plaza	Grand Central	Penn/ Garment	Penn Station	Madison Square	Gramercy /Flatiron	Chelsea	Soho/ Noho	Hudson Sq	City Hall	Broadway	Insurance District	Wall Street	World Trade
Midtown West	1	.802(**)	.323(*)	.690(**)	.610(**)	.624(**)	.407(**)	.579(**)	.436(**)	.434(**)	.268	.361(*)	.555(**)	.540(**)	.506(**)
Midtown East/Plaza	.802(**)	1	.301(*)	.636(**)	.659(**)	.595(**)	.455(**)	.462(**)	.216	.417(**)	.367(*)	.522(**)	.674(**)	.566(**)	.380(*)
Grand Central	.323(*)	.301(*)	1	.402(**)	.336(*)	.329(*)	.129	.600(**)	.160	.159	.265	.191	.276	.482(**)	.188
Penn/Garment	.690(**)	.636(**)	.402(**)	1	.716(**)	.743(**)	.405(**)	.562(**)	.474(**)	.407(**)	.160	.284	.633(**)	.610(**)	.410(**)
Penn Station	.610(**)	.659(**)	.336(*)	.716(**)	1	.616(**)	.391(**)	.301(*)	.528(**)	.408(**)	.259	.390(**)	.587(**)	.511(**)	.411(**)
Madison Square	.624(**)	.595(**)	.329(*)	.743(**)	.616(**)	1	.355(*)	.597(**)	.447(**)	.448(**)	.143	.321(*)	.552(**)	.460(**)	.391(*)
Gramercy/Flatiron	.407(**)	.455(**)	.129	.405(**)	.391(**)	.355(*)	1	.346(*)	.229	.338(*)	.288	.295	.471(**)	.439(**)	.279
Chelsea	.579(**)	.462(**)	.600(**)	.562(**)	.301(*)	.597(**)	.346(*)	1	.352(*)	.405(**)	.144	.198	.355(*)	.547(**)	.288
Soho/Noho	.436(**)	.216	.160	.474(**)	.528(**)	.447(**)	.229	.352(*)	1	.380(*)	.332(*)	.273	.055	.409(**)	.188
Hudson Sq	.434(**)	.417(**)	.159	.407(**)	.408(**)	.448(**)	.338(*)	.405(**)	.380(*)	1	.044	.292	.305(*)	.310(*)	.084
City Hall	.268	.367(*)	.265	.160	.259	.143	.288	.144	.332(*)	.044	1	.446(**)	.080	.444(**)	.340(*)
Broadway	.361(*)	.522(**)	.191	.284	.390(**)	.321(*)	.295	.198	.273	.292	.446(**)	1	.413(**)	.589(**)	.130
Insurance District	.555(**)	.674(**)	.276	.633(**)	.587(**)	.552(**)	.471(**)	.355(*)	.055	.305(*)	.080	.413(**)	1	.445(**)	.324(*)
Wall Street	.540(**)	.566(**)	.482(**)	.610(**)	.511(**)	.460(**)	.439(**)	.547(**)	.409(**)	.310(*)	.444(**)	.589(**)	.445(**)	1	.203
World Trade	.506(**)	.380(*)	.188	.410(**)	.411(**)	.391(*)	.279	.288	.188	.084	.340(*)	.130	.324(*)	.203	1
Share at 5% level[1]	92.9%	92.9%	50.0%	85.7%	92.9%	92.9%	64.3%	78.6%	57.1%	71.4%	35.7%	50.0%	78.6%	92.9%	50.0%
Share at 1% level[1]	85.7%	78.6%	21.4%	85.7%	78.6%	71.4%	42.9%	50.0%	42.9%	50.0%	14.3%	35.7%	57.1%	85.7%	21.4%

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

[1] Share of submarkets with significant correlations at the 0.01 and 0.05 levels respectively

Table 5-4: Correlation matrix of percentage changes in vacancy rates

	Midtown West	Midtown East	Grand Central	Penn/ Garment	Penn Station	Madison Square	Gram./ Flatiron	Chelsea	Soho/ Noho	Hudson Sq	City Hall	Broad-way	Insurance District	Wall Street	World Trade
Midtown West	1	.174	-.018	-.036	.150	.198	.230	.318(*)	.113	.065	-.340(*)	.225	.053	.225	.230
Midtown East/Plaza	.174	1	.193	.175	-.120	.267	.047	.392(**)	.297(*)	.288	.028	.102	.212	.225	.103
Grand Central	-.018	.193	1	.077	.077	-.140	.566(**)	.351(*)	.301(*)	.048	.018	.333(*)	.301(*)	.478(**)	.181
Penn/ Garment	-.036	.175	.077	1	-.002	-.049	.160	-.266	-.162	.411(**)	.140	.158	.033	-.018	-.060
Penn Station	.150	-.120	.077	-.002	1	.005	.259	.265	.036	.081	.034	.278	.120	.184	.138
Madison Square	.198	.267	-.140	-.049	.005	1	-.162	.130	.016	.048	.124	-.261	-.029	.117	.253
Gramercy/ Flatiron	.230	.047	.566(**)	.160	.259	-.162	1	.380(*)	.176	.226	-.221	.363(*)	.362(*)	.571(**)	.110
Chelsea	.318(*)	.392(**)	.351(*)	-.266	.265	.130	.380(*)	1	.110	.005	-.144	.235	.114	.539(**)	.197
Soho/Noho	.113	.297(*)	.301(*)	-.162	.036	.016	.176	.110	1	.144	.058	.360(*)	.124	.084	.023
Hudson Sq	.065	.288	.048	.411(**)	.081	.048	.226	.005	.144	1	.066	.179	.299(*)	.209	-.151
City Hall	-.340(*)	.028	.018	.140	.034	.124	-.221	-.144	.058	.066	1	-.084	-.265	-.159	.046
Broadway	.225	.102	.333(*)	.158	.278	-.261	.363(*)	.235	.360(*)	.179	-.084	1	.158	.199	-.127
Insurance District	.053	.212	.301(*)	.033	.120	-.029	.362(*)	.114	.124	.299(*)	-.265	.158	1	.189	.241
Wall Street	.225	.225	.478(**)	-.018	.184	.117	.571(**)	.539(**)	.084	.209	-.159	.199	.189	1	.235
World Trade	.230	.103	.181	-.060	.138	.253	.110	.197	.023	-.151	.046	-.127	.241	.235	1
Share at 5% level[1]	14.3%	14.3%	42.9%	7.1%	0.0%	0.0%	35.7%	35.7%	21.4%	14.3%	7.1%	21.4%	21.4%	21.4%	0.0%
Share at 1% level[1]	14.3%	14.3%	42.9%	7.1%	0.0%	0.0%	35.7%	35.7%	21.4%	14.3%	7.1%	21.4%	21.4%	21.4%	0.0%

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

[1] Share of submarkets with significant correlations at the 0.01 and 0.05 levels respectively

Table 5-5: Unit Root Tests (Augmented Dickey-Fuller test for trend stationarity)

	Rent			Employment			Vacancy		
Submarket	OLS estimate	t-value	conclusion*	OLS estimate	t-value	conclusion*	OLS estimate	t-value	conclusion*
Midtown West	-0.106	-1.474	unit root	0.257	1.994	unit root	-0.138	-1.970	unit root
Midtown East , Plaza	-0.031	-0.378	unit root	-0.273	-2.279	unit root	-0.078	-1.171	unit root
Grand Central	-0.124	-0.806	unit root	-0.075	-1.188	unit root	-0.094	-1.062	unit root
Penn/Garment	-0.122	-1.446	unit root	0.009	0.151	unit root	-0.454	-1.676	unit root
Penn Station	-0.156	-2.234	unit root	0.039	0.465	unit root	-0.165	-1.532	unit root
Madison Square	-0.075	-1.098	unit root	-1.385	-3.604	stationary	-0.198	-2.575	stationary
Gramercy/Flatiron	-0.141	-1.361	unit root	-0.436	-2.116	unit root	-0.136	-0.684	unit root
Chelsea	-0.031	-0.370	unit root	-0.883	-2.431	unit root	-0.293	-1.572	unit root
Soho/Noho	-0.151	-1.267	unit root	-0.373	-2.732	stationary	-0.163	-1.161	unit root
Hudson Sq	-0.075	-1.176	unit root	-0.130	-0.477	unit root	-0.103	-1.703	unit root
City Hall	-0.415	-1.273	unit root	-0.109	-0.981	unit root	-0.529	-1.642	unit root
Broadway	-0.194	-1.765	unit root	0.144	1.610	unit root	-0.125	-1.167	unit root
Insurance District	-0.196	-1.468	unit root	-0.065	-0.439	unit root	-0.352	-1.300	unit root
Wall Street	-0.275	-2.261	unit root	-0.067	-0.457	unit root	-0.037	-0.860	unit root
WTC/WFC	-0.651	-1.979	unit root	-0.096	-0.119	unit root	-0.444	-2.385	unit root
Manhattan	-0.111	-1.568	unit root	-0.041	-0.621	unit root	-0.064	-1.389	unit root

* at 10% significance level

To explore the time series properties of the data series in more depth, a test for unit roots using the standard Augmented Dickey-Fuller (ADF) procedure is applied (Table 5-5). The results regarding hypothesis ***H2*** demonstrate that the majority of time-series variables presented here are I (1). In the next stage of the analysis, we test for a cointegrating relationship between the rental rates of submarkets and the overall Manhattan market (hypothesis ***H3***). As Table 5-6 shows, the null hypothesis of no cointegration cannot be rejected in 8 out of 15 submarkets. Conversely, there is simultaneous evidence of at least one cointegrating vector so that inclusive evidence arises in eight cases where both the null and the alternative hypotheses are accepted. Notwithstanding the inconclusive results, about half of the submarkets exhibit a clear cointegrating relationship of rental rates with the overall Manhattan market. Since these results suggest that cointegrated submarkets are driven by the same market fundamentals, intracity diversification may not be possible for these submarkets.

Table 5-6: Johansen cointegration analysis of submarkets and Manhattan market

	Lambda-max test		trace test	
	r = 0	r = 1	r = 0	r = 1
Midtown West.	20.3	1.9**	22.2	1.9**
Midtown East, Plaza	6.2**	0.8**	7.0**	0.8**
Grand Central	34.5	0.7**	35.1	0.7**
Penn/Garment	4.4**	3.0**	7.4**	3.0**
Penn Station	32.1	1.4**	33.5	1.4**
Madison Square	14.2	1.9**	16.1	1.9**
Gramercy/Flatiron	8.3**	0.8**	9.1**	0.8**
Chelsea	8.4**	2.0**	10.4**	2.0**
Soho/Noho	26.0	0.8**	26.9	0.8**
Hudson Square	5.8**	1.5**	7.3**	1.5**
City Hall	49.2	1.1**	50.3	1.1*
Broadway	18.4	1.3**	19.7	1.3**
Insurance District	5.7**	1.5**	7.3**	1.5**
Wall Street	9.8**	3.8**	7.3**	3.8**

** hypothesis accepted at 5% level, *hypothesis accepted at 10% level

critical values

Lambda-max test			trace test		
20%	10%	5%	20%	10%	5%
11.6	13.8	15.8	5.9	7.6	9.1
5.9	7.6	9.1	15.4	18.0	20.2

Turning to hypothesis ***H4***, I perform three tests for Granger causality with the aim of exploring further the interaction and causality patterns between important office market indicators. I estimate the bivariate autoregressive processes for rents, vacancy rates and office employment. The first hypothesis tested is that submarket rental rates respond significantly to overall Manhattan rents albeit with individual lag structures and are thus Granger-caused by Manhattan rents (Equation 3). Table 5-7 shows that only about one quarter of the submarkets are significant at the 1% level (40% at the 5% level) for this test. This can be interpreted as an indication of less than perfect integration of submarket rental rates within the office market of Manhattan. The second test to be carried out concerns the impact of overall vacancy rates on submarket rental rates and to compare the results with the impact of each submarket's own vacancy rate on its rental rate (Equation 4). This test is useful in determining whether the main drivers of rental rates are to be found at the submarket or overall market level. The empirical results reported in Table 5-8 provide strong evidence that overall vacancy conditions are more important as a causal factor for submarket rental rates than local submarket conditions. The results appear to confirm the assumption that submarkets are interlinked entities with overall market signals overriding small-scale submarket conditions. Nevertheless, submarket conditions were found to also exert significant impact on rental rates at least at the 5% percent significance level. The number of significant causal relationships stays below that of the overall market in all cases, however.

Table 5-7: Granger Causality: Null hypothesis: rent Manhattan does not Granger-cause submarket rent

	F test	Prob.	Chi2	Prob.
Midtown West	4.89	0.03	5.20	0.02
Midtown East, Plaza	3.02	0.09	3.22	0.07
Grand Central	34.49	0.00	36.74	0.00
Penn/Garment	0.24	0.63	0.26	0.61
Penn Station	5.78	0.02	6.15	0.01
Madison Square	1.38	0.25	1.47	0.23
Gramercy/Flatiron	0.42	0.52	0.45	0.50
Chelsea	0.38	0.54	0.40	0.52
Soho/Noho	2.86	0.10	3.04	0.08
Hudson Sq	0.48	0.49	0.51	0.47
City Hall	58.78	0.00	62.62	0.00
Broadway	20.04	0.00	21.34	0.00
Insurance District District	3.50	0.07	3.73	0.05
Wall Street, Waterfront	6.88	0.01	7.32	0.01
WTC/WFC	2.90	0.10	3.08	0.08
Percent submarkets significant at 1%		26.67		26.67
Percent submarkets significant at 5%		40.00		46.67

Table 5-8: Granger Causality: Null hypothesis (1): Manhattan vacancy rate does not cause submarket rental rate and null hypothesis (2): submarket's own vacancy rate does not -cause submarket rental rate.

	(1) Manhattan to submarket				(2) submarket to submarket			
	F test	Prob.	Chi2	Prob.	F test	Prob.	Chi2	Prob.
Midtown West	28.54	0.00	30.44	0.00	4.79	0.03	5.11	0.02
Midtown East, Plaza	23.24	0.00	24.79	0.00	15.23	0.00	16.25	0.00
Grand Central	11.98	0.00	12.77	0.00	6.75	0.01	7.20	0.01
Penn/Garment	17.74	0.00	18.92	0.00	14.64	0.00	15.62	0.00
Penn Station	14.94	0.00	15.94	0.00	13.63	0.00	14.54	0.00
Madison Square	23.94	0.00	25.54	0.00	9.20	0.00	9.81	0.00
Gramercy/Flatiron	16.81	0.00	17.93	0.00	6.25	0.02	6.67	0.01
Chelsea	21.21	0.00	22.62	0.00	5.39	0.02	5.75	0.02
Soho/Noho	22.04	0.00	23.51	0.00	11.52	0.00	12.29	0.00
Hudson Sq	42.60	0.00	45.44	0.00	23.98	0.00	25.57	0.00
City Hall	10.88	0.00	11.60	0.00	0.01	0.93	0.01	0.92
Broadway	20.21	0.00	21.55	0.00	4.70	0.04	5.01	0.03
Insurance District	9.01	0.00	9.61	0.00	2.06	0.16	2.20	0.14
Wall Street, Waterfront	10.91	0.00	11.64	0.00	6.30	0.02	6.71	0.01
WTC/WFC	1.81	0.19	1.93	0.16	0.37	0.55	0.39	0.53
Percent submarkets significant at 1%		93.33		93.33		46.67		60.00
Percent submarkets significant at 5%		93.33		93.33		80.00		80.00

In the next step, I test to what extent changes in demand for office space trigger subsequent changes in occupancy rates (Equation 5). Hypotheses tests are conducted both for overall changes in office employment and submarket changes in office employment. To control for varying space usage patterns in submarkets I introduce 'space per worker' as an exogenous variable in the calculation as described in the methodology section. The empirical evidence reported in Table 5-9 demonstrates that the overall causal relationship between employment changes and changes in occupancy rates is much weaker than the relationship between vacancy rates and rents. Whether or not changes in employment have a subsequent impact on occupancy rates varies greatly both at the Manhattan and submarket levels. Based on chi2 significance at the 5% level, there are five instances where both Manhattan and local submarket employment is significant (Penn Station, Madison Sq., Chelsea, NoHo), three instances where only Manhattan employment is significant (MT West, Grand Central, Wall Street), four instances where only submarket employment is significant (Midtown East, Penn Garment, City Hall, World Trade Center) and four instances where neither Manhattan nor submarket employment are significant (Insurance District, SoHo, Gramercy/Flatiron, Hudson Sq.).

These findings do not provide a clear answer to our initial question of possible intracity portfolio diversification. They demonstrate, however, that there localized or partially localized patterns prevail in a number of submarkets independently of the overall market movement, which in turn should bode well for the prospects of intracity portfolio diversification.

Table 5-9: Granger Causality: Null hypothesis (1): Manhattan office employment does not Granger-cause submarket occupancy and null hypothesis (2): submarket office employment does not Granger-cause submarket occupancy with square feet per worker as exogenous variable

	(1) Manhattan to submarket				(2) submarket to submarket			
	F test	Prob.	Chi2	Prob.	F test	Prob.	Chi2	Prob.
Midtown West	7.03	0.01	7.66	0.01	0.09	0.76	0.10	0.75
Midtown East, Plaza	3.25	0.08	3.55	0.06	5.24	0.03	5.74	0.02
Grand Central	9.91	0.00	10.81	0.00	0.02	0.90	0.02	0.89
Penn/Garment	2.28	0.14	2.49	0.11	3.89	0.06	4.26	0.04
Penn Station	18.09	0.00	19.73	0.00	28.65	0.00	31.38	0.00
Madison Square	8.64	0.01	9.43	0.00	27.74	0.00	30.38	0.00
Gramercy/Flatiron	2.48	0.12	2.70	0.10	1.00	0.32	1.09	0.30
Chelsea	5.18	0.03	5.65	0.02	25.58	0.00	28.01	0.00
Soho/Noho	6.60	0.01	7.20	0.01	44.96	0.00	49.25	0.00
Hudson Sq	1.97	0.17	2.15	0.14	0.03	0.86	0.03	0.85
City Hall	0.08	0.78	0.08	0.77	3.51	0.07	3.84	0.05
Broadway	14.66	0.00	15.99	0.00	2.43	0.10	113.27	0.00
Insurance District	0.01	0.91	0.02	0.90	0.25	0.98	18.15	0.15
Wall Street, Waterfront	21.09	0.00	23.01	0.00	3.09	0.09	3.38	0.07
WTC/WFC	0.53	0.47	0.58	0.45	37.56	0.00	41.14	0.00
Percent submarkets significant at 1%		46.67		46.67		40.00		40.00
Percent submarkets significant at 5%		53.33		53.33		46.67		60.00

To illustrate the findings of the Granger causality tests in ***H4***, I also conduct impulse response analyses based on non-structural VAR. The impulse response analysis illustrates the hypothetical impact of a unit shock in one variable to all other variables in the model. Because of a dynamic lag structure facilitated by the VAR models unit shocks are transmitted between variables. This experimental arrangement enables us to compare the responses to shocks in submarket variables versus overall market variables. Consequently, introducing a positive shock to vacancy rates should result in decreasing rents. Figure 5-4 through Figure 5-63 illustrate the results of the impulse response analysis. As implied by economic theory, positive shocks in vacancy rates entail a negative response in rental rates (except in the City Hall submarket which does not show any detectable response). The order of magnitude of the responses varies greatly among and within submarkets. In the majority of cases, the vacancy impulse reaches its full impact several quarters after the initial onset which is also in line with the theory of lagged adaptive responses of rental rates to changes in market conditions observed in many other studies. A clear predominance of submarket or overall market impulses is not discernable in the graphs. A preliminary conclusion of the visual inspection of impulse response analyses is that both submarket and overall market conditions have an impact on submarket rental rates. The strength of the responses, however, varies individually with each submarket.

In the second part of the impulse response analysis, graphs are plotted for the impact of changes in employment on vacancy rates (Figure 5-34 through Figure 5-63). The underlying assumption is that a unit shock in employment creates increased demand for office space which in turn causes vacancy rates to decrease. While this assumption is confirmed in the majority of cases, the amplitude of the impact is generally low and tends to die out in many cases over the course of the 10 periods or is reversed after several periods. This may indicate an 'overshooting effect' in that companies typically take up more space than currently needed in anticipation of future expansions. This space is returned to the market as sublease or directly vacant space when it becomes clear that the space will not be needed in the foreseeable future. The impact of submarket office employment appears to have a slightly stronger impact on vacancy rates than changes in overall Manhattan office employment which is in line with the findings of the previous section.

Impulse response analysis

Response of rental rates to a unitary shock in vacancy rates

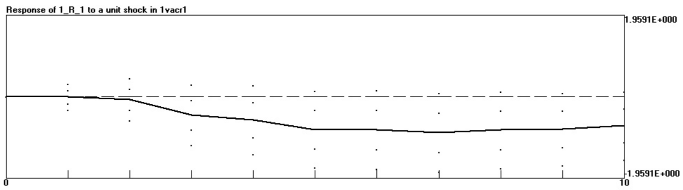


Figure 5-4: R (rent)_Midtown West - V (vacancy)_Midtown West

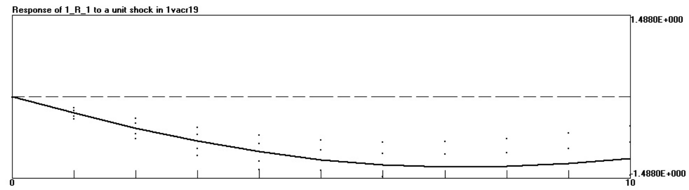


Figure 5-5:: R_Midtown West – V _Manhattan

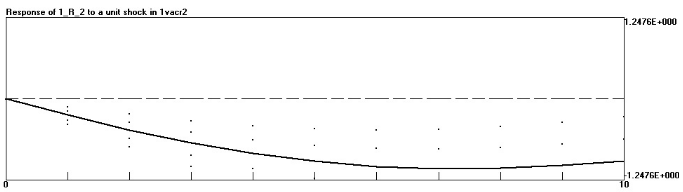


Figure 5-6:.1: R_Midtown East – V_ Midtown East

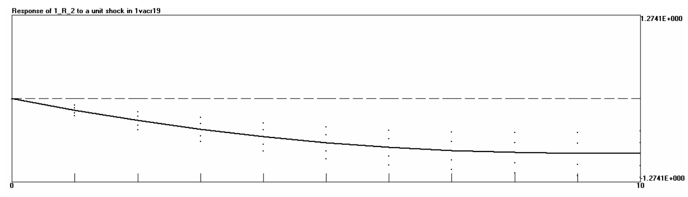


Figure 5-7: R_Midtown East – V_Manhattan

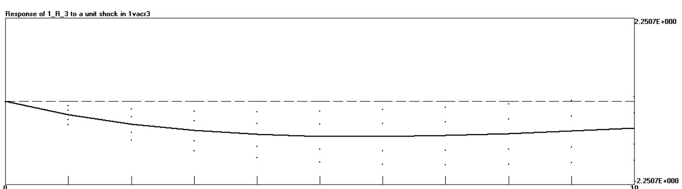


Figure 5-8: :R_Grand Central – V_ Grand Central

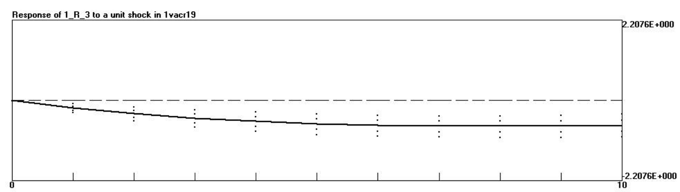


Figure 5-9: R_ Grand Central – V_Manhattan

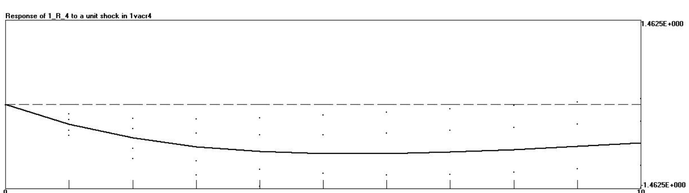


Figure 5-10: R_Penn/Garment – V_Penn/Garment

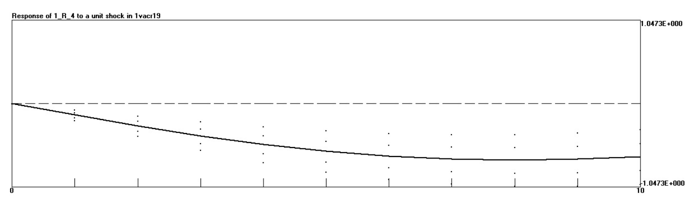


Figure 5-11:: R_Penn/Garment – V_Manhattan

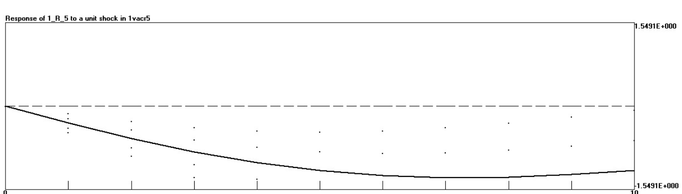


Figure 5-12: R_Penn Station – V_Penn Station

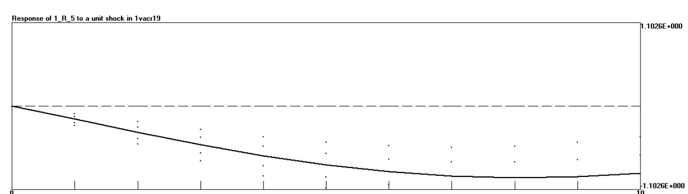


Figure 5-13: R_Penn Station – V_Manhattan

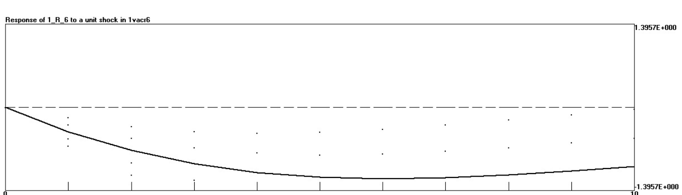


Figure 5-14: R_Madison Square – V_Madison Square

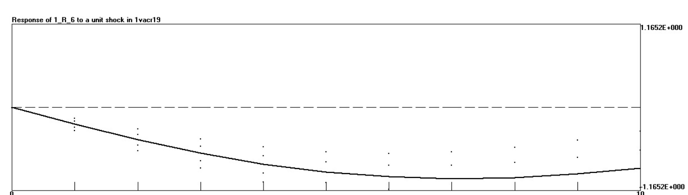


Figure 5-15: R_Madison Square – V_Manhattan

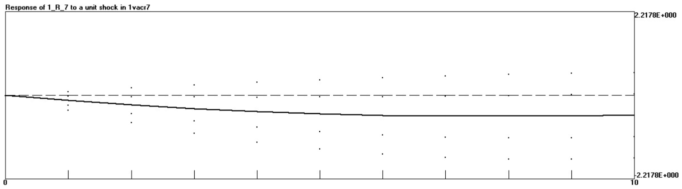


Figure 5-16: R_Gramercy/Flatiron – V_Gramercy/Fl.

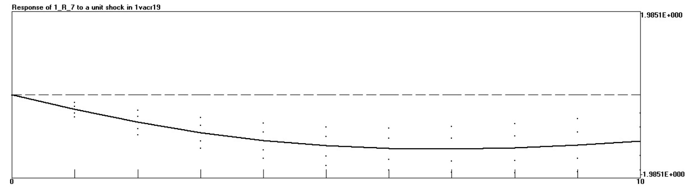


Figure 5-17: R_Gramercy/Flatiron – V_Manhattan

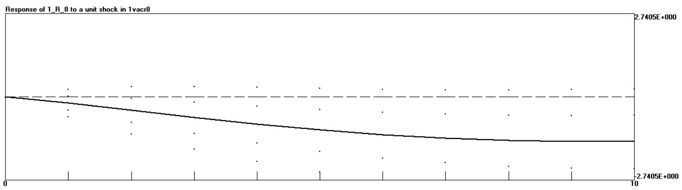


Figure 5-18: R_Chelsea – V_Chelsea

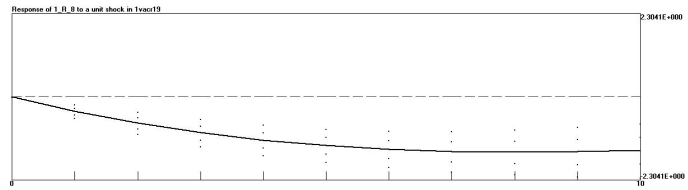


Figure 5-19: R_Chelsea – V_Manhattan

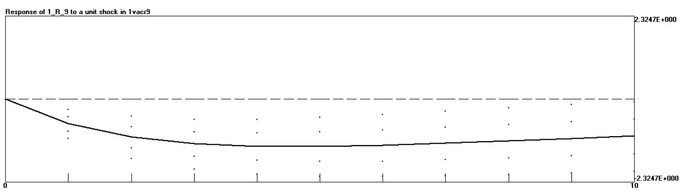


Figure 5-20: R_Soho/Noho – V_Soho/Noho

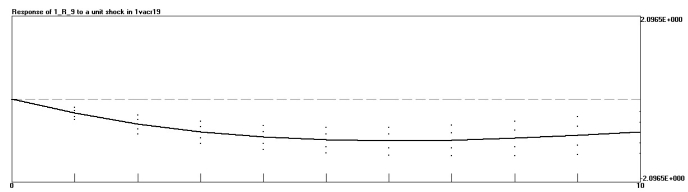


Figure 5-21: R_Soho/Noho – V_Manhattan

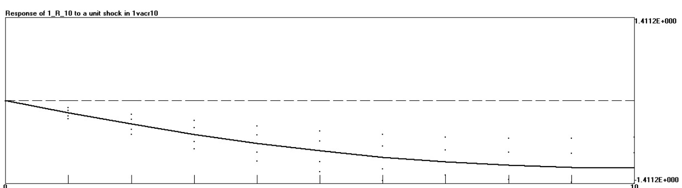


Figure 5-22: R_Hudson Sq – V_Hudson Sq

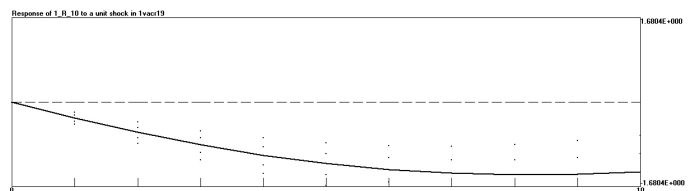


Figure 5-23: R_Hudson Sq – V_Manhattan

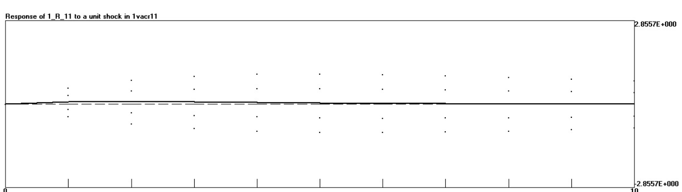


Figure 5-24: R_City Hall – V_City Hall

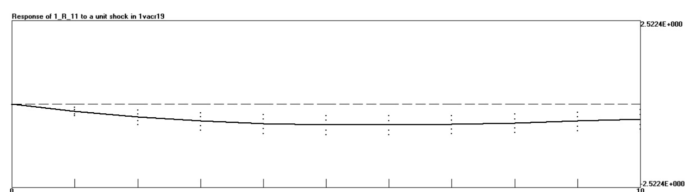


Figure 5-25: R_City Hall – V_Manhattan

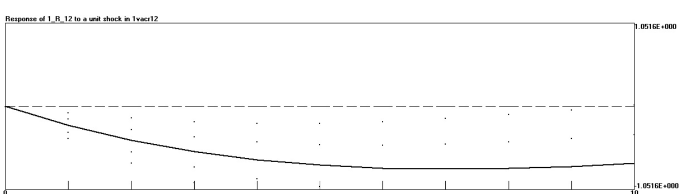


Figure 5-26: R_Broadway – V_Broadway

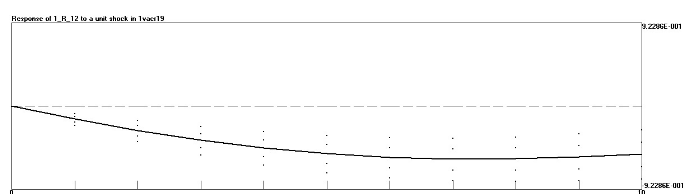


Figure 5-27:R_Broadway – V_Manhattan

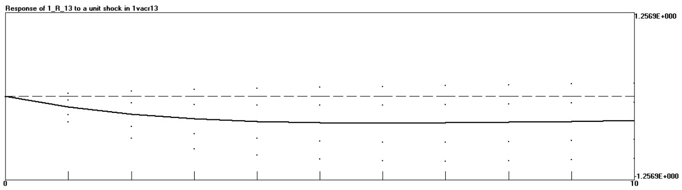


Figure 5-28: R_ Insurance District – V_Insurance D.

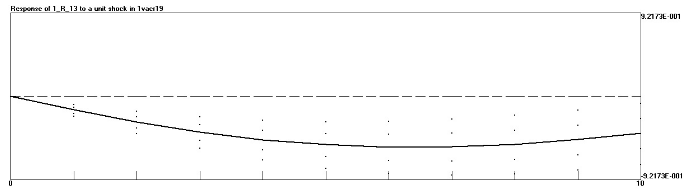


Figure 5-29: R_Insurance District – V_Manhattan

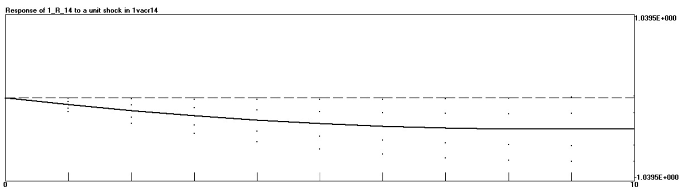


Figure 5-30: R_ Wall St, Waterfront – V_ Wall St

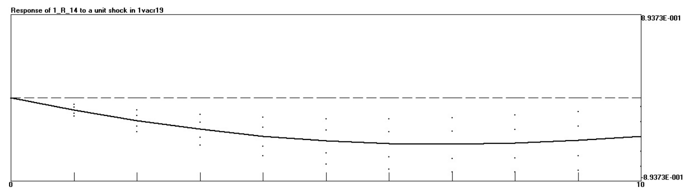


Figure 5-31: R_Wall St – V_Manhattan

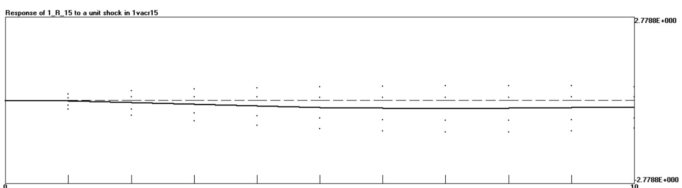


Figure 5-32: R_WTC/WFC – V_WTC/WFC

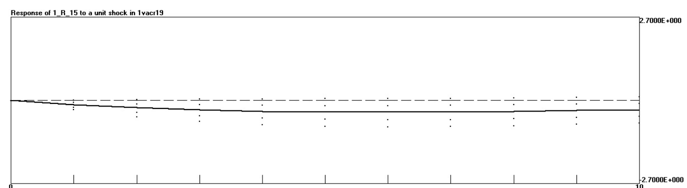


Figure 5-33: R_WTC/WFC – V_Manhattan

Response of vacancy rates to a unitary shock in office employment

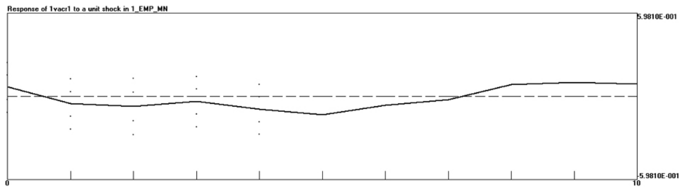


Figure 5-34: V_Midtown West – E_ Midtown West

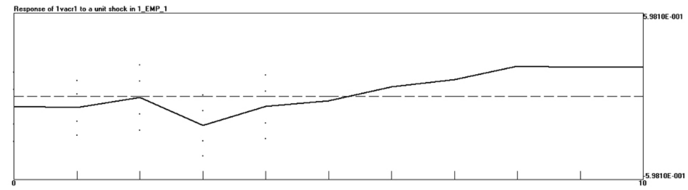


Figure 5-35: V_Midtown West – E_Manhattan

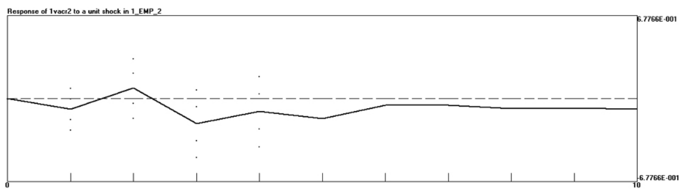


Figure 5-36: V_ Midtown East – E_ Midtown East

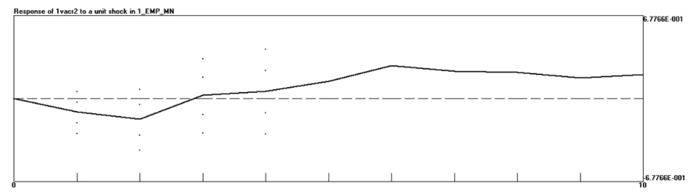


Figure 5-37: V_ Midtown East – E_Manhattan

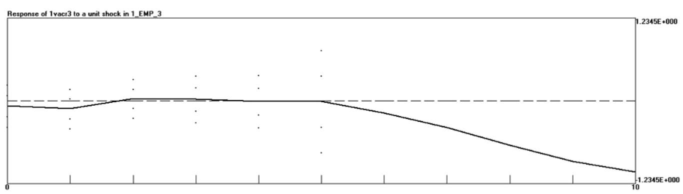


Figure 5-38: V_ Grand Central – E_ Grand Central

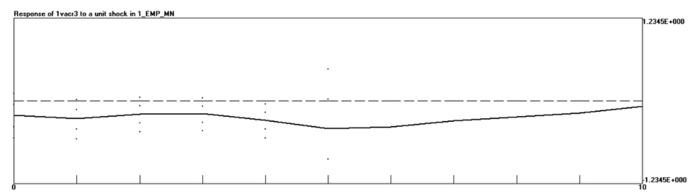


Figure 5-39: V_Grand Central – E_Manhattan

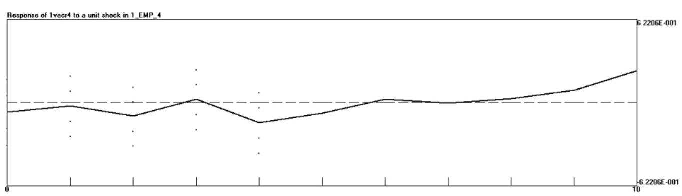


Figure 5-40: V_Penn/Garment – E_ Penn/Garment

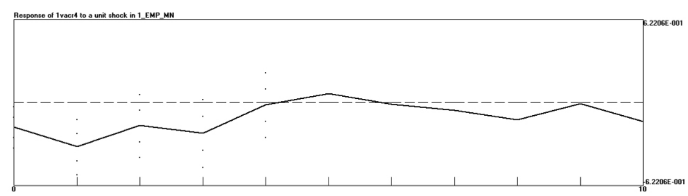


Figure 5-41: V_Penn/Garment – E_Manhattan

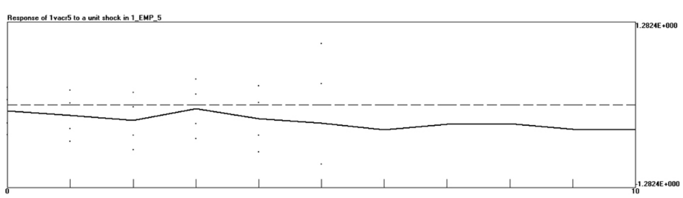


Figure 5-42: V_Penn Station – E_ Penn Station

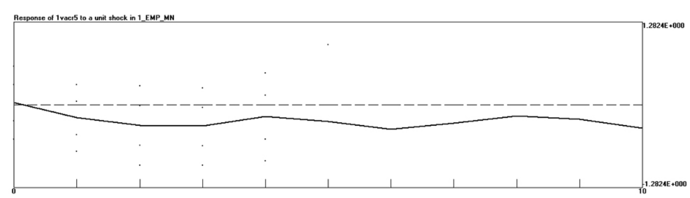


Figure 5-43: V_Penn Station – E_Manhattan

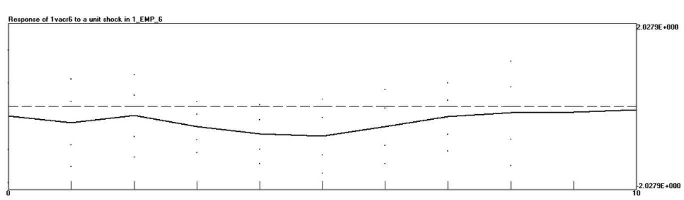


Figure 5-44: V_Madison Square – E_Madison Square

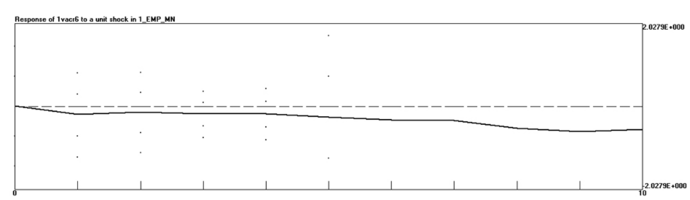


Figure 5-45: V_Madison Square – E_Manhattan

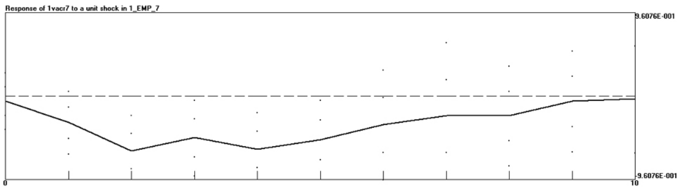


Figure 5-46: V_Gramercy/Flatiron – E_Gramercy/Fl.

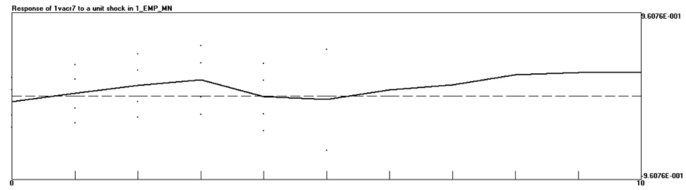


Figure 5-48: V_Gramercy/Flatiron – E_Manhattan

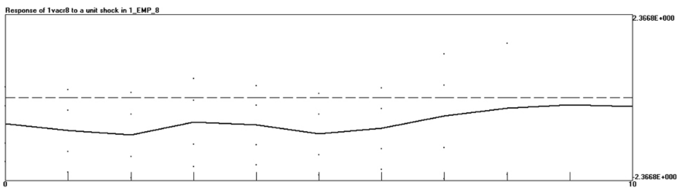


Figure 5-47: V_Chelsea – E_Chelsea

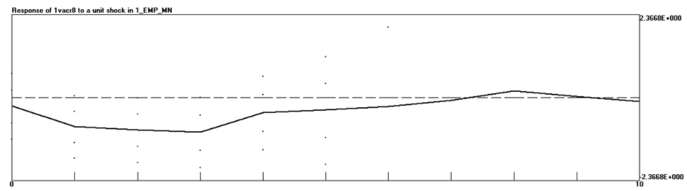


Figure 5-49:V_Chelsea – E_Manhattan

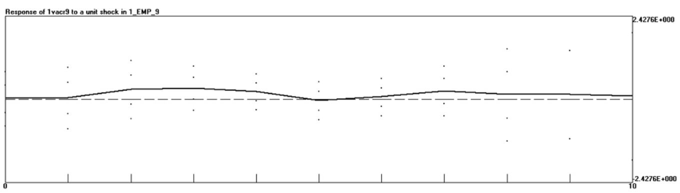


Figure 5-50:V_Soho/Noho – E_Soho/Noho

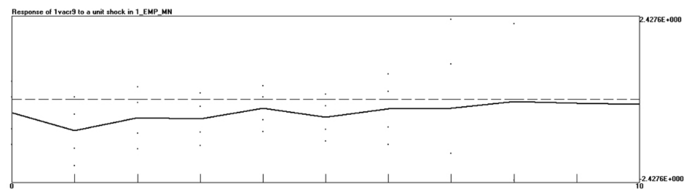


Figure 5-51: V_Soho/Noho – E_Manhattan

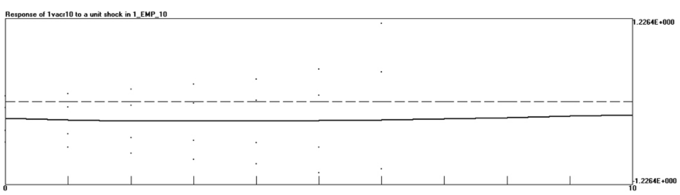


Figure 5-52: V_Hudson Sq – E_Hudson Sq

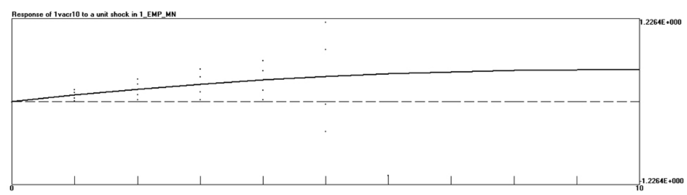


Figure 5-53:V_Hudson Sq – E_Manhattan

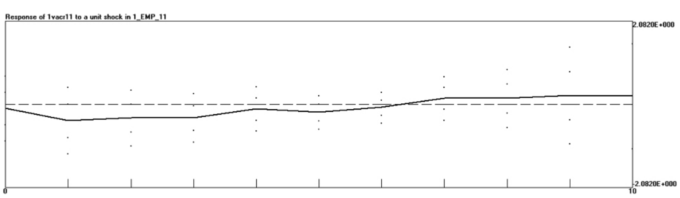


Figure 5-54: V_City Hall – E_City Hall

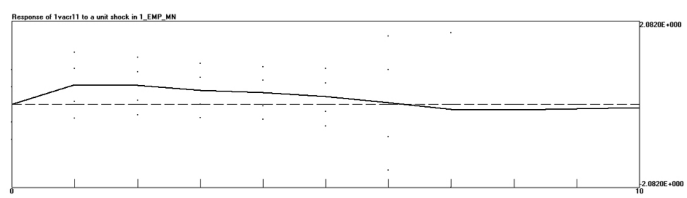


Figure 5-55: V_City Hall – E_Manhattan

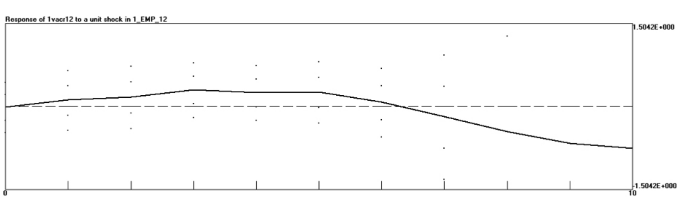


Figure 5-56: V_Broadway – E_Broadway

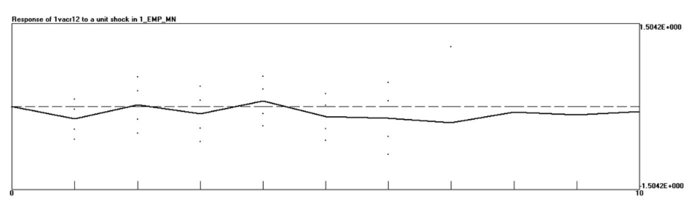


Figure 5-57: V_Broadway – E_Manhattan

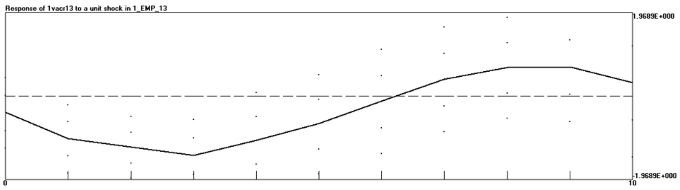


Figure 5-58: V_Insurance District – E_Insurance D.

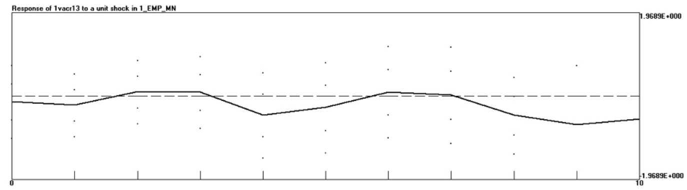


Figure 5-59: V_Insurance District – E_Manhattan

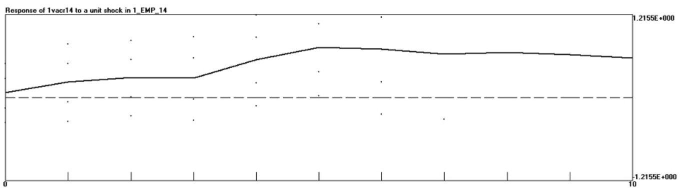


Figure 5-60: V_Wall Street – E_Wall Street

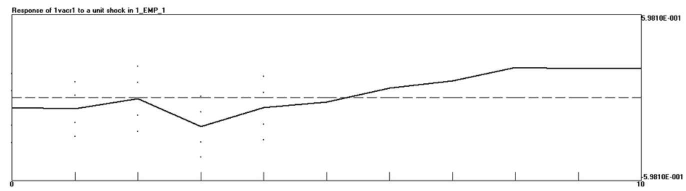


Figure 5-61: V_Wall Street – E_Manhattan

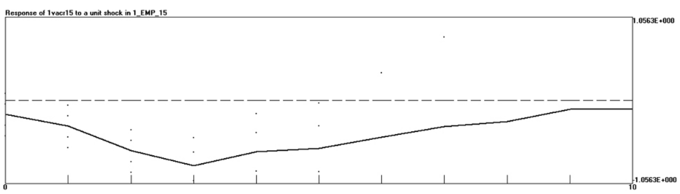


Figure 5-62: V_WTC/WFC – E_WTC/WFC

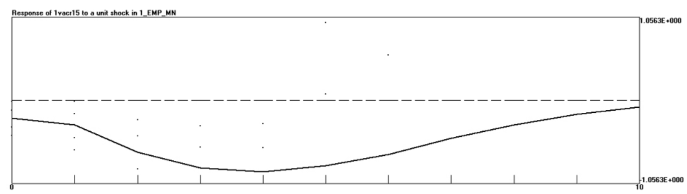


Figure 5-63: V_WTC/WFC – E_Manhattan

As outlined earlier, real estate investors seek out investments that produce returns commensurate with risk. To determine this relationship more accurately, beta measures were calculated as outlined in the previous section by comparing the volatility of submarket rental rates to aggregate national values of the US office market. Table 5-10 shows that Manhattan submarkets differ greatly regarding the volatility of rental rates between 1992 and 2004. The right hand column of this table reports Sharpe Ratios for each submarket. When taking into account average quarterly change in office rental rates (risk-adjusted to the interest rates of ten-year treasure bonds), some submarkets including Wall Street, the Insurance and Plaza districts as well as the World Trade Center area, exhibit an unfavorable relationship of risk and return during the study period. Clearly, all submarkets with negative signs yield rental income streams below the risk-free rate, in some cases combined with high volatility. The Midtown South area is interesting because it reaches by high Sharpe Ratios despite high volatility of rental rates, due to exceptionally strong growth rates in this subarea of Manhattan in the course of the last decade.

Table 5-10: Betas and Sharpe ratios of rental rates (reference of betas: U.S. average)

	beta (rental rates)	Sharpe Ratio
Midtown West, Avenue of the Americas	2.356	0.062
Midtown East, Plaza	1.973	-0.018
Grand Central	1.920	0.056
Penn/Garment	1.652	0.112
Penn Station	1.651	0.017
Madison Square	1.698	0.087
Gramercy/Flatiron	2.435	0.080
Chelsea	3.214	0.220
Soho/Noho	2.238	0.083
Hudson Sq	2.801	0.163
City Hall	1.777	0.035
Broadway	1.280	0.013
Insurance District	1.300	-0.071
Wall Street, Waterfront	1.236	-0.096
WTC/WFC	1.523	0.001
Manhattan	1.746	0.027
One-sample t-test	4.290	4.809
Significance (2-tailed)	0.001	0.000

A second fundamental component of risk in real estate income streams besides variations in rental rates is vacancy risk. Table 5-11 shows the beta measures of submarkets using national vacancy rates as a benchmark. The compound beta measure adds the beta values for rental and vacancy rates of each submarket. According to these beta values the highest investment risk as measured by combined volatility is found in the submarkets of Midtown South.

Based on one-sample t-tests, we reject the null hypothesis of both ***H5*** and ***k*** and accept the alternative hypotheses of significantly unequal beta and Sharpe ratio values in submarkets.

Table 5-11: Beta of vacancy rates and compound beta indices

	Beta	Compound beta index
Midtown West,		
Avenue of the Americas	1.21	3.57
Midtown East, Plaza	1.22	3.19
Grand Central	1.24	3.16
Penn/Garment	0.47	2.12
Penn Station	1.28	2.93
Madison Square	1.62	3.32
Gramercy/Flatiron	1.14	3.58
Chelsea	1.68	4.90
Soho/Noho	2.15	4.39
Hudson Sq	1.87	4.67
City Hall	1.71	3.48
Broadway	1.54	2.82
Insurance District	1.42	2.72
Wall Street, Waterfront	2.45	3.69
WTC/WFC	1.46	2.99
Manhattan	1.22	2.96
One-sample t-test	4.081	4.106
Significance (2-tailed)	0.001	0.001

5.4 Conclusions

The objective of this chapter was to test whether intracity portfolio diversification can be a feasible strategy for commercial real estate investors. More specifically, I tested whether office submarkets are driven by the same economic fundamentals in a highly diversified and functionally specialized market such as Manhattan. If this were the case, investors ought to be able to reduce the systematic risk of their income streams by investing in different submarkets within a city. Datasets used in this analysis included time-series information on the 15 submarkets of the Manhattan office market. The most important findings include:

- Both rent and vacancy levels differ significantly from one another across submarkets throughout the analyzed period.
- First-order differences of quarterly rental rate changes are relatively highly correlated among submarkets, whereas changes in vacancy rates are only weakly correlated in most cases. Thus, changes in rental rates appear to be interlinked more strongly across the market than vacancy changes, whose dynamics appear to be more localized.
- About half of all submarkets exhibit a clear cointegrating relationship of rental rates with the overall Manhattan market, thus limiting the prospects of intracity diversification benefits.
- While Manhattan rents do not Granger-cause submarket rents in the majority of cases, strong evidence is found that the overall Manhattan vacancy rate is generally a slightly better predictor of submarket rental rates than submarket vacancy rates themselves.
- When testing for office employment Granger-causing occupancy rates, the empirical evidence is mixed regarding the comparative relevance of submarket versus overall market conditions.
- Simulated responses to system shocks reveal that these shocks unfold with a lag of several quarters in the majority of examined submarkets. The results of the impulse response analysis do not provide conclusive evidence, however, whether overall market or local submarket conditions exert a greater influence on rent formation processes.

- Risk-reward measures such as the beta and Sharpe ratio are significantly different in submarkets, which is an indication of possible intracity diversification benefits.

Overall, the results of the empirical analysis do not warrant any strong conclusions in either direction as both micro-scale submarket and overall market conditions are found to have a significant impact on rental returns. Volatility and risk measures along with Granger causality and cointegration tests indicate that it may be possible to construct well-diversified real estate portfolios within a metropolitan office market. Despite this, the results suggest that sufficient diversification within a city is not achievable in all submarkets. A careful selection based on comparisons of underlying demand and supply patterns of submarkets is therefore required.

Directions for future research

The scope for future research in the area of integrating portfolio theory and disaggregated real estate market analysis is tremendous. The benefits to investors arising from better knowledge of how intracity property portfolios behave under various circumstances are obvious. Refinements of the models presented in this chapter are strongly recommended, not only in order to more accurately analyze the risk-return profiles associated with certain types of intracity portfolios but also to model the impact and decay of hierarchical variables on submarket performance. Further studies of a large number of metropolitan markets are needed in order to arrive at generalizable results and predictions.

6 The spatiotemporal stability of rent determinants: A hedonic panel analysis of the Manhattan office market

It has been frequently observed that office markets are subject to particularly high fluctuations in rents and vacancy levels, thus exposing real estate investors to considerable risk regarding expected future income streams. This study tries to analyze the determinants of office rents and their variability over time and across submarkets of a city in order to gain additional empirical insights into the rent price formation process.

6.1 Introduction

The determining factors of office rental rates are well researched and documented in a host of empirical studies. The existing research literature converges on a number of relevant factors to explain the variation in office rental rates such as age and size of the property as well as accessibility by various modes of transportation. The relevance of these factors appears to be almost universally acknowledged in the empirical literature. Commercial real estate markets, however, are characterized by spatial constraints, extensive product differentiation and information asymmetries that give rise to economically fragmented markets. A number of previous studies have demonstrated that such distinct submarkets do exist within urban office markets. The highly localized patterns of occupancy and rental rate determination found in these studies are indicative of market fragmentation. The question of market fragmentation is of immediate relevance for rental rate determinants. If markets are fragmented, office rents are highly likely to be determined by heterogeneous pricing schemes. Therefore, two identical properties would yield different rental rates if they are located in two different submarkets.

Similarly, the relative weight of rent determinants may change over time favoring buildings with certain features over others depending on the position in the real estate cycle. To date, very few studies have sought to systematically analyze the stability of office rent determinants. A closer examination of their spatio-temporal variability appears therefore warranted.

The remainder of this chapter is organized as follows. The first section reviews previous studies on spatial differentiation and cyclical fluctuations of commercial real estate markets. Next, the volatility of the Manhattan office market is examined using descriptive statistics. In a further step, I test if variables reflecting individual characteristics of buildings such as average age, density and accessibility are able to explain the variation in rental rates. Next, I test the significance of various characteristics in different phases of the market cycle using a hedonic model. The stability of parameters is analyzed cross-sectionally to test the independence of submarket observations. Instead of applying a classical fixed-effects model, hedonic regressions are estimated separately for each time period and submarket. In order to take the analysis one step further, full panel data models (Arellano-Bond models, random effects models) are estimated and the results of both the OLS estimation and the panel data analysis are discussed. Finally, I discuss the implications of the empirical results.

6.2 Relevant background

There exists a host of studies on the relevance of the intrametropolitan level-data in explaining the functional structure and development of office markets (Clapp 1980; Ihlanfeldt and Raper, 1990; Mills 1990; Hanink 1997; Bollinger et al. 1998). These studies, however, typically neglect the dynamic time-series aspect of the data. Conversely, most of the time-series research on real estate market cycles is aspatial in that it assumes a simultaneous adjustment of all intraurban locations to changing supply and demand relations at the metropolitan level. Hence, very few studies seek to combine cross-sectional and time series office market data at the intra-urban level (Mourouzi-Sivitanidou 2002).

Market efficiency

In general, all empirical models take one of the two possible positions: 1) The metropolitan area forms a unitary real estate market and 2) submarkets within a city are fragmented and in many cases out-of-sync with the overall development of a metropolitan area. The first research tradition bases its assumptions on urban location theory which implies that the relative price differences between intra-urban submarkets remain stable over time irrespective of cyclical oscillations in absolute prices (constant ratio hypothesis). This stability is ascribed to the high degree of intraurban mobility of office tenants, a high price elasticity of demand and possibilities to arbitrate in a situation of mispricing (DiPasquale and Wheaton 1996). Following this theory, a change in the relative price hierarchy of an urban market is only possible if major changes in either the physical attributes of particular locations or in transportation and communication technologies occur.

If, however, one assumes a less than fully efficient market, office buildings turn out not to be close substitutes for each other and information asymmetries cause the market to split up into several functional or spatial submarkets (Evans 1995). Empirical studies supporting this hypothesis also point out that the increasing functional specialization of spatial submarkets has resulted in additional economic fragmentation of markets (Sivitanidou 1995, 1996, Bollinger et al. 1998). In a further study of the housing market, Can (1996) examined the presence of spatial segmentation, as reflected in heterogeneous pricing schemes. She contends that if neighborhood effects enter as direct determinants of housing prices, such as a premium, then one can assume a uniform housing market under investigation, since there will be one price schedule. In contrast, if neighborhood differentials lead to varying attribute prices, one can assume the presence of independent price schedules, thus the existence of a spatially segmented market.

Do submarkets matter?

Numerous empirical studies have shown that an elaborate functional division of labor exists indeed between various submarkets in a metropolitan area. This functional specialization which may give rise to fragmented submarkets is reflected in the spatial organization patterns of office firms, such as front office – back office divisions and industry clusters in particular areas of a city (Shilton 1999, Schwartz 1992, Hanink 1997, Sivitanidou 1996). It is thus pertinent for commercial real estate analysis to devise methods that are capable of capturing the cross-sectional and time-series dynamics of rent determining factors. In this context, one promising approach is panel data analysis, which is applied in this study along with OLS hedonic regression models.

In their seminal study of the constancy of rent variations and the robustness of coefficient estimates, Glascock, Kim and Sirmans (1993) apply random effects and heteroskedastic autroregressive models. The authors find that the coefficients vary across time, location and class of building. They also conclude that random-effects models are superior over fixed-effects methodologies. The present study also applies a random-effects model and compares the results to the OLS regression analysis. In an empirical study of the Orlando office market, Archer (1997) found that there is at least limited evidence of a transitory and in some cases even permanent segmentation of submarkets. Moreover, he finds that segmentation of submarkets is continuous rather than divided by sharp boundaries. Slade (2000) estimated rent determinants during market decline and recovery but did not include any explicitly spatial variables in his study. Dolde and Tirtiroglu (1997) included submarkets in their analysis and found distinct patterns of temporal and spatial diffusion of real estate prices using GARCH-M methods. The present study revisits the question of spatiotemporal stability by analyzing the coefficients of rent determinants in a hedonic OLS and random-effects framework.

Rent determinants

The following section gives an overview of the most important rent determinants identified in previous empirical studies. Most of these studies apply a hedonic model to test the relative importance and order of these factors.

Vacancy levels are among the most important drivers of rental rate formation in the existing research literature. Sirmans, Sirmans and Benjamin (1989) find an the inverse relationship between vacancy rates and rents for apartment buildings and Sirmans and Guidry (1993) confirm these results for retail rents. Studies of office rent determinants, such as Clapp (1993) and Mills (1992) also find this variable to be highly significant in their respective empirical studies. In general, vacancy rates may be interpreted as a proxy for the general attractiveness of a building. This hypothetical relationship is transmitted in practice by the behavior of landlords who tend to lower asking rents in response to rising vacancy in a building in order to attract new tenants.

The *rentable building area* of a given property is a proxy for increased opportunity for face-to-face interaction within a large building. Clapp (1980) confirms the value of face-to-face contact in management decisions. More recent studies have shown that the value of face-to-face communication persists despite widespread availability of information and communication technology (Gat 1998). Apart from this, large tenants are typically willing to pay a rent premium for sizable units of contiguous office space (10,000 square feet and above) that enable their internal operations to run more smoothly than a situation with several scattered locations. Thus, Bollinger, Ihlanfeldt, and Bowes (1998) find average floor area to be a significant variable in determining rents in the Atlanta office market, most likely for the same reason.

Building age shows up significant in a host of studies on office market rent determinants (Bollinger, Ihlanfeldt and Bowes 1998, Slade 2000, Dunse et al 2003). In this study, building age is expressed as year built so that a more recent construction date has a positive impact on rental rates. In case a property underwent major renovation, the original construction date is replaced by the renovation completion date. The age of a building is typically a proxy for the quality of the technological infrastructure and adequacy of the floor layout.

The *number of stories* of a building represents more sophisticated elevator systems in tall buildings, the availability of panoramic views and a potential landmark status for very tall buildings. Shilton and Zaccaria (1994) found a convex relationship of building height in an earlier study of the Manhattan office market,

Amenities and in-house services are included in many hedonic studies of office rents. Ho et al (2005) report that functionality, services, access and circulation, presentation, management and overall amenities are the order of importance in assessing office building quality. The amenities variable used in this study is a compound measure of the availability of up to 34 building amenities, including banking, mailing, medical, retail and hotel facilities in the building as well as onsite facility management, availability of large trading floors, showrooms, courtyards, fitness clubs and atriums, subway access on premises, waterfront location, and onsite management. It is expected that tenants pay a premium for convenient access to these amenities which is confirmed in the significance levels of this variable throughout the estimated period.

Turning to location-specific price determinants, a number of variables were included in the hedonic model used in this study. The importance of spatial variables in hedonic modeling is almost universally acknowledged in the literature. The broad variety and potential cross-influence of spatial variables poses some intricate methodological problems, however. The goal of hedonic modeling should be to maximize the efficiency of the estimators while minimizing information loss due to elimination of important variables in an effort to reduce multicollinearity. In an effort to categorize spatial variables, Can (1996) proposed to distinguish between adjacency and neighborhood effects. Adjacency effects which are externalities and spillover effects due to the geographic position of a property relative to other points of reference (i.e. other properties, transportation infrastructure) can be captured by geostatistical methods and various accessibility measures. Neighborhood effects, which are distinct perceived or observable characteristics of an area, also have an impact upon property prices and rental rates although their contribution to price formation is more difficult to measure.

Access to commercial centers is included in various forms in hedonic studies of office rents (see Sivitanidou 1995). In a study of Atlanta office rents, Bollinger, Ihlanfeldt and Bowes (1998) find that proximity to concentrations of office workers exert a positive impact on rent levels. In general, this variable reflects ease of access to clients and business services in the immediate vicinity of the building. In the present study, this variable is operationalized as the average distance to the 20 closest office buildings and is calculated with a nearest neighbor algorithm in a Geographic Information System. The inverse of the distances calculated for each building distance pair is weighted by the square footage of the neighboring building and entered into the model. Therefore a positive sign is expected for the coefficients to the extent that larger square footage and shorter distances yield higher values. Similarly, the amount of office space located within 1500 feet of an office building indicates whether a building is located in a major office cluster. Therefore, a positive impact of this variable is expected. Rosenthal and Strange (2001) found evidence that such knowledge spillovers operate almost exclusively at the small-scale level. The authors conclude from their observations that such spillovers evaporate rapidly across space.

The *distance to the nearest subway station* measures ease of access to public transit network. Cervero and Duncan (2002) found that office properties located close to a public transit public transit stations command higher prices per unit in the order of 120 percent for commercial land in a business district within a quarter mile of a commuter rail station. Although very few office buildings in Manhattan are located outside a radius of this size, this variable is included to test whether even smaller differences in average distance to mass transit stations have an impact on rental rates.

Finally, the *latitude* and *longitude* coordinates of a property are included in various hedonic models. While not meaningful per se, these variables are potentially capable of capturing spatial effects not operationalized in the other variables of the model as the coefficients of these variables are allowed to vary parametrically over space. This approach was developed and applied in a number of previous studies such as Can and Megbolugbe (1997), Casetti (1997) and Clapp (2003, 2004).

6.3 Methodology

In the first step of the empirical analysis, some basic descriptive measures are used to investigate volatility and cross-sectional variability of rental rates. To explore potential lags in the adjustment of submarkets to changing market conditions, cross-correlation measures will be examined.

Hedonic analysis

Hedonic regression modeling has become the standard methodology for examining price determinants in real estate research. The quintessential log-linear hedonic rent model is specified in the following form:

$$\ln R_i = \alpha_i + \beta x_i + \phi Z_i + \varepsilon_i \tag{1}$$

Where R_i is asking rent per square foot in dollars for a given office building, x_i is a vector of the natural log of several explanatory locational and physical characteristics, β and ϕ are the respective vectors of parameters to be estimated. Z_i is a vector of time-related variables and ε_i is a random error and stochastic disturbance term that is expected to take the form of a normal distribution with a mean of zero and a variance of σ_e^2. The hedonic weights assigned to each variable are equivalent to this characteristic's overall contribution to the rental price (Rosen 1984).

Rent determinants can be roughly grouped into neighborhood/building-specific and accessibility/location factors (see for example Des Rosiers et al 2000) For the purpose of this study, I specify two hedonic models. While Model I captures building-specific factors, Model II contains locational attributes. The final specification of Model I used to estimate the empirical results reported below is:

(Model I) $$\ln R_i = \alpha_i + \beta_1 \ln V_i + \beta_2 \ln B_i + \beta_3 \ln T_i + \beta_4 \ln S_i + \beta_5 \ln A_i + \varepsilon_i \qquad (2)$$

where V_i represents the vacancy rate of a building, B_i is the rentable building area in square feet, T_i indicates the year of construction or major renovation, S_i is the number of stories and A_i is a vector of in-house amenities. Model II was specified as follows:

(Model II) $$\ln R_i = \alpha_i + \beta_6 \ln D_i + \beta_7 \ln F_i + \beta_8 \ln M_i + \beta_9 \ln N_i + \beta_{10} \ln W_i + \varepsilon_i \qquad (3)$$

where D_i represents the inverse of the distance of the twenty office buildings with the shortest distance to the property in question (weighted by their square footage), F_i is the amount of square feet of office space within a distance of 1500 feet, M_i is the distance to the nearest subway station and N_i and W_i are the longitude and latitude coordinates of the property.

To detect differences in the weight of parameter estimates across submarkets, a standard fixed effects model can be estimated (Hsiao 2003):

$$\ln R_{it} = \alpha_1 \delta_{1it} + \alpha_2 \delta_{2it} + \ldots \alpha_n \delta_{nit} + \beta x_i + \varepsilon_i \qquad (4)$$

In this model, the incidental parameters α_i are fixed constants and δ_{iit} is a submarket-specific indicator (dummy variable). This Least Squares Dummy Variable (LSDV) model can be used to detect both longitudinal and cross-sectional heterogeneity. The drawback of the LSDV model is, however, that it only allows intercepts to differ across space while assuming constant variable coefficients. Thus, instead of estimating a single LSDV model, it is more appropriate to estimate the full hedonic model separately for each submarket and time period when investigating the time-series cross-sectional variability of rent determinants. Alternatively, a full random-effect panel model can be estimated as outlined in the following section.

Random-effects panel data estimation

In order to expand the scope of the hedonic framework by simultaneously analyzing the longitudinal and cross-sectional components of the data, a panel regression model is introduced. The fixed-effects model as outlined in the previous section assumes that differences across units of observation are captured by differences in the constant term.

$$\ln R_{it} = \beta x_{it} + \alpha_i + \varepsilon_{it} \qquad (5)$$

A fixed effects model estimation is limited, however, by the fact that this model assumes the intercepts α_i are fixed, estimable parameters so that individual effects cannot be captured with this approach. The random effects model assumes that the observations are random draws from the same distribution and therefore part of a composite error term of the following form:

$$\ln R_{it} = \beta x_{it} + \alpha_i + \mu_i + \varepsilon_{it} \qquad (6)$$

where u_i is a group-specific random element which captures unobserved property-specific factors. In the random effects model all three components (intercept, time-specific and cross-sectional error components) are assumed random and not fixed. The prerequisite for applying a random-effects model is, however, that this unobserved heterogeneity be normally distributed and uncorrelated with the explanatory variables X_{it}. The main advantage of this approach is that the number of parameters to be estimated is substantially reduced compared to a fixed-effects approach or any repeated-measurement sequential estimation. Especially when there is serial correlation of the composite error term, the random effects GLS approach yields superior results compared to the OLS and fixed effects approach.

In a time-series estimation of rental rate determinants, it appears reasonable to assume that one of the more important determinants is the rental rate of the past period. Inclusion of lagged values of the dependent variable is problematic, however, because these values are typically correlated with the residuals. Therefore, the lagged dependent variable must be instrumented. Arellano and Bond (1991) and Arellano and Bover (1995) developed an estimation approach that solves this problem.

Parameters are estimated by assuming that future error terms do not affect current values of the explanatory variables and that the error term ε_{it} is serially uncorrelated. It is also assumed that changes in the explanatory variables are uncorrelated with the unobserved property-specific and/or subarea-specific effects. This set of assumptions generates moment conditions that allow estimation of the relevant parameters. The instruments corresponding to these moment conditions are appropriately lagged values of both levels and differences of the explanatory and dependent variables. A frequent problem with this type of estimation is that the moment conditions tend to overidentify the regression model, which can be diagnosed using the Sargan test for overidentifying restrictions. A second important diagnostic test is the Arellano-Bond test for autocovariance of the residuals. While the presence of first-order autocovariance does not preclude that the estimators of the hedonic model are consistent and efficient, the presence of second-order autocovariance would be a clear sign of misspecification (Arellano-Bond 1991, 281-2).

Testing for longitudinal and cross-sectional structural change

Based on Slade's (2000) proposition that market participants value physical, rental and locational characteristics of a building differently during distinct phases of the market cycle, I estimate the parameters of both model specifications for each quarter from 1999 through 2004 individually and compare the resulting parameter estimates over time. Each of the quarterly estimates is assigned to one of three periods in the market cycle that occurred during the observed period: (1) market recovery, (2) peak, and (3) decline. I then test for cross-sectional parameter stability of the hedonic estimates across submarkets in the next step. Under the assumption of an efficient market with a city-wide unified pricing scheme, the expectation is that the coefficients of the hedonic characteristics be equal in all areas. This is expressed by the null hypothesis:

H_0: $\beta_1 = \beta_{1r} = \beta_{1p} = \beta_{1d}$;

$\beta_2 = \beta_{2r} = \beta_{2p} = \beta_{2r}$;

…

$\beta_n = \beta_{nr} = \beta_{np} = \beta_{nd}$

against the alternative

H_a: H_0 is not true

In this notation the coefficients βn are the parameter estimates of a particular variable with the second subscript denoting the respective phase of the market cycle (r= recovery, p=peak, d=decline). A Chow test can be applied to determine whether the set of regression parameters is equal across groups (Chow 1960):

$$F_{CHOW} = \frac{(RSS_p - RSS_i - RSS_j)/(R-1)}{(RSS_i - RSS_j)/(n+m-2(k+1))} \tag{7}$$

where RSS_p is the residual sum of squares of the pooled regression model, i and j are the two subsamples to be compared, and n and m are the number of observations in the subsamples i and j respectively. If the resulting F statistic is significant, we discard the null hypothesis of structural stability of hedonic regression parameters and accept the alternative hypothesis of structural heterogeneity.

In the cross-sectional analysis, the hedonic regressions for each of the three quality classes (A,B,C) are estimated separately and the results are compared to one another. Hence, accepting the alternative hypothesis would provide evidence of heterogeneous pricing schemes. Besides the Chow test, the Tiao-Goldberger F-statistic is computed to test for individual parameter stability.

The Tiao-Goldberger test (1962) is an F-test of the following form:

$$F_{TG} = \frac{\sum_{j=1}^{L}(\hat{b}_{ij} - \overline{b}_j)^2}{\sum_{j=1}^{L} SSR_j} \times \frac{\sum_{j=1}^{L}(T_j - K_j)}{L-1} \qquad (8)$$

with

$$\overline{b} = \frac{\sum_{j=1}^{L}\frac{\hat{b}_{ij}}{P_{ij}}}{\sum_{j=1}^{L}\frac{1}{P_{ij}}}$$

where L is the number of models, $\hat{b}_{ij}$ are the OLS estimates of the ith parameter in the jth independent model, P_{ij} is the diagonal element for the ith parameter of $(X'X)_j$-1, SSR_j the sum of squared residuals for the jth model; T_j the number of observations used to estimate the jth model and K_j the number of parameters in the jth model. Alternatively, the Chow and Tiao-Goldberger test statistics can be calculated by including an interaction term in a General Linear Model (GLM) framework. The GLM pools the sums of squares and degrees of freedom for submarkets and submarkets times the independent variable (*X*) in question and reports the F-test value. Computed separately for each of the variables, the resulting F test values indicate parameter stability of each of the variables used in the regression.

In the next step, hypothesis test outlined above is applied to time-series observations. Under the assumption of an efficient market with a unified pricing scheme, we expect the coefficients of the hedonic characteristics to be equal in all time periods. We reject the null hypothesis of equal coefficients if the test statistics reveal that the coefficients differ significantly at various points of the market cycle.

Defining the phases of the market cycle

In order to test the implications of quarterly parameter estimates for the cyclical development of the market, it is necessary to first identify the phases and turning points of the market cycle. This is typically achieved by estimating a general trend around which cyclical fluctuations occur. There exist several econometric tools, most notably the Hodrick-Prescott filter, for detrending time series data. The present study does not follow this methodological strand of defining turning phases in that no effort is made to determine time series trends and/or hypothetical long-term equilibria. Instead, phases are defined based on the sign and strength of rental rate growth rates over a minimum duration of four quarters. Other applications of this method can be found in Mintz (1969), Watson (1994), Artis, Kontolemis and Osborn (1997), Mueller (1999) and more recently in Krystaloggiani, Matysiak and Tsolacos (2004).

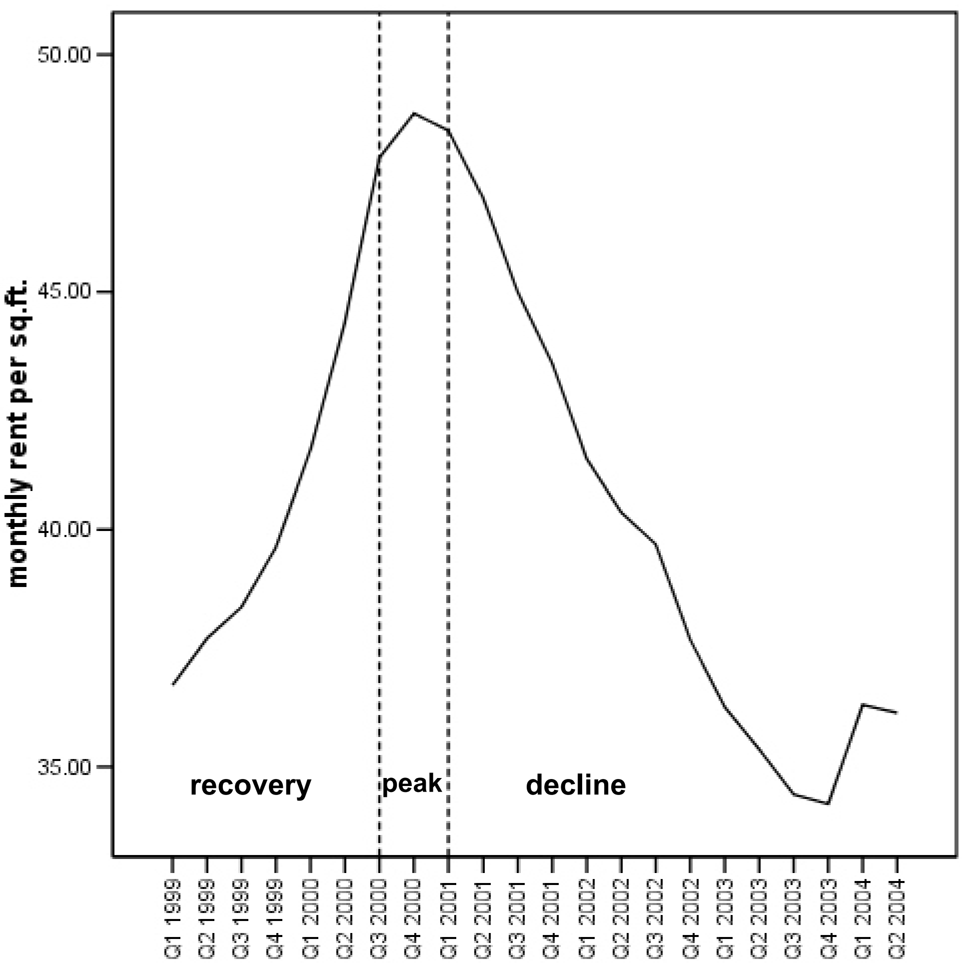
The time series data analyzed in this study –albeit rather short for detecting generalizable patterns- lends itself particularly well for the study of real estate market cycles since the individual phases are clearly discernable with practically no ambiguous periods or 'noisy' oscillations. Consequently, no smoothing methods have to be applied prior to defining the start and end points of cycle phases. The five-year rental rate time series of Manhattan exhibits three distinct phases of the cycle: recovery, peak and decline. Each dataset in the quarterly series is assigned to one of the three phases that occurred within the observed time span by applying three simple rules.

If $\Delta R_{t-2} \wedge \Delta R_{t-1} \wedge \Delta R_t > 0$, Phase = recovery

If $\Delta R_{t-2} \wedge \Delta R_{t-1} \wedge \Delta R_t < 0$, Phase = decline

If $R_{t-1} = \max(3) \wedge R_t = \max \wedge R_{t+1}(\max(3)$, Phase = peak

Put differently, periods of positive growth of rental rates for more than three quarters are identified as part of the recovery phase while negative rental rate growth for more than three quarters is considered to mark the decline phase of the market. The peak phase includes the three consecutive quarters with the highest absolute rental rates in the time series. Additionally, the maximum point is also defined as the turning point from positive growth (recovery) to contraction (decline) to make sure that the sequence of the phases is recovery-peak-decline. Figure 6-1 contains an illustration of the timeline of the three cycles.



Recovery	Q1-1999 through Q2-2000
Peak	Q3-2000 through Q1-2001
Decline	Q2-20001 through Q2-2004

Figure 6-1: Phases of the Manhattan office market cycle

6.4 Data issues

The empirical estimation of the model is drawn from the CoStar property information system which covers the Manhattan office market almost completely on a building-to-building basis. The time increment used in this model is one quarter, which is different from most other modeling studies which use either annual or semi-annual data. Quarterly data are typically subject to greater fluctuations than annual or semi-annual averages. The longer time-intervals eliminate a large part of the variation of more fine-grained data which contains important information on dynamic adjustment mechanisms of the market. Although the time-series of building data was relatively short (22 quarterly observations in 6 years), three distinct phases of the real estate market cycle could be identified during this period. To put this relatively short period in perspective, the two subsequent figures demonstrate the longer term development of rental rates in Manhattan and its major subdivisions. Figure 6-2 illustrates the trajectory of quarterly Manhattan rental rates from 1980 through 2004. Figure 6-3 shows rental rates broken down by subarea from 1992 through 2004.

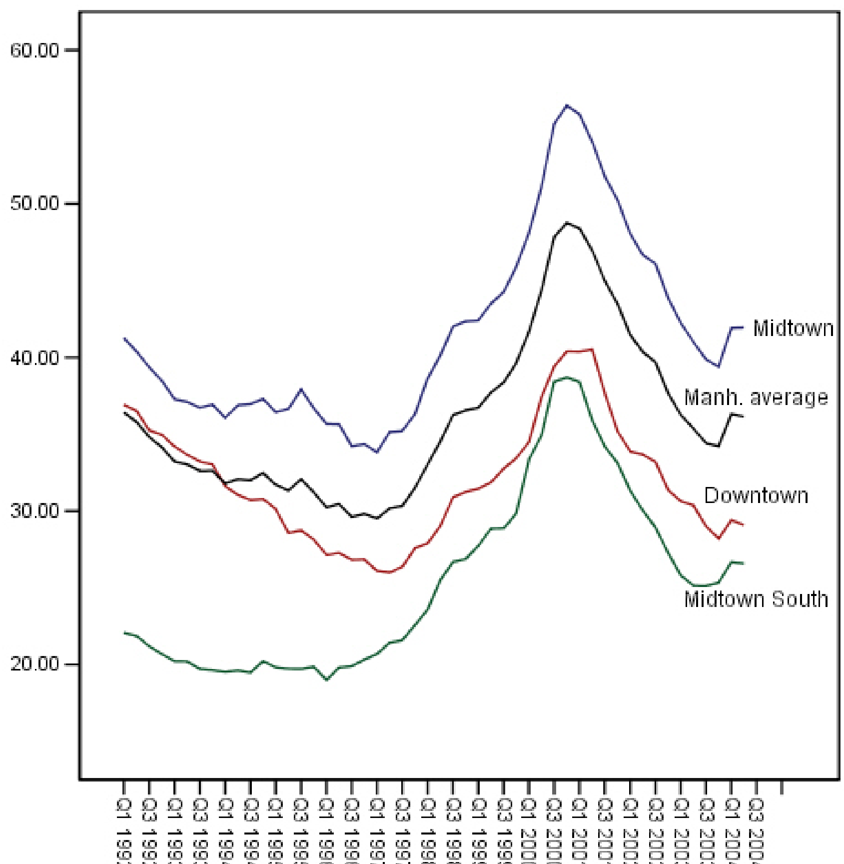


Figure 6-2: Average rental rates in the analyzed period by subarea (in constant dollars).

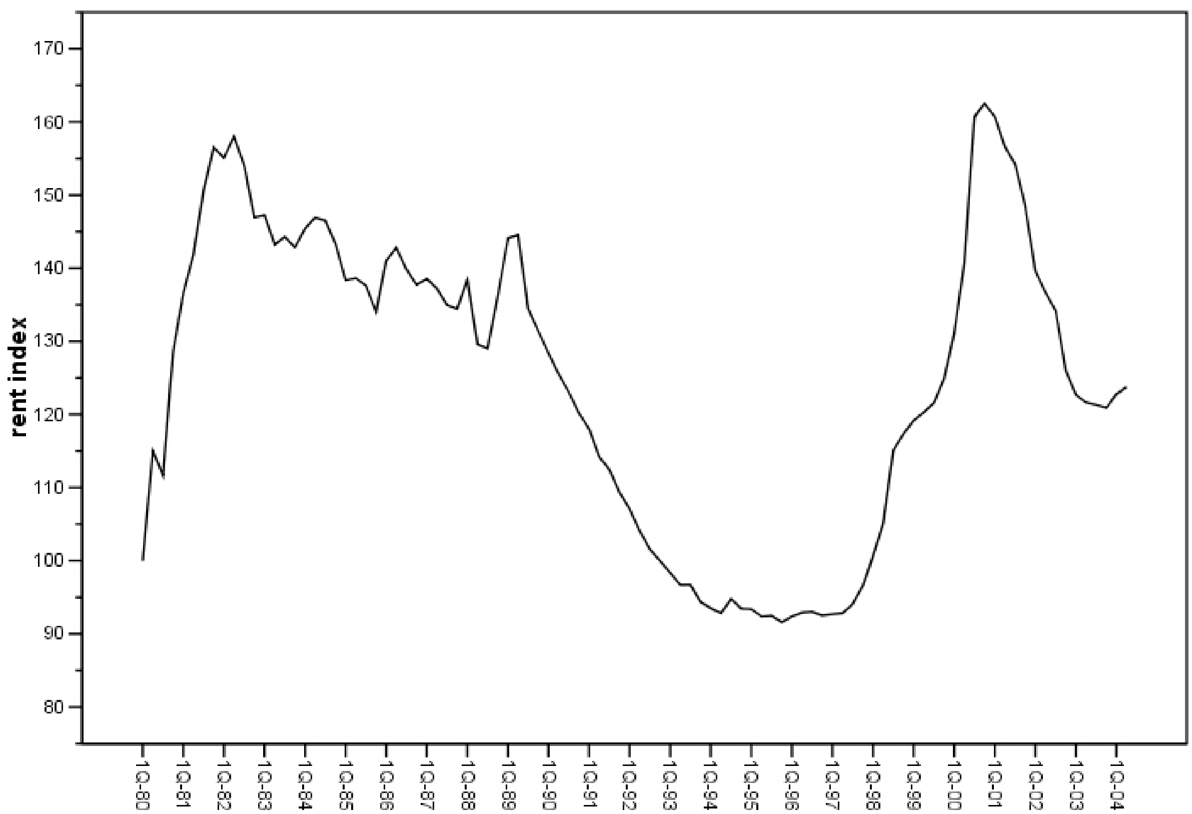


Figure 6-3: Longer-term index of Manhattan real rental rates (Q1-1980=100)
Data: Real Estate Board of New York, Grubb & Ellis

Inventory, occupancy and vacancy data

Quarterly building data were obtained from CoStar spanning a period of about six years. The sample contains data on location, building area, story height, asking rents, vacancy rates, sublet space as well as other building characteristics. The entire sample contains 492 million square feet of office space and nearly 3,000 Manhattan office buildings. While this database contains practically all Manhattan office buildings with more than 10,000 square feet, only 870 to 950 buildings (depending on the time period and number of variables included in the specification) of the full sample could be used for the purpose of the hedonic analysis due to missing data for most of the smaller office buildings. While six years or 16 quarterly observations constitute a rather short time series, three typical phases of the real estate market cycle are contained within them. Moreover, longer time-series hedonics typically face the problem of controlling for the effect of new product being introduced into the market while the obsolete stock is being phased out (Hulten

2003). While this heterogeneity of the analyzed sample potentially hampers comparability over time, changes in the composition of office inventory due to new construction and demolition are below one percent and thus not critical for the longitudinal comparability of parameter estimates.

Rental data

The data on rent used in this study are asking rents per square foot aggregated from a large sample of buildings in the CoStar property information system. Asking rents, as opposed to actual rents which are based on lease transactions, are known to be inaccurate. Assuming that the error is systematic but not fixed, the differences between asking and actual rents vary with the position in the market cycle. For instance, it can be assumed that the difference between asking rents and actual rents will be highest immediately at the outset of a recession. This is due to the fact that landlords are reluctant to lower asking rents after a prolonged period of growth but will instead concede free rent periods and other incentives to prospective tenants. Only when market conditions have deteriorated considerably and vacant space becomes a serious problem, landlords will adaptively discount asking rents in order to attract tenants. While rents based on actual leases would be preferable, they are generally not available to researchers and pose additional problems, such as the adequate incorporation of non-monetary or non-rent-related incentives in the lease. In the absence of actual rents, asking rents are being used in this study despite their known inaccuracies and shortcomings. The asking rents and all other monetary variables are adjusted for inflation with the implicit price deflator as applied in the National Income and Product Accounts (NIPA).

Accessibility data

A number of accessibility measures were calculated to capture spatial variables at the submarket and building level. All buildings in the database provided by CoStar were geocoded using a Geographic Information System. After assigning x and y coordinates to each building, the distance between each building and the closest subway station was calculated (see Figure 6-4 for a visualization of the geocoded buildings). As a measure of regional accessibility, the distance from each building to the three major public transit hubs Grand Central Station, Penn Station and the World Trade Center PATH Station was calculated. Moreover, the distance from each office building to the closest office buildings was calculated using a nearest neighbor algorithm. To capture the opportunity of face-to-face interaction within walking distance, the amount of square feet of office space within a distance of 1500 feet was calculated. Instead of using straight line distances, so-called Manhattan distances were used which take into account the grid structure of the case study area.

Class A/B/C categorization

Although the A,B,C distinction of buildings is mainly used in industry market reports to describe the development of the three quality segments of the markets, it also proved to be useful and significant in a number of previous academic studies. Archer and Smith (2003) present a model of industry economies of scale for Class A space and tenants and introduce a working definition whereby Class A office space is characterized by a lesser degree of sensitivity to rental expenses and a higher relevance of image and prestige factors of tenants compared to the Class B and C categories. CoStar (2005) defines Class A as investment-grade properties that are well located and provide efficient tenant layouts and floor plans, have above-average maintenance and management as well as the best quality materials and workmanship in their trim and interior fittings. Class B buildings offer functional space without special attractions, and have ordinary design, if new or fairly new; good to excellent design if an older non-landmark building. These buildings typically have average to good maintenance, management and tenants. Class C comprises older buildings that offer basic space and command lower rents or sale prices. Such buildings typically have below-average maintenance and management, and could have mixed or low tenant prestige, inferior elevators, and/or mechanical/electrical systems. These buildings lack prestige and must depend chiefly on a lower price to attract tenants and investors.

Figure 6-4: Spatial distribution of office space in Manhattan (snapshot of geocoded properties). Data: CoStar Group

Study area

The Manhattan office market is characterized by a number of distinctive features. It is by far the largest agglomeration of office space in the United States - more than twice as large as Chicago. Second, growth rates of office employment and demand for office space are on average low compared to younger markets in Southern and Western regions. Nevertheless, Manhattan exhibits a unique concentration of financial services firms and is one of the most important financial centers in the world. About 80 percent of New York City's office space is concentrated in Manhattan. The market suffered a significant shock by the destruction of 14.5 million square feet of office space on September 11, 2001.

Despite these unique features, Manhattan is an ideal case study for exploring submarket fragmentation and small-scale locational dynamics. It has a large number of specialized sub-centers such as the Wall Street area and the Insurance District with large industry clusters. Regarding the inventory of office buildings, the market exhibits a great degree of heterogeneity regarding the vintage, size, technology and amenities of buildings. Because of the high density and maturity of Manhattan, submarkets with distinctly different supply and demand characteristics can be found within a relatively short distance from one another.

For the purpose of real estate market studies, Manhattan is commonly divided into three subareas (Midtown Core, Midtown South and Downtown). Each of these subareas is further subdivided into submarket areas.

6.5 Empirical Results

In the first step, hedonic regressions are estimated based on the Manhattan office property database described in the previous section. Table 6-1 shows descriptives of the variables included in the final specifications. As mentioned above, two separate models were estimated in this study. A log-linear specification was found to perform best in all regressions reported here. Table 6-2 shows the results of the quarterly estimation for the building-specific model (Model I). As expected, vacancy levels of a building have a negative impact on rents although this variable does not reach the desired significance level in all cases. In contrast, the rentable area of a building exerts a positive impact on rent levels. The variable 'year built', which reflects either the construction date or year of major renovation shows a particularly strong impact and is highly significant. Although building age was reported as a relevant factor in most hedonic studies, it is remarkable that it is also valid in the Manhattan context with its relatively mature inventory of office buildings (median age of 85 years). Building amenities such as in-house retail facilities, facility management, availability of large trading floors, showrooms, courtyards, fitness clubs and atriums and subway access on premises. The expectation that tenants pay a premium for the availability of these amenities is confirmed in the present study, particularly in the more recent periods.

Table 6-1: Descriptive statistics of the Manhattan office building database
Data: CoStar Group

		Average rent	*Building area*	*Year built*	*Year renovated*	*No. of stories*	*Typical floor size*
Midtown	*Mean*	37.5	196,977	1932	1989	15.0	10,459
(n=594)	*Median*	35.8	66,000	1925	1990	12.0	6,000
	Std. Dev.	19.5	352,236	25.0	13.3	12.6	12,382
Midtown South	*Mean*	27.3	87,941	1914	1988	8.3	9,057
(n=332)	*Median*	26.0	42,550	1911	1990	7.0	5,200
	Std. Dev.	7.7	183,011	18.9	15.6	4.9	13,598
Downtown	*Mean*	30.0	242,603	1924	1985	14.0	12,196
(n=147)	*Median*	29.0	45,000	1920	1986	7.0	6,643
	Std. Deviation	7.6	436,319	29.7	14.9	12.8	14,621
Total	*Mean*	33.3	165,746	1923	1988	12.5	10,227
(n=1,073)	*Median*	30.0	53,508	1920	1990	9.0	5,750
	Std. Dev.	16.1	325,076	25.3	14.4	11.0	13,195

The results of the location-specific model (Model II) are reported in Table 6-3. The inverse of the weighted average distance of the 20 closest office buildings proves significant in this estimation as well as the number of square feet of office space located within 1500 feet. Distance to a subway station is also confirmed to be relevant in rental rate determination. Finally, latitude and longitude coordinates, proxying spatial effects not operationalized in the other variables of the model are also significant in the hedonic regression. The negative coefficient of the latitude variable indicates that average rental rates decrease the further south a property is located in Manhattan. While this is a highly generalized finding, it is in line with observations that office rents are highest in the northern section of Midtown while buildings in Midtown South and Downtown command lower rents on average. Similarly, the longitude variable also has a negative sign which entails that buildings located in the western part of Manhattan have lower rents than those located in the eastern part. While office locations on the western sections of Midtown Manhattan have experienced positive dynamics in recent years, the overall prime office locations are still to be found in the largest office cluster around the Plaza District located in the northeastern section of Midtown Manhattan.

Table 6-2: Hedonic regression model I: property-specific price determinants (t-values in parentheses)

	Q1 1999	Q2 1999	Q3 1999	Q4 1999	Q1 2000	Q2 2000	Q3 2000	Q4 2000	Q1 2001	Q2 2001	Q3 2001	Q4 2001
Intercept	-75.466 (-6.647)	-83.207 (-8.053)	-77.820 (-7.848)	-70.762 (-7.376)	-62.077 (-7.658)	-62.492 (-7.275)	-57.725 (-6.412)	-53.817 (-5.761)	-56.055 (-6.308)	-52.422 (-5.699)	-69.820 (-7.046)	-64.763 (-7.816)
Ln vacancy	-.025 (-1.579)	-.024 (-1.600)	-.027 (-1.878)	-.027 (-1.958)	-.021 (-1.859)	-.015 (-1.259)	-.008 (-.681)	-.018 (1.428)	-.003 (.241)	-.012 (.900)	-.013 (.965)	-.021 (-1.878)
Ln building area	.065 (2.538)	.051 (2.142)	.054 (2.307)	.082 (3.643)	.076 (3.919)	.035 (1.755)	.039 (1.851)	.042 (1.930)	.048 (2.446)	.054 (2.655)	.032 (1.474)	.060 (3.294)
Ln year built	10.231 (6.772)	11.302 (8.222)	10.593 (8.029)	9.644 (7.553)	8.498 (7.869)	8.618 (7.538)	7.986 (6.669)	7.464 (6.007)	7.775 (6.575)	7.276 (5.946)	9.587 (7.272)	8.876 (8.037)
Ln stories	.184 (3.454)	.140 (2.941)	.133 (2.902)	.104 (2.333)	.114 (3.155)	.144 (3.876)	.176 (4.441)	.196 (4.746)	.129 (3.383)	.150 (3.785)	.182 (4.394)	.159 (4.920)
Ln amenities	.063 (1.180)	.051 (1.021)	.064 (1.328)	-.017 (-.363)	.050 (1.165)	.049 (1.194)	-.011 (-1.277)	-.011 (-.254)	-.017 (-.437)	-.027 (-.643)	.032 (.753)	.067 (1.783)
Adjusted R^2	.375	.365	.364	.361	.361	.297	.304	.297	.284	.285	.333	.372

	Q1 2002	Q2 2002	Q3 2002	Q4 2002	Q1 2003	Q2 2003	Q3 2003	Q4 2003	Q1 2004	Q2 2004
Intercept	-69.999 (-8.416)	-64.899 (-8.130)	-65.103 (-7.648)	-64.956 (-7.727)	-73.074 (-8.819)	-75.443 (-9.546)	-76.143 (-10.178)	-76.143 (-10.086)	-74.748 (-9.585)	-71.229 (-9.400)
Ln vacancy	-.015 (-1.387)	-.018 (-1.685)	-.013 (-1.271)	-.013 (-1.106)	-.016 (-1.404)	-.009 (-.825)	-.011 (-1.010)	-0.011 (-1.156)	-0.012 (-1.367)	-0.015 (-.887)
Ln building area	.052 (2.849)	.060 (3.389)	.041 (2.243)	.042 (2.304)	.042 (2.342)	.038 (2.164)	.038 (2.317)	0.038 (2.248)	0.037 (1.935)	0.032 (1.732)
Ln year built	9.570 (8.632)	8.876 (8.343)	8.917 (7.860)	8.902 (7.947)	9.974 (9.033)	10.287 (9.765)	10.384 (10.415)	10.384 (10.327)	10.202 (9.833)	9.742 (9.652)
Ln stories	.163 (5.020)	.179 (5.707)	.215 (6.366)	.177 (5.337)	.174 (5.319)	.174 (5.522)	.155 (5.176)	0.155 (5.032)	0.149 (5.532)	0.164 (5.649)
Ln amenities	.074 (1.927)	.078 (2.136)	.060 (1.580)	.092 (2.378)	.088 (2.322)	.098 (2.624)	.115 (3.199)	0.115 (3.532)	0.127 (3.235)	0.117 (3.606)
Adjusted R^2	.371	.405	.401	.362	.392	.396	.408	.408	.396	.393

Table 6-3: Hedonic regression model II: location-specific price determinants (t-values in parentheses)

	Q1 1999	Q2 1999	Q3 1999	Q4 1999	Q1 2000	Q2 2000	Q3 2000	Q4 2000	Q1 2001	Q2 2001	Q3 2001
Intercept	13542.529 (14.385)	12452.781 (13.416)	11584.101 (12.120)	10472.02 (11.180)	9742.249 (11.757)	8588.324 (10.189)	6669.696 (8.029)	7335.746 (8.998)	7867.670 (10.408)	8644.790 (11.196)	8616.976 (10.675)
Ln distance 20 buildings	.236 (5.042)	.225 (4.928)	.234 (5.090)	.251 (5.426)	.183 (4.547)	.240 (5.924)	.179 (4.505)	.185 (4.784)	.188 (5.198)	.159 (4.287)	.210 (5.177)
Ln space 1500 feet	.130 (4.900)	.135 (5.229)	.137 (5.237)	.126 (4.796)	.104 (4.507)	.058 (2.499)	.054 (2.370)	.042 (1.887)	.044 (2.093)	.058 (2.694)	.101 (4.356)
Ln distance subway	-.103 (-5.210)	-.116 (-5.989)	-.090 (-4.495)	-.097 (-4.824)	-.084 (-4.855)	-.077 (-4.368)	-.059 (-3.430)	-.070 (-4.075)	-.083 (-5.197)	-.081 (-4.978)	-.067 (-3.889)
Ln longitude	-2619.724 (-15.549)	-2422.694 (-14.584)	-2269.622 (-13.271)	-2069.593 (-12.352)	-1939.261 (-13.077)	-1740.284 (-11.534)	-1401.444 (-9.424)	-1515.498 (-10.386)	-1614.531 (-11.937)	-1754.600 (-12.699)	-1757.736 (-12.186)
Ln latitude	-611.613 (-9.633)	-546.380 (-8.725)	-489.820 (-7.580)	-422.035 (-6.651)	-376.260 (-6.722)	-295.910 (-5.200)	-171.616 (-3.060)	-218.802 (-3.968)	-247.303 (-4.829)	-294.320 (-5.615)	-283.495 (-5.086)
Adjusted R2	.486	.462	.422	.419	.412	.374	.326	.337	.387	.388	.407

	Q4 2001	Q1 2002	Q2 2002	Q3 2002	Q4 2002	Q1 2003	Q2 2003	Q3 2003	Q4 2003	Q1 2004	Q2 2004
Intercept	9133.281 (11.689)	9710.602 (11.762)	10014.96 1 (12.724)	9918.972 (12.065)	9858.484 (11.760)	10125.224 (12.170)	9361.697 (11.722)	8661.810 (11.134)	8089.104 (10.712)	8292.458 (11.087)	8081.672 (10.735)
Ln distance 20 buildings	.242 (6.157)	.248 (5.955)	.285 (7.106)	.224 (5.335)	.170 (3.950)	.169 (3.968)	.209 (5.113)	.185 (4.618)	.197 (5.162)	.204 (5.395)	.200 (5.259)
Ln space 1500 feet	.092 (4.080)	.077 (3.294)	.086 (3.831)	.113 (4.798)	.124 (5.162)	.123 (5.169)	.106 (4.632)	.113 (5.025)	.107 (4.947)	.099 (4.574)	.106 (4.897)
Ln distance subway	-.098 (-5.866)	-.101 (-5.769)	-.096 (-5.764)	-.085 (-4.867)	-.098 (-5.517)	-.108 (-6.128)	-.109 (-6.451)	-.105 (-6.408)	-.106 (-6.630)	-.100 (-6.280)	-.096 (-6.021)
Ln longitude	-1849.154 (-13.253)	-1949.926 (-13.214)	-2011.385 (-14.282)	-1994.628 (-13.559)	-1972.055 (-13.147)	-2019.687 (-13.568)	-1877.094 (-13.139)	-1747.962 (-12.572)	-1648.635 (-12.209)	-1688.421 (-12.627)	-1651.520 (-12.271)
Ln latitude	-316.623 (-5.869)	-355.315 (-6.257)	-366.185 (-6.787)	-359.761 (-6.375)	-369.580 (-6.426)	-386.220 (-6.767)	-345.822 (6.309)	-306.933 (-5.730)	-267.765 (-5.150)	-276.417 (-5.363)	-262.427 (-5.061)
Adjusted R2	.438	.415	.463	.439	.427	.439	.440	.431	.431	.434	.429

Parameter estimates and phases of the market cycle

The explanatory power of the quarterly estimations varies considerably with R squares of the hedonic models ranging from 0.284 in the first quarter of 2001 to 0.408 in the third quarter of 2001 for Model I and 0.486 in the first quarter of 1999 to 0.326 in the third quarter of 2000 for Model II. Among individual parameter estimates, it is noteworthy that the parameter value of the amenities variable appears to be low in times of increasing rents and increases during the subsequent recession, which may indicate that the predictive power of these distinctive quality features for the average rent level of a building diminishes during a general shortage of space in the peak phase of the real estate cycle.

In the next step, the two hedonic models outlined above were pooled for each of the phases of the market cycle as defined in the methodology section. The results are reported in Table 6-4. There are considerable differences in parameter estimates between the peak phase on the one hand and the recovery and decline phases on the other as evidenced by the Chow tests for the entire model and the Tiao-Goldberger F tests for individual parameters. The Chow tests reject the null hypothesis of equal parameters in all three phases for all variables in both models. Individual F_{TG} values show that parameter values are significantly different in each phase of the market cycle.

The results appear counter-intuitive at first sight. All variables with the exception of the number of stories have higher coefficients during the recovery and decline phase than they do during the peak phase. A possible explanation for this phenomenon is that the price convergence during the peak phase lowers the explanatory value of most quality features of buildings. During the peak phase of the market, Class A buildings are typically fully rented and demand for office space spills over to Class B buildings. As a consequence, the rent gap between Class A and Class B buildings narrows. Figure 6-5 illustrates the convergence dynamics of the three categories. I will explore this potential 'spillover effect' in more detail in the next section.

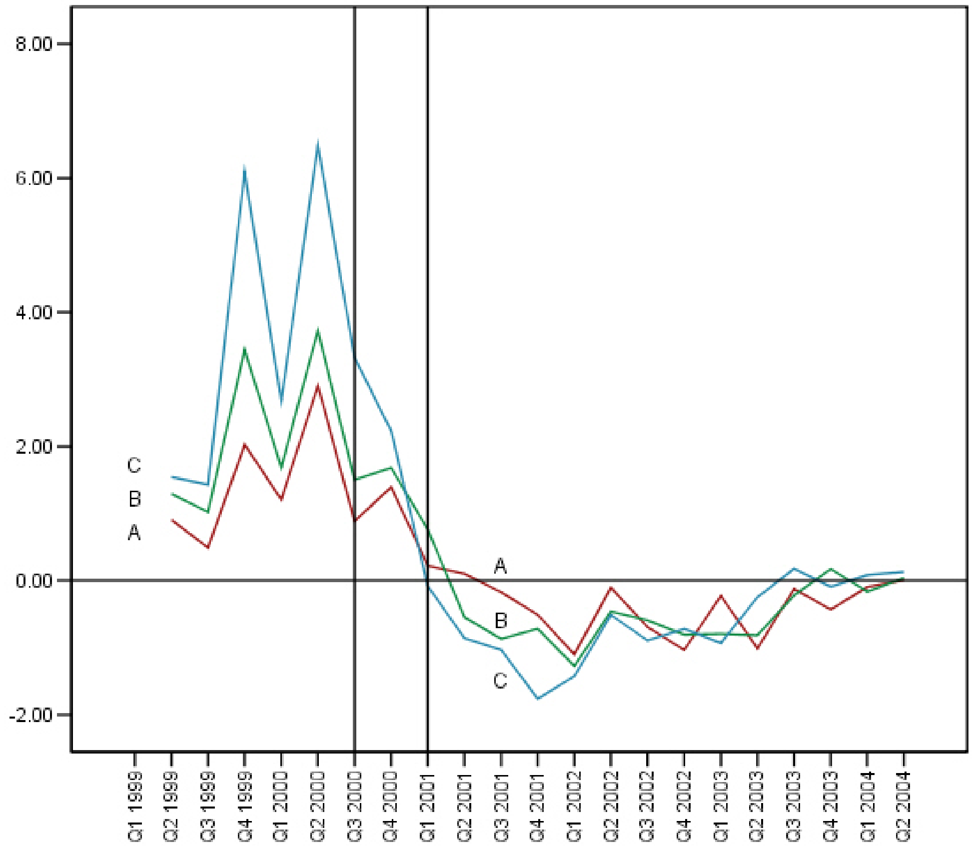


Figure 6-5: Quarterly growth rates of office rents by A/B/C quality class

Table 6-4: Hedonic regression (Model I and II) at various phases in the market cycle (longitudinal)

Model I

	recovery	peak	decline	pooled	F_{TG}
Intercept	-69.577	-43.771	-65.781	-63.376	
	(-19.974)	(-10.033)	(-29.584)	(-35.708)	12.39*
Ln vacancy	-.003	.012	-.005	-.005	
	(-1.142)	(4.114)	(-2.715)	(-3.840)	8.24*
Ln building area	.072	.038	.041	.051	
	(8.881)	(3.853)	(8.410)	(12.757)	4.109*
Ln year built	9.466	6.132	9.005	8.676	
	(20.395)	(10.559)	(30.382)	(36.685)	4.218*
Ln stories	.121	.145	.172	.159	
	(8.113)	(7.866)	(19.523)	(21.893)	3.956*
Ln amenities	.130	.147	.157	.148	
	(8.008)	(7.406)	(15.583)	(18.261)	3.699*
Adjusted R^2	.344	.289	.373	.345	
Chow Test					17.483*

Model II

	recovery	peak	decline	pooled	F_{TG}
Intercept	9447.545	6709.689	7763.999	7997.713	
	(29.516)	(17.436)	(40.165)	(50.637)	12.87*
Ln distance 20 buildings	.064	.057	.061	.062	
	(15.472)	(11.283)	(21.948)	(28.663)	7.353*
Ln space 1500 feet	.170	.117	.164	.159	
	(17.520)	(9.804)	(27.944)	(33.173)	3.955*
Ln distance subway	-.103	-.087	-.105	-.101	
	(-15.127)	(-10.607)	(-24.737)	(-29.406)	8.022*
Ln longitude	-1863.439	-1370.784	-1558.919	-1601.620	
	(-32.276)	(-19.761)	(-44.859)	(-56.321)	8.191*
Ln latitude	-384.823	-217.973	-284.172	-297.632	
	(-18.042)	(-8.427)	(-21.505)	(-27.848)	8.119*
Adjusted R^2	.405	.360	.423	.392	
Chow Test					27.494*

* significant at the 5% level

Cross-sectional parameter stability and market fragmentation

To test the hypothesis of parameter stability across submarkets, both hedonic models are parametrized separately for each of the three aggregated submarkets (Midtown, Midtown South and Downtown Manhattan) and subsequently compared to the pooled model. Table 8 shows the parameter estimates for both models. Among the three submarkets tested, the model performs best for Midtown and Downtown Manhattan but barely reaches the required significance levels for Midtown South. The t values of individual coefficients indicate that some variables that are positive and significant in the other two submarkets do not necessarily show the expected contribution to rental rates in a third market. Moreover, building age has a negative signs in the Midtown South market. This might be attributable to specifics of the Midtown South submarket inventory. A large proportion of the buildings in this market are either historic buildings with landmark status (Madison Square, Gramercy Park) or former warehouse buildings converted for office use, particularly for the information technology industry. Consequently, older buildings generally command higher rents in this submarket than more recently constructed buildings.

With regard to the submarket estimates of location-specific variables (Model II), Midtown Manhattan exhibits significantly better explanatory power than the other two submarkets (Table 6-5). This is particularly evident in the Downtown market where the spatial variables barely reach the desired significance levels. Geographical characteristics of the Downtown area may explain this phenomenon. First, due to the narrowness of the land area between the Hudson and East Rivers there is no distinct differentiation of the submarket into a western and an eastern section as is the case in Midtown Manhattan. Second, because of the narrowness of the geographic shape of the area and the resulting high density of the subway system in the Downtown area, accessibility by subway and proximity to other office buildings are of lesser predictive value for rental rates than in Midtown South which exhibits a more even grid-like pattern with both core and peripheral locations and longer average distances between subway stations. While easy access to rapid transit is almost ubiquitous in the Downtown area, this is not necessarily the case in the Midtown Manhattan.

Again, the Chow test confirms that the estimated parameters are significantly different from one another in the three submarket areas. The individual F_{TG} values show that parameters differ significantly both across subareas with two notable exceptions (the amount of space within 1500 feet and the distance to the nearest subway station). Since the parameters of these variables are not significantly different, one may conclude that these variables are valued similarly in all submarkets in determining the rental rate of a given building. For all other parameters, significant differences were found.

Table 6-5: Hedonic regression (Model I and II) for subareas (cross-sectional)

Model I

	Midtown	*Midtown South*	*Downtown*	*Pooled*	F_{TG}
Intercept	-75.906 (-34.516)	18.220 (3.492)	2.879 (-6.092)	-63.376 (-35.708)	4.56*
Ln vacancy	-.001 (-.483)	-.001 (-.502)	-.002 (-.913)	-.005 (-3.840)	6.06*
Ln building area	.041 (8.112)	.144 (18.469)	.111 (12.189)	.051 (12.757)	5.28*
Ln year built	10.338 (35.294)	-2.214 (-3.190)	2.563 (6.678)	8.676 (36.685)	6.08*
Ln stories	.181 (18.645)	.034 (2.367)	.060 (3.969)	.159 (21.893)	4.02*
Ln amenities	.195 (19.317)	.035 (2.144)	-.036 (-2.294)	.148 (18.261)	3.08*
Adjusted R^2	.399	.122	.246	.345	
Chow Test					9.866*

Model II

	Midtown	Midtown South	Downtown	*Pooled*	F_{TG}
Intercept	6934.917 (39.304)	4625.633 (12.583)	-5764.091 (-6.805)	7997.713 (50.637)	8.87*
Ln distance 20 buildings	.060 (18.758)	.039 (10.454)	.057 (11.384)	.062 (28.663)	9.69*
Ln space 1500 feet	.134 (21.049)	.038 (2.451)	.050 (5.043)	.159 (33.173)	1.41
Ln distance subway	-.091 (-22.179)	-.010 (-1.288)	.006 (.659)	-.101 (-29.406)	1.26
Ln longitude	-1962.017 (-64.949)	-562.577 (-8.506)	994.468 (6.430)	-1601.620 (-56.321)	9.95*
Ln latitude	407.473 (17.593)	-593.907 (-18.413)	400.899 (7.952)	-297.632 (-27.848)	9.59*
Adjusted R^2	.513	.114	.102	.392	
Chow Test					13.589*

* significant at the 5% level

Rental rate convergence of Class A/B/C properties and the market cycle

As reported above, a convergence effect of rental rates of the three quality classes of office buildings (A,B,C) is observed around the peak of the market cycle. Figure 6-6 illustrates how rental rates of Class B buildings approach Class A rents during the peak phase of the market. Thus, distinctive quality features of buildings as represented by the variables of the two hedonic regressions lose some of their explanatory power as rental rates converge. As soon as the decline phase begins, rental rates start to diverge again, as tenants have a larger variety of available office buildings to choose from in times of higher vacancy rates. Therefore, the quality features of buildings regain their relative importance and predictive power as the spread of rental rates increases. To corroborate these results, I apply a one-way ANOVA test for equal means of rental rates to office buildings of the three quality categories A, B, C (Table 7). While the mean rental rates differ significantly for these three groups throughout the analyzed period (all values are significant at the 1% level), the F test values as well as the robust Welch and Brown-Forsythe values are lower at the peak of the cycle (Q3-2000 through Q1-2001), indicating that the mean rental rates of the three categories become more similar at the peak of the market cycle. Interestingly, as differences of mean rental rates decrease between groups, within-group variation increases and vice versa. This may indicate that the reported convergence of rental rates affects only a selective group of Class B and C properties with competitive features, while the rest of buildings in these categories remain largely unaffected by the upswing of the market. Further research is needed, however, to confirm these results.

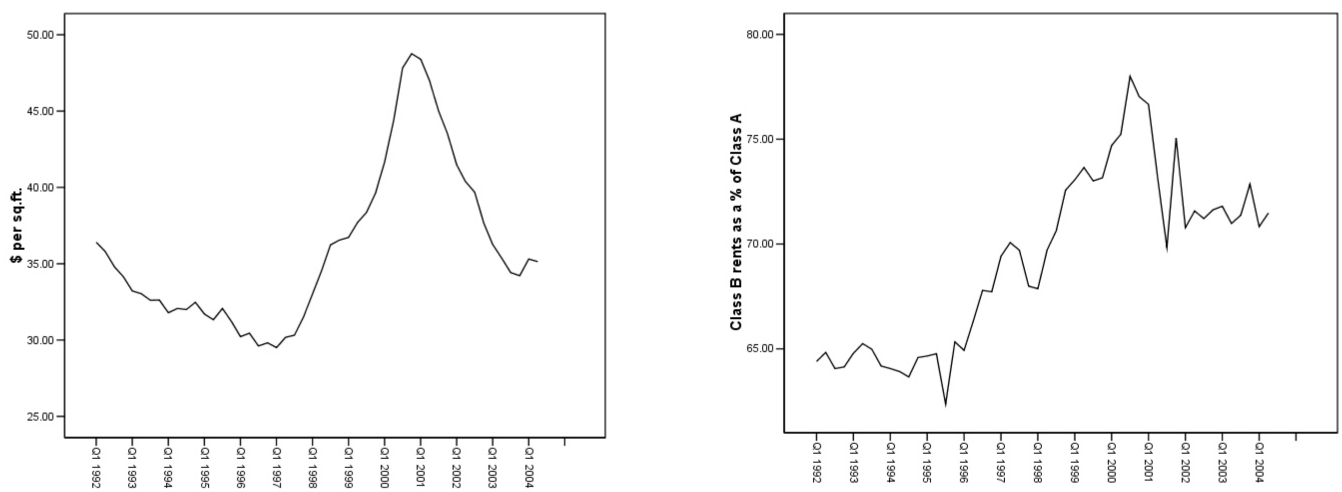


Figure 6-6: Convergence of rental rates during the peak phase of the market cycle: average rental rates (above) and rental rates in Class B buildings as a percentage of Class A rental rates. Data: CoStar Group, Grubb & Ellis.

Panel estimation

In the next step of the empirical investigation, I estimate random-effects GLS models to simultaneously capture cross-sectional and time-series effects.

Table 6-6 shows the results of the location-specific model containing all 16,857 observations. The significance of the variables a) distance to subway, b) 20 closest buildings as well as the c) square footage within a 1500 feet radius are confirmed. The R square measures reveal that within effects equal zero since the explanatory variables used in this specification remain fixed throughout the observed period. The GLS random-effects model is then estimated for the property-specific factors (Table 6-7). Again, the results confirm that rentable building area, age, height and amenities are significant and show the expected signs.

In the next step, I modify the model so that both location- and property-specific variables are included along with the time-varying variables. Not surprisingly, pooling the variables of Model I and Model II into a single model yields a larger joint explanation of variance (Table 6-8). At the same time, the number of valid observations decreases sharply from over 15,000 in the separate models to below 5,000 in the pooled model. This is due to the fact that only one third of all buildings have complete and valid entries in all variable columns. Thus, the selected sample that fulfills the requirement of complete information is much smaller. Because multicollinearity is a more serious concern in the pooled model than it is in the separate models, all variables inducing significant multicollinearity are removed automatically.

This pooled model is then used to estimate separate regressions for each of the three quality classes (A/B/C). The results illustrate that the hedonic model exhibits the highest explanatory power for Class A properties (Table 6-9) while the model is less significant in the Class B (Table 6-10) and Class C (Table 6-11). This observation is in line with the expectation of a more competitive pricing scheme in the upper segments of the market. A closer inspection of individual coefficients yields that many of the variables in the specified random-effects model fail to be significant. One possible explanation for this is that the prevalence of time-invariant hedonic features in the model reduces the overall goodness of fit in a panel data model compared to the initially estimated cross-sectional OLS model where no such effect is measured.

When estimating the pooled model separately for the three subareas, the highest explanatory power is found for the Midtown South area and the lowest for the Downtown area with Midtown Manhattan taking an intermediate position (Tables 18 to 20). Among individual variables, the distance to the 20 closest buildings does not show up significant in any of the estimates. It is noteworthy that the time-varying variables sublet rate (significant at 10%) and vacancy rate (significant at 1%) fail to generate a within-effect of a sufficiently large order of magnitude (R square of 0.0034). There are several possible explanations for this. First, the weight of the time-invariant variables diminishes the within effects so that the effect of the two time-varying variables is underestimated. Second, while vacancy rates contribute to explaining differences in rental rates between buildings, the dynamic relationship of vacancy and rental rates within a building over time is not easily captured by this model. Detailed estimation results of the GLS random effects model for the more disaggregated submarkets are presented in the Appendix B of this dissertation. Although all submarket estimations are jointly significant, the values of the coefficients and their individual significance levels vary to a great degree. R square values range from 0.13 in Gramercy Park to 0.60 in the World Trade Center submarket. The R square of *within* effects is largely a function of the significance of the vacancy rate variable in the model, the only time-varying variable in this specification. Direct comparisons of variable coefficients in submarkets are encumbered by large differences in sample size, however. Nevertheless, these findings corroborate the results regarding non-homogenous parameters across spatial units obtained earlier in Chow tests of the OLS models.

Finally, Table 6-15 reports the Arellano-Bond dynamic panel-data estimation. As outlined above, the exogenous variables are used as instrumental variables in the two-step estimation process. The included dynamic variables (lagged rent, sublet vacancy rate and overall vacancy rate) are significant with a p-value below 5%. While the lagged value r_{it-1} explains the largest part of the panel dynamics, the lagged vacancy measures exhibit the expected negative impact on subsequent changes in rental rates.

These results have to be interpreted with caution, however, since the value of the Sargan test for over-identifying restrictions indicates problems with the correct model specification in this case. More importantly, however, the Arellano-Bond tests for autocovariance in residuals of order 2 fail to reject the null hypothesis of no autocorrelation, which speaks in favor of the selected model specification.

Table 6-6: Pooled model, all observations location-specific model

Random-effects GLS regression					Number of obs		=	**16857**
					Number of groups		=	**999**
R-sq:	within	= **0.0000**			Obs per group:	min	=	**1**
	between	= **0.3302**				avg	=	**16.9**
	overall	= **0.2770**				max	=	**22**
Random effects u_i		~ **Gaussian**			Wald chi2(4)		=	**491.79**
corr(u_i, X)		= **0** (assumed)			Prob > chi2		=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	206.5662	20.77073	9.95	0.000	165.8564	247.2761
ln_subway	-.0910125	.0131596	-6.92	0.000	-.1168048	-.0652202
ln_distance_20 bldgs	.0640123	.0077423	8.27	0.000	.0488376	.079187
ln_sq.ft within1500 ft	.2196119	.0183301	11.98	0.000	.1836856	.2555382
_cons	-765.7518	76.99502	-9.95	0.000	-916.6592	-614.8443
sigma_u	.275489					
sigma_e	.18886561					
rho	.6802724	(fraction of variance due to u_i)				

Table 6-7: Pooled model, all observations building-specific model

Random-effects GLS regression					Number of obs		=	**17338**
					Number of groups		=	**1055**
R-sq:	within	= **0.0000**			Obs per group:	min	=	**1**
	between	= **0.3567**				avg	=	**16.4**
	overall	= **0.3298**				max	=	**22**
Random effects u_i		~ **Gaussian**			Wald chi2(4)		=	**597.48**
corr(u_i, X)		= **0** (assumed)			Prob > chi2		=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_building area	.0507835	.0138267	3.67	0.000	.0236837	.0778833
ln_year built	7.406912	.8038323	9.21	0.000	5.831429	8.982394
ln_stories	.1215857	.023873	5.09	0.000	.0747954	.168376
ln_amenities	.159432	.027396	5.82	0.000	.1057367	.2131272
_cons	-53.66099	6.028466	-8.90	0.000	-65.47656	-41.84541
sigma_u	.27087204					
sigma_e	.18898711					
rho	.6725928	(fraction of variance due to u_i)				

Table 6-8: Variables of Model I and Model II combined into a single model

Random-effects GLS regression			Number of obs	=	**4342**
			Number of groups	=	**643**
R-sq:	within	= **0.0034**	Obs per group:	min =	**1**
	between	= **0.5001**		avg =	**6.8**
	overall	= **0.4457**		max =	**12**
Random effects u_i		~ **Gaussian**	Wald chi2(10)	=	**649.01**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	228.0741	21.62577	10.55	0.000	185.6883	270.4598
ln_subway distance	-.0501038	.0143679	-3.49	0.000	-.0782644	-.0219433
ln_distance 20 bldgs	.0001392	.0119052	0.01	0.991	-.0231946	.0234731
ln_sq.ft within1500 ft	.1087543	.0197927	5.49	0.000	.0699614	.1475473
ln_rba	.0377657	.0156743	2.41	0.016	.0070446	.0684868
ln_year built	6.29816	.9242095	6.81	0.000	4.486742	8.109577
ln_stories	.1300208	.0336101	3.87	0.000	.0641461	.1958954
ln_amenities	.1032081	.0304887	3.39	0.001	.0434513	.1629649
ln_sublet	.006864	.003874	1.77	0.076	-.0007289	.0144568
ln_vacancy	-.0132697	.0050022	-2.65	0.008	-.0230737	-.0034656
_cons	-892.0535	79.61368	-11.20	0.000	-1048.093	-736.0136
sigma_u	.22661135					
sigma_e	.14696903					
rho	.70391878	(fraction of variance due to u_i)				

Table 6-9: Random-effects-model Class A buildings

Random-effects GLS regression			Number of obs	=	**2619**
			Number of groups	=	**182**
R-sq:	within	= **0.0110**	Obs per group:	min =	**1**
	between	= **0.2579**		avg =	**14.4**
	overall	= **0.2057**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(9)	=	**91.18**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	184.2246	32.99628	5.58	0.000	119.5531	248.8961
ln_subway distance	-.0251698	.0215871	-1.17	0.244	-.0674798	.0171403
ln_distance 20 bldgs	.0180864	.0245378	0.74	0.461	-.0300068	.0661795
ln_sq.ft within1500 ft	.0810942	.031123	2.61	0.009	.0200942	.1420942
ln_building area	.010583	.0247113	0.43	0.668	-.0378502	.0590162
ln_year built	3.789131	1.372138	2.76	0.006	1.099789	6.478473
ln_stories	.0033969	.0473833	0.07	0.943	-.0894726	.0962664
ln_amenities	.072654	.0429925	1.69	0.091	-.0116098	.1569177
ln_vacancy	-.0126262	.0024825	-5.09	0.000	-.0174918	-.0077607
_cons	-709.4369	121.0197	-5.86	0.000	-946.6311	-472.2426
sigma_u	.19089527					
sigma_e	.19530804					
rho	.48857548	(fraction of variance due to u_i)				

Table 6-10: Random-effects-model Class B buildings

Random-effects GLS regression		Number of obs	=	**2199**
		Number of groups	=	**178**
R-sq: within	= **0.0389**	Obs per group:	min =	**1**
between	= **0.1764**		avg =	**12.4**
overall	= **0.1439**		max =	**22**
Random effects u_i	~ **Gaussian**	Wald chi2(9)	=	**117.20**
corr(u_i, X)	= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	162.5227	40.43929	4.02	0.000	83.26311	241.7822
ln_subway distance	-.0352427	.0243292	-1.45	0.147	-.082927	.0124417
ln_distance 20 bldgs	.0076225	.0184202	0.41	0.679	-.0284805	.0437255
ln_sq.ft within1500 ft	.0303925	.0360899	0.84	0.400	-.0403424	.1011274
ln_building area	.0193292	.0287236	0.67	0.501	-.036968	.0756264
ln_year built	-1.772343	2.036062	-0.87	0.384	-5.762951	2.218266
ln_stories	.0673277	.0611454	1.10	0.271	-.0525151	.1871704
ln_amenities	.0883962	.054194	1.63	0.103	-.0178221	.1946146
ln_vacancy	-.0231804	.0024416	-9.49	0.000	-.0279659	-.0183949
_cons	-586.502	149.3964	-3.93	0.000	-879.3136	-293.6904
sigma_u	.19686389					
sigma_e	.16766166					
rho	.5795994	(fraction of variance due to u_i)				

Table 6-11: Random-effects-model Class C buildings

Random-effects GLS regression			Number of obs	=	**1158**
			Number of groups	=	**92**
R-sq:	within	= **0.0133**	Obs per group:	min =	**2**
	between	= **0.1166**		avg =	**12.6**
	overall	= **0.1526**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(9)	=	**25.95**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0021**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-142.4296	111.2004	-1.28	0.200	-360.3785	75.51925
ln_subway distance	-.0861889	.0553612	-1.56	0.120	-.1946948	.022317
ln_distance 20 bldgs	.0352	.0378861	0.93	0.353	-.0390554	.1094555
ln_sq.ft within1500 ft	-.0492671	.0940412	-0.52	0.600	-.2335844	.1350502
ln_building area	.0564381	.0545466	1.03	0.301	-.0504712	.1633475
ln_year built	-.2391288	6.213188	-0.04	0.969	-12.41675	11.9385
ln_stories	-.0190665	.1278381	-0.15	0.881	-.2696245	.2314915
ln_amenities	.1454508	.0811379	1.79	0.073	-.0135765	.3044781
ln_vacancy	-.0134591	.0038312	-3.51	0.000	-.0209681	-.0059502
_cons	533.2705	404.1833	1.32	0.187	-258.9142	1325.455
sigma_u	.27561645					
sigma_e	.20277583					
rho	.64881131	(fraction of variance due to u_i)				

Table 6-12: Random-effects-model Midtown

Random-effects GLS regression				Number of obs	=	**757**
				Number of groups	=	**58**
R-sq:	within	= **0.0031**		Obs per group:	min =	**1**
	between	= **0.4719**			avg =	**13.1**
	overall	= **0.2334**			max =	**22**
Random effects u_i		~ **Gaussian**		Wald chi2(9)	=	**42.98**
corr(u_i, X)		= **0** (assumed)		Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	56.14352	58.11728	0.97	0.334	-57.76425	170.0513
ln_subway distance	.0041066	.0364894	0.11	0.910	-.0674114	.0756245
ln_distance 20 bldgs	-.0025864	.0300022	-0.09	0.931	-.0613896	.0562168
ln_sq.ft within1500 ft	-.0038186	.0551354	-0.07	0.945	-.1118819	.1042447
ln_building area	.1372989	.0529966	2.59	0.010	.0334274	.2411704
ln_year built	2.838532	2.395083	1.19	0.236	-1.855743	7.532808
ln_stories	.0579221	.0999664	0.58	0.562	-.1380084	.2538526
ln_amenities	-.0756849	.0896722	-0.84	0.399	-.2514391	.1000694
ln_vacancy	-.0049055	.0040693	-1.21	0.228	-.0128812	.0030703
_cons	-227.9104	212.2494	-1.07	0.283	-643.9116	188.0908
sigma_u	.19294431					
sigma_e	.15661679					
rho	.60281283	(fraction of variance due to u_i)				

Table 6-13: Random-effects-model Midtown South

Random-effects GLS regression			Number of obs	=	**4150**
			Number of groups	=	**295**
R-sq:	within	= **0.0127**	Obs per group:	min =	**1**
	between	= **0.4777**		avg =	**14.1**
	overall	= **0.4241**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(8)	=	**59537.30**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-20.62291	2.853249	-7.23	0.000	-26.21518	-15.03065
ln_subway distance	-.0378858	.0241077	-1.57	0.116	-.085136	.0093643
ln_distance 20 bldgs	.0047784	.0219977	0.22	0.828	-.0383363	.0478931
ln_sq.ft within1500 ft	.1393581	.0383795	3.63	0.000	.0641356	.2145806
ln_building area	.0110209	.0255407	0.43	0.666	-.0390379	.0610797
ln_year built	10.21902	1.418607	7.20	0.000	7.4386	12.99944
ln_stories	.0996927	.0549891	1.81	0.070	-.0080839	.2074694
ln_amenities	.2012367	.0485637	4.14	0.000	.1060535	.2964198
ln_vacancy	-.0139584	.0019563	-7.14	0.000	-.0177927	-.0101242
_cons	(dropped)					
sigma_u	.24843076					
sigma_e	.18964999					
rho	.63180495	(fraction of variance due to u_i)				

Table 6-14: Random-effects-model Downtown

Random-effects GLS regression			Number of obs	=	**1069**
			Number of groups	=	**99**
R-sq:	within	= **0.0708**	Obs per group:	min =	**2**
	between	= **0.2678**		avg =	**10.8**
	overall	= **0.1914**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(9)	=	**106.65**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-519.0381	163.7756	-3.17	0.002	-840.0324	-198.0437
ln_subway distance	.0146929	.045372	0.32	0.746	-.0742346	.1036204
ln_distance 20 bldgs	.0128909	.0307674	0.42	0.675	-.047412	.0731938
ln_sq.ft within1500 ft	.0221679	.0789422	0.28	0.779	-.132556	.1768918
ln_building area	.0855394	.0455937	1.88	0.061	-.0038226	.1749013
ln_year built	-7.219225	3.747701	-1.93	0.054	-14.56458	.1261337
ln_stories	.1859558	.1060475	1.75	0.080	-.0218934	.393805
ln_amenities	-.0060239	.0634921	-0.09	0.924	-.1304661	.1184182
ln_vacancy	-.0343947	.0039245	-8.76	0.000	-.0420865	-.0267029
_cons	1980.111	610.7183	3.24	0.001	783.1249	3177.097
sigma_u	.24506945					
sigma_e	.19543874					
rho	.6112547	(fraction of variance due to u_i)				

Table 6-15: Arellano-Bond estimation of dynamic variables

Arellano-Bond dynamic panel-data estimation				Number of obs	=	**13944**
				Number of groups	=	**991**
				Obs per group:	min =	**1**
					avg =	**14.07064**
					max =	**20**
				Wald chi2(2)	=	**5394.32**
One-step results						

Ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_rent (lag 2)	.7953525	.0110236	72.15	0.000	.7737467	.8169583
ln_sublet (lag 5)						
ln_vacancy (lag 2)	-.0070155	.0011367	-6.17	0.000	-.0092434	-.0047876
_cons	-.0020764	.0002489	-8.34	0.000	-.0025642	-.0015887

Sargan test of over-identifying restrictions:

chi2(**438**) = **647.74** Prob > chi2 = **0.0000**

Arellano-Bond test that average autocovariance in residuals of order 1 is 0:

H0: no autocorrelation z = **-47.07** Pr > z = **0.0000**

Arellano-Bond test that average autocovariance in residuals of order 2 is 0:

H0: no autocorrelation z = **2.01** Pr > z = **0.0607**

6.6 Chapter conclusions

The objective of this study was to test whether rent determinants are stable both cross-sectionally and over time. Volatility of rental rates is a major source of risk for real estate investors. A hedonic regression framework was developed to produce estimates of rent determinants for three submarket areas and 15 submarkets. Datasets used in this analysis included time-series information on submarkets and individual buildings. Although the time-series of building data was relatively short (22 quarterly observations in 6 years), three distinct phases of the real estate market cycle could be identified during this period.

The final specification of the building-specific hedonic model included the following significant variables:

- Vacancy rate of the building,
- Square footage,
- Age
- Height (number of stories)
- Number of in-house amenities.

Variables of the location-specific models included:

- Weighted sum of distances to the 20 closest buildings,
- Square feet of office space within walking distance,
- Proximity to a subway station,
- Geographic x and y coordinates of the building.

In a further step, a number of hypotheses were investigated with regard to the stability of these rental rate determinants. First, tests for structural change confirmed that rent determinants differ significantly when measured at different phases of the market cycle. Further tests for structural change revealed that rent determinants also differ significantly across subareas of Manhattan. Consequently, no support of a unified rental pricing scheme was found in this empirical study. More specifically, building-specific measures were found to differ to a greater degree across submarkets than location-specific measures which appear to follow a more unitary scheme. We also found support for the existence of price convergence and spillover effects towards the peak of the market cycle.

A GLS panel estimation confirmed the relevance of the variables identified in the OLS model. Estimating the model separately for the quality classes A/B/C confirmed the assumption that pricing of hedonic building and location quality features is reflected more consistently in the rental rates of Class A buildings than it is in Class B and particularly Class C buildings. Results of a dynamic estimation using an Arellano-Bond panel model confirmed that past rental rates along with overall vacancy and sublet vacancy conditions in a building are suitable for explaining variations in rental rates.

Overall, the results of this study indicate that panel models and tests for structural change may be useful tools for gaining additional information about the specific cyclical and submarket-related conditions of hedonic rent determinants. Especially the use of dynamic panel models such as the Arellano-Bond model are promising as to their potential for incorporating time lags and dynamic relationships at the individual building level. A number of relevant research questions could be addressed with such a model, for instance about the dynamic interaction of vacancy and rental rates in a building. Further research is needed, however, to arrive at a truly dynamic model of rental pricing in the presence of submarkets and real estate market cycles. Finally, it will be necessary to explore the theoretical underpinnings of the empirical results in much greater detail, especially the role of market imperfections in explaining market fragmentation and heterogeneous valuation of hedonic features.

7 Overall conclusions and further work

The primary objective of this dissertation was to explore the usefulness of disaggregated methods for understanding the dynamics of office markets by highlighting and empirically testing a number of key research questions that share both a temporal and spatial dimension. In this context, I demonstrated that a combined analysis of various layers of spatial aggregation is capable of yielding additional insights in a number of research questions regarding demand composition, portfolio management and building valuation.

Review of key results

In Chapter 2, evidence of significant concentration patterns in office-using industries was found in Manhattan despite longstanding decentralization processes in many of these industries over the last twenty years. Financial services tend to be highly concentrated in Manhattan whereas administrative and support services are the least concentrated of the six major office-using industry groups. Although office employment has been stagnant in Manhattan for at least two decades, growth of output per worker has outpaced the CMSA as well as the national average. A shift-share type analysis revealed that the productivity differential is mainly attributable to competitive advantages of office-using industries in Manhattan and not to differences in industry composition. This may indicate knowledge spillovers due to spatial proximity, although other reasons may account for the higher productivity of Manhattan office firms as well, such as higher quality of physical capital, a generally higher skill level of the labor force, more efficient workplace practices and institutional arrangements. A zip-code level analysis of the Manhattan core area yielded further evidence of significant spillover effects at the small-scale level. Co-agglomeration of office-using industries at the zip code level is particularly strong between FIRE industries and business-oriented service industries, confirming earlier reports of extensive linkages between these industries. All in all, about one quarter of all office-using industries are coagglomerated at the zip code level. These results bode well for the future of the two Central Business Districts in Midtown and Downtown Manhattan where productivity gains due to spatial proximity and spillover effects appear to outweigh the high cost of office occupancy.

In Chapter 3, I investigated the impact of the September 11 terrorist attack on the New York office market. The evidence suggests that the attack will have a very limited impact on the New York office market in the medium to long term. Particularly in the submarkets of Midtown Manhattan, no significant impact could be detected beyond the market adjustment process that took place in the two quarters following 9/11. The area of Lower Manhattan, however, was more deeply affected by the attack and its various effects. The Manhattan office market as a whole does not show any signs of lasting economic damage. Of the companies that decided not to return to Lower Manhattan after 9/11, the majority relocated to Midtown Manhattan. An industry analysis demonstrated that both urbanization and localization economies were dominant forces in the relocation process as companies preferred to settle in preexisting large industry clusters in Manhattan. Taken together, the core markets of Midtown and Downtown Manhattan captured about 80% of the stream of displaced tenants after 9/11 while areas outside of these two core clusters captured only 20%, which bodes well for Manhattan’s ability to remain a prime office location even in the face of a severe crisis. Nevertheless, a more decentralized development of office space and a more dynamic increase in office workers in the wider CMSA region outside of Manhattan –a process that has been evolving for at least two decades - is likely to continue over the next years. Although security concerns are likely to accelerate this development at least temporarily as firms seek to create backup facilities and distribute key functions across various locations to protect their operations, preliminary analysis of the period after 9/11 shows that agglomeration economies and firm efficiency criteria are restraining and mitigating such dispersion tendencies in Manhattan. Both the exploratory data analysis and the event analysis demonstrate that markets reacted efficiently and predictably to the 9/11 attack. One the most notable phenomena are the downward corrections in occupied space across Manhattan when displaced tenants had the choice of leasing new space after 9/11. On the aggregate, companies rented about 25% less space than they had occupied in the World Trade Center. Space reduction was particularly pronounced in high-priced buildings and submarkets. Moreover, the set of so-called 'trophy' buildings proved to be less affected by the recession than the general market, a finding which runs counter to initial assumptions about the future of office high-rises. Only the group of tallest buildings in the city (more than 50 stories) exhibited slightly higher vacancies after 9/11, arguably because of an aversion effect towards the very tallest and most famous structures in the city as potential targets of further terrorist attack. In addition to a drastic reduction in leased space, accommodation of displaced tenants within the existing office space portfolio of large companies contributed further to lower occupancy rates than had been expected after the destruction of 10% of the inventory. This phenomenon, also known as backfill, caused overall absorption to be negative in the quarters following 9/11 since the positive demand created by displaced tenants was more than offset by losses of the accelerated recession. Positive absorption of approximately 7 million square feet of office space in various submarkets of Manhattan can be attributed to tenants who were displaced by the 9/11 attack. This figure is much lower than expected given the square footage of the destroyed buildings. Approximately half of the anticipated demand dissipated trough backfill into existing space, reduced staff, subleasing and more economical space usage per office worker.

A more formal econometric approach was pursued in Chapter 4 by developing a three-stage system of simultaneous equations to model and predict the overall Manhattan office market. The first stage of this model incorporates the office space market in terms of occupied space and absorption of new space, the second stage captures the adjustment of office rents to changing market conditions and the third stage specifies the supply response to market signals in terms of construction of new office space.

The model demonstrates that the Manhattan markets reacts efficiently and predictably to changes in market conditions, especially to the economic shock generated by the 9/11 attack. The significance of the estimated parameters underscores the general validity and robustness of the simultaneous equation approach. The modifications of the standard model, notably the inclusion of sublet space in the rent equation, contributed considerably to improving the explanatory power of the model. In a final step, I generated contingent office market forecasts until the year 2010 under three exogenous assumptions of employment growth.

Disaggregating the market area further, I tested a number of hypotheses about the economic relationship of city to submarket level (Chapter 5). In this context, I investigated the chances for and limits of intracity portfolio diversification. The main question of interest was whether office submarkets are driven by the same economic fundamentals in a highly diversified and functionally specialized market. If this were the case investors ought to be able to reduce the systematic risk of their income streams by investing in different submarkets within a city. I found that only about half of all submarkets exhibit a clear cointegrating relationship of rental rates with the overall market. While Manhattan rents do not Granger-cause submarket rents in the majority of cases, strong evidence is found that the overall Manhattan vacancy rate is generally a slightly better predictor of submarket rental rates than submarket vacancy rates themselves. When testing for office employment Granger-causing occupancy rates, the empirical evidence is mixed regarding the comparative relevance of submarket versus overall market conditions. Simulated responses to system shocks reveal that these shocks unfold with a lag of several quarters in the majority of examined submarkets. Overall, the results of the empirical analysis do not warrant any strong conclusions in either direction as both micro-scale submarket and overall market conditions are found to have a significant impact on rental returns. Volatility and risk measures along with Granger causality and cointegration tests indicate that it may be possible to construct well-diversified real estate portfolios within a metropolitan office market. Despite this, the results suggest that sufficient diversification within a city is not achievable in all submarkets. A careful selection based on comparisons of underlying demand and supply patterns of submarkets is therefore required.

Proceeding to an even more disaggregated analysis, we turned from the submarket to the individual building level to test whether rent determinants of individual buildings are stable both cross-sectionally and over time. A hedonic regression framework was developed to produce estimates of rent determinants for three submarket areas and 15 submarkets. Datasets used in this analysis included time-series information on submarkets and individual buildings. Three distinct phases of the real estate market cycle were identified during the analyzed period. The final specification of the hedonic model included the vacancy rate of the building, square footage, age, height and number of in-house amenities. Variables of the location-specific models included the added and weighted distances to the 20 closest buildings, square feet of office space within walking distance, proximity of subway stations as well as the geographic coordinates of the building. Tests for structural change confirmed that rent determinants differ significantly according to the position in the market cycle. Cross-sectional tests for structural change revealed that rent determinants also differ significantly in various areas and submarkets of Manhattan so that no support of a unified rental pricing scheme (i.e. the 'law of one price') was found. Investigating differences in quality classes, I found that locational and building-specific quality features are better predictors of rental rates in Class A office buildings than in the lower-grade Class B and C buildings. This is indicative of a higher sensitivity of rental rates in the highly competitive segment of Class A buildings to variations in quality features and amenities. Consequently, Class B are less price sensitive and Class C buildings are the least sensitive of the three categories regarding variations of quality features. I also found support for the existence of price convergence and spillover effects towards the peak of the market cycle. A GLS random-effects panel estimation confirmed the relevance of the variables identified in the OLS model. Results of a dynamic estimation using an Arellano-Bond panel model confirmed that past rental rates along with overall vacancy and sublet vacancy conditions in a building are suitable for explaining variations in rental rates.

Directions for further research

Within the scope of this dissertation, only a small set of spatiotemporal research questions could be addressed. More sophisticated research tools will be developed over the course of the next few years to analyze office markets as more detailed and higher-quality datasets become available. The opportunities for extending the research on each of questions addressed in the individual chapters are plentiful.

Our study of the dynamics of office employment yielded some insights regarding potential explanatory factors but did allow us to come to a definitive conclusion could be derived regarding the underlying causal forces. Further studies are necessary to elucidate the causal relationships of agglomeration effects and the locational behavior of office-using industries. More specifically, the empirical base of the zip-code level analysis needs to be broadened to arrive at generalizable results by including suburban zip code areas and a longer time series, an endeavor that has up to now been hampered by the transition from the SIC to the NAICS industry classification system. As time progresses, more years with NAICS data will become available for repeating the analysis conducted in this chapter. Finally, to expand the validity of the results, similar studies of office employment would need to be conducted in other metropolitan regions.

A longer time series of data is also required to arrive at a more comprehensive evaluation of the September 11 attack. The long-run rent implications of 9/11-related factors such as increased security and insurance costs as well as government subsidies to New York City are not entirely clear at this point. Moreover, the recovery trajectory of the Lower Manhattan market needs to be explored in detail with an econometric model, which is able to take into account a number of factors that influence supply and demand. This dissertation examined mainly the immediate and direct impact of the 9/11 attack on rental prices and vacancy rates. As more time elapses, it will be possible to separate short-term adjustment processes from potential long-term impacts.

A number of further refinements are also possible for the simultaneous equation forecasting model. First, a more comprehensive integration of capital markets would be desirable to capture the impact of these markets on investment in and construction of office real estate. In this context, the explicit modeling of urban land markets could enhance the validity of predictions considerably. Moreover, it may be preferable to model office employment endogenously, for instance through tracking structural changes in the composition and trends in the spatial organization of office employment. This, however, would require a further module capable of forecasting the dynamics of individual office-using industries over a number of years which is not a trivial task. Lastly, it remains to be explored if a model specification can be found that fully captures the oscillations of individual market cycles. There is clear potential for the simultaneous equation model to evolve further because this approach is a relatively open system in contrast to atheoretical time series prediction methods used to extrapolate past trends.

Particularly the study of portfolio management and intracity diversification merits further research as many essential questions remain unexplored to date. Refinements of the models and measures presented in this dissertation (Granger causality, cointegration, impulse response analysis, Sharpe ratio etc.) are strongly recommended, not only in order to more accurately analyze the risk-return profiles associated with certain types of intracity portfolios but also to model the impact and decay of hierarchical variables on submarket performance. Further studies of a large number of metropolitan markets and possibly international comparisons are needed in order to arrive at truly generalizable results and predictions.

Regarding building-level analysis, the results of this dissertation indicate that panel models and tests for structural change may be useful tools for gaining additional information about the specific cyclical and submarket-related conditions of hedonic rent determinants. Further research is needed, however, to arrive at a truly dynamic model of rental pricing in the presence of submarkets and real estate market cycles. Methodological problems arising from the presence of unbalanced panels of building data could be mitigated by the expected availability of more complete datasets in the future. Nevertheless, the advantages of applying panel data analysis in office market research doubtlessly outweigh the shortcomings. The use of panel models allows researchers to analyze a number of relevant economic questions not readily answerable by either a cross-section or a time-series data. In particular, it allows for the analysis of dynamic effects which cannot be estimated using cross-sectional data. Even time series data are imprecise because valuable information on the dynamic interaction among the units is lost by lumping together all the cross-sectional observations. Panel data models are also capable of taking into account a greater degree of the heterogeneity that characterizes submarkets and individual buildings over time. To broaden the validity and generalizability of the findings of this dissertation, however, the research carried out for one market area needs to be replicated in other cities and regions to validate the abstract findings.

In summary, the scope for future research in the area of integrating the spatial and temporal dimensions in real estate market analysis is tremendous. The next few years are likely to bring significant progress in understanding and predicting office markets based on advances in econometric techniques and a more widespread ability of meticulously compiled building-level datasets.

Appendix

Appendix A: Fixed and random effects approaches and the Arellano-Bond model

In the hedonic regression approach used in this dissertation (Chapter 6), I enriched the standard OLS framework previously used in most hedonic real estate analyses with a Generalized Least Squares (GLS) procedure that endows the model with both a spatial and temporal dimension. In general, the repeated-measurement OLS procedure is to be considered less efficient than a GLS model.

Our point of departure was a pooled OLS hedonic model of the following form:

$$y_{it} = \alpha + \beta x_{it} + u_{it}$$

with $i=1,......,N;\ t=1,....T$.

In this model, the observations of each building over time are simply stacked on top of one another. This standard pooled model is rather austere because intercepts and slope coefficients are forced to be homogeneous across all *n* cross-sections (buildings) and through all t time periods. The application of standard OLS to this model ignores the temporal and space dimension of the data and hence discards useful information. One problem with this approach is, however, that the general assumption of consistent and unbiased estimators requires that the independent variables are uncorrelated with any cross-section specific effects (e.g. submarket effects). Each observation is given equal weight. Due to the obvious limitations of OLS in this research setting, more advanced procedures such as the Generalized Least Squares (GLS) approach are superior to the standard approach. Following the specification of Hsiao (2003), the GLS estimator is defined by:

$$\beta = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}y$$

The coefficient of interest is Φ^{-1}. We pre-multiply the vectors $y_i=(y_{i1}, y_{i2}, y_{i3}......,y_{iT})'$, $x_i=(x_{i1}, x_{i2}, x_{i3}......,x_{iT})'$ by:

$$\Phi^{-1} = \frac{1}{\sigma_u^2}\left(I_T - \frac{\sigma_\alpha^2}{\sigma_u^2 + T\sigma_\alpha^2} ee'\right)$$

where I_T is the identity matrix of dimensions $T \times T$ and e is a $T \times 1$ vector of ones encountered earlier in the lecture. T is the number of time period units.

Moreover, the variance of the GLS estimator is:

$$Var(\beta) = \sigma_u^2 (X'\Phi^{-1}X)^{-1}$$

In practice, the variance components σ_α^2 and σ_u^2 are unknown and have to be estimated. The GLS estimator is a weighted average of a 'within-group' and a 'between-group' estimator. The variance of the 'within estimator' is σ_u^2 whereas the variance of the between estimator is denoted σ_B^2. Finally, the variance of α is defined as:

$$\sigma_\alpha^2 = \sigma_B^2 - \frac{\sigma_u^2}{T}$$

Thus, the Φ matrix is constructed by:

$$\beta_{RE} = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}y$$

The fixed-effects approach

The basic assumption of the fixed effects model is that all α_i are constant across time and that λ_t constant across units (in our case buildings or submarkets). Thus, unit effects are absorbed within the constant term:

$$E(\alpha i\ ) = E(\ \lambda t\ ) = E(uit) = 0;$$

$$E(\alpha i\ Xit) = E(\ \lambda t\ \ Xit) = E(uitXit) = 0;$$

Var(αi) = σ^2_α; Var(λt) = σ^2_λ; σ2λ ; Var(uit) = σ^2_u.

This type of model is typically referred to as a two-way error components model. In this case, the disturbance term consists of a cross-sectional component (α_i) and a combined time series and cross-sectional component (u_{it}). Time series data are pooled with cross-sectional data. The general structure of such a model is as follows:

$y_{it} = \alpha + \beta x_{it} + u_{it}$ where $u_{it} \sim IID(0, \sigma^2)$ and $i = 1,2,\ldots\ldots., N$ individual-level observations, and $t = 1,2,\ldots\ldots.,T$ time series observations.

The 'between' estimator

The last section introduced what has become known in the literature as the 'within' estimator. This is so called because it only uses the temporal or 'within' variation of the data to construct the relevant $\hat{\beta}$ estimator. It is also possible to introduce a 'between' estimator that exploits only the variation across (or between) groups. This is implemented by taking average values for each of the separate groups over the specified time period. Thus, we have:

$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$ and $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$

The following regression is then performed using the group means:

$$\bar{y}_i = \mu + \bar{x}_i \beta_{Between} + u_B$$

where u_B is the error term and N would be the number of observations used in the analysis. The estimator is constructed as:

$$\hat{\beta}_{Between} = [\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})]^{-1} [\sum_{i=1}^{N} (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})]$$

In this case the estimator $\hat{\beta}_{\text{Between}}$ represents the between estimator and explains the extent to which $\bar{y}_i$ is different from $\bar{y}$ (the overall mean). It exploits the variation between or across groups and this is why it is called a between estimator. The number of observations used in estimation is N – the number of groups in the panel. The 'between' estimator ignores any information within the individual group.

The random effects approach

In the random effects model, individual intercepts are allowed. These individual intercepts are expressed as a random deviation from a mean intercept. The intercept is drawn from a distribution for each unit, and is independent of the error for a particular observation. Instead of attempting to estimate N parameters as in the fixed effects approach, I estimate parameters describing the distribution from which each unit's intercept is drawn. For panel data with a large N (panel data) random effects will be more efficient than fixed effects. It has N more degrees of freedom, and uses information from the "between" estimator. The random-effects model can be written as follows:

$$y_{it} = \mu + \beta x_{it} + (\alpha_i - \mu) + \varepsilon_{it}$$

The error is defined as

$$u_{it} = (\alpha_i - \mu) + \varepsilon_{it}$$

We can then rewrite the equation as

$$y_{it} = \mu + \beta x_{it} + u_{it}$$

The random-effects approach takes into account both the 'between' and the 'within' dimensions of the data but, in contrast to the initially described pooled OLS, it does so efficiently by applying a GLS estimator which can be determined as a weighted average of the 'between' and 'within' estimators. The individual weight depends on the relative variances of the two estimators. The estimation of a random-effects model requires implementing a Generalised Least Squares (GLS) procedure. For an efficient estimation, we may therefore proceed as follows:

$$\theta = 1 - \frac{\sigma_\varepsilon}{\sigma_1}$$

with $\sigma_1^2 = T\sigma_\alpha^2 + \sigma_\varepsilon^2$

Within differences are calculated by:

$$y_{it}^* = y_{it} - \theta \overline{y}_{i.}\ , \quad x_{it}^* = x_{it} - \theta \overline{x}_{i.}$$

This can be estimated by simple OLS regression in the following manner:

$$y_{it}^* = \mu^* + \beta x_{it}^* + u_{it}^*$$

with $\mu^* = (1-\theta)\mu$

A Random Effects estimate of β is then obtained by:

$$\hat{\beta}_{re} = \frac{\sum\sum(x_{it}^* - \overline{x}_{i.}^*)(y_{it}^* - \overline{y}_{i.}^*)}{\sum\sum(x_{it}^* - \overline{x}_{i.}^*)^2}$$

Model selection: Random effects versus fixed effects

Since both approaches yield significantly different results, the question of which approach to select is an important one. Hsiao and Sun (2000) point out that there is no reliable statistical test to guide model selection so that the choice should be theoretically and practically driven. At the core of the selection problem is the question whether the intercepts α_i are treated as fixed or random.

An important consideration is that the estimation of the fixed effects model consumes degrees of freedom. This becomes particularly problematic when the N of a dataset is large and the T is small as is the case for the data used in this dissertation. The random effects approach treats the random effects as independent of the independent variables. The main strengths of the Fixed Effects approach are the simplicity of the estimation process and the fact that independence of the fixed effects from the independent variables is not required. On the other hand, a large part of the variation in the data is lost in the process of estimating N separate intercepts. Therefore, the estimated coefficients of the independent variables in the fixed-effects regression model may be biased.

Arellano-Bond Dynamic Panel Data Methodology

The Arellano-Bond approach is a dynamic technique suitable for analyzing autoregressive-distributed lag models for panel data with many cross-sectional units observed over relatively few time periods (Arellano 2003). It uses General Method of Moments (GMM) for estimating coefficients. The regression model is generally described by:

$$y_{it} = \alpha y_{i,t-1} + \beta_0 + \beta_1{}' x_{1it} + \beta_2{}' x_{2it} + \gamma_1{}' f_{1i} + \gamma_2{}' f_{2i} + \varepsilon_{it} + u_i$$

This approach has several advantages. First, unobserved building- or submarket-specific heterogeneity is eliminated by first-differencing, or by subtracting the lagged values of regressors. Second, problems of correlated independent variables are resolved by using lagged values of the regressors as instrumental variables of the first-differenced regressors. Moreover, the General Method of Moments estimation provides superior parameter estimate when unknown heteroskedasticity and autocorrelation is present which is often the case in dynamic panel datasets. Finally, the Arellano-Bond approach is particularly suitable for analyzing markets with lagged adjustment and imperfect competition. In the context of the present dissertation, it allows for analyzing the lagged adjustment of rental rates to changes in direct and sublet vacancy rates.

Appendix B: Estimations results of GLS random effects models by submarket

Table 0-1

Submarket Chelsea						
Random-effects GLS regression			Number of obs	=	**473**	
			Number of groups	=	**43**	
R-sq:	within	= **0.1121**	Obs per group:	min =	**2**	
	between	= **0.4964**		avg =	**11.0**	
	overall	= **0.2818**		max =	**22**	
Random effects u_i		~ **Gaussian**	Wald chi2(8)	=	**11437.74**	
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**	

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	36.53663	13.00004	2.81	0.005	11.05702	62.01624
ln_subway	-.0022211	.0540332	-0.04	0.967	-.1081242	.103682
ln_distance 20 bldgs	.0513795	.0442308	1.16	0.245	-.0353112	.1380703
ln_space within 1500ft	.1173232	.1223965	0.96	0.338	-.1225695	.3572159
ln_building area	.1630563	.0602178	2.71	0.007	.0450317	.281081
ln_yearbuilt	-18.08763	6.423844	-2.82	0.005	-30.67814	-5.49713
ln_stories	.216533	.1397997	1.55	0.121	-.0574695	.4905354
ln_amenities	-.0905451	.1098488	-0.82	0.410	-.3058449	.1247546
ln_vacancy	-.0403587	.0055241	-7.31	0.000	-.0511858	-.0295317
_cons	(dropped)					
sigma_u	.19056651					
sigma_e	.17647451					
rho	.53833703	(fraction of variance due to u_i)				

Table 0-2

Submarket Midtown West/Columbus Circle						
Random-effects GLS regression			Number of obs	=	**529**	
			Number of groups	=	**38**	
R-sq:	within	= **0.0062**	Obs per group:	min =	**2**	
	between	= **0.6031**		avg =	**13.9**	
	overall	= **0.5063**		max =	**22**	
Random effects u_i		~ **Gaussian**	Wald chi2(8)	=	**9120.04**	
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**	

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-12.79739	6.531154	-1.96	0.050	-25.59821	.0034377
ln_subway	-.1064976	.0647992	-1.64	0.100	-.2335017	.0205066
ln_distance 20 bldgs	.0608572	.0550872	1.10	0.269	-.0471117	.1688261
ln_space within 1500ft	.00746	.1195683	0.06	0.950	-.2268896	.2418097
ln_building area	-.0185694	.066694	-0.28	0.781	-.1492873	.1121486
ln_yearbuilt	6.714455	3.335184	2.01	0.044	.1776138	13.2513
ln_stories	.0602043	.1194071	0.50	0.614	-.1738293	.2942379
ln_amenities	.2603008	.1229655	2.12	0.034	.0192929	.5013087
ln_vacancy	-.0072463	.0042092	-1.72	0.085	-.0154962	.0010036
_cons	(dropped)					
sigma_u	.23175383					
sigma_e	.15290232					
rho	.69672544	(fraction of variance due to u_i)				

Table 0-3

Submarket Financial District

Random-effects GLS regression			Number of obs	=	**318**
			Number of groups	=	**22**
R-sq:	within	= **0.0154**	Obs per group:	min =	**1**
	between	= **0.5553**		avg =	**14.5**
	overall	= **0.3653**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(8)	=	**7399.07**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-14.22934	9.090721	-1.57	0.118	-32.04683	3.588144
ln_subway	-.0378992	.0741641	-0.51	0.609	-.1832582	.1074597
ln_distance 20 bldgs	.0896609	.0562115	1.60	0.111	-.0205116	.1998334
ln_space within 1500ft	-.281968	.2053229	-1.37	0.170	-.6843935	.1204574
ln_building area	-.1143856	.1063329	-1.08	0.282	-.3227942	.094023
ln_yearbuilt	7.95739	4.54039	1.75	0.080	-.9416112	16.85639
ln_stories	.4668671	.2152446	2.17	0.030	.0449954	.8887387
ln_amenities	.1217354	.1258576	0.97	0.333	-.124941	.3684117
ln_vacancy	-.0092548	.005182	-1.79	0.074	-.0194113	.0009018
_cons	(dropped)					
Sigma_u	.18579373					
Sigma_e	.13571953					
Rho	.65205697	(fraction of variance due to u_i)				

Table 0-4

Submarket Gramercy Park						
Random-effects GLS regression				Number of obs	=	**323**
				Number of groups	=	**31**
R-sq:	within	= **0.0259**		Obs per group:	min =	**3**
	between	= **0.2645**			avg =	**10.4**
	overall	= **0.2016**			max =	**22**
Random effects u_i		~ **Gaussian**		Wald chi2(8)	=	**7742.41**
corr(u_i, X)		= **0** (assumed)		Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	34.70065	16.96056	2.05	0.041	1.458574	67.94273
ln_subway	.0581822	.0866599	0.67	0.502	-.111668	.2280324
ln_distance 20 bldgs	-.0350029	.0563948	-0.62	0.535	-.1455346	.0755289
ln_space within 1500ft	-.0962919	.1180724	-0.82	0.415	-.3277095	.1351257
ln_building area	.0369271	.1278885	0.29	0.773	-.2137298	.287584
ln_yearbuilt	-16.45853	8.300352	-1.98	0.047	-32.72692	-.1901346
ln_stories	.1266145	.2815396	0.45	0.653	-.4251929	.678422
ln_amenities	-.1884874	.1545442	-1.22	0.223	-.4913885	.1144137
ln_vacancy	-.0242571	.0074847	-3.24	0.001	-.0389268	-.0095873
_cons	(dropped)					
Sigma_u	.20611762					
Sigma_e	.20749022					
Rho	.49668143	(fraction of variance due to u_i)				

Table 0-5

Submarket Grand Central

Random-effects GLS regression			Number of obs	=	**870**
			Number of groups	=	**59**
R-sq:	within	= **0.0010**	Obs per group:	min =	**2**
	between	= **0.3458**		avg =	**14.7**
	overall	= **0.1382**		max =	**22**
Random effects u_i		~ **Gaussian**	Wald chi2(8)	=	**27246.59**
corr(u_i, X)		= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-5.935944	5.030738	-1.18	0.238	-15.79601	3.924121
ln_subway	.0155906	.0417992	0.37	0.709	-.0663343	.0975155
ln_distance 20 bldgs	.0404254	.0647238	0.62	0.532	-.0864309	.1672816
ln_space within 1500ft	.0379442	.0713298	0.53	0.595	-.1018595	.177748
ln_building area	.0499348	.0495929	1.01	0.314	-.0472656	.1471351
ln_yearbuilt	3.14436	2.459869	1.28	0.201	-1.676894	7.965614
ln_stories	.0621226	.0961843	0.65	0.518	-.1263951	.2506403
ln_amenities	.0760609	.072462	1.05	0.294	-.065962	.2180838
ln_vacancy	-.0026574	.0050966	-0.52	0.602	-.0126466	.0073317
_cons	(dropped)					
Sigma_u	.15726676					
Sigma_e	.24270392					
Rho	.29571278	(fraction of variance due to u_i)				

Table 0-6

Submarket Hudson Square						
Random-effects GLS regression				Number of obs	=	**150**
				Number of groups	=	**13**
R-sq:	within	= **0.0199**		Obs per group:	min =	**2**
	between	= **0.6470**			avg =	**11.5**
	overall	= **0.3096**			max =	**22**
Random effects u_i		~ **Gaussian**		Wald chi2(8)	=	**4895.15**
corr(u_i, X)		= **0** (assumed)		Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-43.88266	15.94335	-2.75	0.006	-75.13105	-12.63426
ln_subway	.0353942	.3066985	0.12	0.908	-.5657237	.6365121
ln_distance 20 bldgs	.0170987	.0941874	0.18	0.856	-.1675051	.2017026
ln_space within 1500ft	-.5237164	.4307244	-1.22	0.224	-1.367921	.320488
ln_building area	-.0670705	.220806	-0.30	0.761	-.4998424	.3657014
ln_yearbuilt	22.94792	8.220762	2.79	0.005	6.835521	39.06032
ln_stories	.4110824	.407565	1.01	0.313	-.3877303	1.209895
ln_amenities	.2203249	.0816936	2.70	0.007	.0602084	.3804414
ln_vacancy	-.0122499	.0120129	-1.02	0.308	-.0357948	.011295
_cons	(dropped)					
sigma_u	.14993678					
sigma_e	.23972366					
rho	.28119409	(fraction of variance due to u_i)				

Table 0-7

Submarket Insurance District							
Random-effects GLS regression				Number of obs	=	**116**	
				Number of groups	=	**9**	
R-sq:	within	= **0.0047**		Obs per group:	min =	**4**	
	between	= **0.6209**			avg =	**12.9**	
	overall	= **0.4679**			max =	**22**	
Random effects u_i		~ **Gaussian**		Wald chi2(8)	=	**41563.54**	
corr(u_i, X)		= **0** (assumed)		Prob > chi2	=	**0.0000**	

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	-18.57947	3.477168	-5.34	0.000	-25.3946	-11.76435
ln_subway	.335439	.1325398	2.53	0.011	.0756659	.5952122
ln_distance 20 bldgs	-.0101508	.0465144	-0.22	0.827	-.1013172	.0810157
ln_space within 1500ft	.0415382	.1142938	0.36	0.716	-.1824735	.26555
ln_building area	.2393395	.0667393	3.59	0.000	.1085329	.370146
ln_yearbuilt	9.011415	1.70073	5.30	0.000	5.678045	12.34478
ln_stories	-.2220034	.1841586	-1.21	0.228	-.5829477	.1389408
ln_amenities	-.7550614	.2439574	-3.10	0.002	-1.233209	-.2769137
ln_vacancy	.0259222	.0123653	2.10	0.036	.0016867	.0501578
_cons	(dropped)					
sigma_u	0					
sigma_e	.13983776					
rho	0	(fraction of variance due to u_i)				

Table 0-8

Submarket Madison Square/ Murray Hill						
Random-effects GLS regression				Number of obs	=	**200**
				Number of groups	=	**17**
R-sq:	Within	= **0.0239**		Obs per group:	min =	**1**
	Between	= **0.5263**			avg =	**11.8**
	Overall	= **0.3817**			max =	**22**
Random effects u_i		~ **Gaussian**		Wald chi2(8)	=	**5993.23**
corr(u_i, X)		= **0** (assumed)		Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	8.671116	42.39905	0.20	0.838	-74.42949	91.77172
ln_subway	.0544399	.1164914	0.47	0.640	-.173879	.2827587
ln_distance 20 bldgs	.0245256	.081142	0.30	0.762	-.1345099	.1835611
ln_space within 1500ft	-.16837	.2792416	-0.60	0.547	-.7156734	.3789334
ln_building area	.0386894	.0856237	0.45	0.651	-.1291301	.2065088
ln_yearbuilt	-3.74189	20.58828	-0.18	0.856	-44.09418	36.6104
ln_stories	.5080597	.3829139	1.33	0.185	-.2424378	1.258557
ln_amenities	-.0843246	.236209	-0.36	0.721	-.5472857	.3786365
ln_vacancy	-.0146045	.0096256	-1.52	0.129	-.0334704	.0042614
_cons	(dropped)					
sigma_u	.17136748					
sigma_e	.15885925					
Rho	.53782342	(fraction of variance due to u_i)				

Table 0-9

Submarket-Penn Garment						
Random-effects GLS regression				Number of obs	=	**1251**
				Number of groups	=	**83**
R-sq: within	= **0.0232**			Obs per group:	min =	**2**
between	= **0.2535**				avg =	**15.1**
overall	= **0.2060**				max =	**22**
Random effects u_i	~ **Gaussian**			Wald chi2(8)	=	**13208.30**
corr(u_i, X)	= **0** (assumed)			Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	.0481222	10.14343	0.00	0.996	-19.83264	19.92888
ln_subway	-.0513604	.0627044	-0.82	0.413	-.1742587	.071538
ln_distance 20 bldgs	-.0257926	.0412657	-0.63	0.532	-.1066718	.0550867
ln_space within 1500ft	-.013992	.1034476	-0.14	0.892	-.2167454	.1887615
ln_building area	.1568765	.0526505	2.98	0.003	.0536835	.2600696
ln_yearbuilt	.203366	4.942196	0.04	0.967	-9.483161	9.889893
ln_stories	.0647258	.1338264	0.48	0.629	-.197569	.3270207
ln_amenities	.1436204	.151916	0.95	0.344	-.1541294	.4413702
ln_vacancy	-.0182947	.0036539	-5.01	0.000	-.0254562	-.0111332
_cons	(dropped)					
sigma_u	.25334813					
sigma_e	.19027067					
Rho	.63937069	(fraction of variance due to u_i)				

Table 0-10

Submarket Midtown East, Plaza District							
Random-effects GLS regression				Number of obs	=	**1300**	
				Number of groups	=	**98**	
R-sq: Within	= **0.0273**			Obs per group:	min =	**1**	
Between	= **0.3190**				avg =	**13.3**	
Overall	= **0.1879**				max =	**22**	
Random effects u_i	~ **Gaussian**			Wald chi2(8)	=	**46525.07**	
corr(u_i, X)	= **0** (assumed)			Prob > chi2	=	**0.0000**	
ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]		
ln_latitude	-1.124756	3.975387	-0.28	0.777	-8.916372	6.66686	
ln_subway	-.01988	.0269086	-0.74	0.460	-.0726198	.0328598	
ln_distance 20 bldgs	-.0515889	.0299946	-1.72	0.085	-.1103773	.0071994	
ln_space within 1500ft	.0562304	.0478296	1.18	0.240	-.0375139	.1499747	
ln_building area	.0281084	.0337262	0.83	0.405	-.0379937	.0942105	
ln_yearbuilt	.8791906	1.949119	0.45	0.652	-2.941012	4.699393	
ln_stories	.1639763	.0716097	2.29	0.022	.0236239	.3043287	
ln_amenities	.1128653	.0524172	2.15	0.031	.0101294	.2156012	
ln_vacancy	-.0175647	.0029376	-5.98	0.000	-.0233222	-.0118072	
_cons	(dropped)						
sigma_u	.17158962						
sigma_e	.16388325						
rho	.52295957	(fraction of variance due to u_i)					

Table 0-11

Submarket World Trade Center

Random-effects GLS regression		Number of obs	=	**160**
		Number of groups	=	**15**
R-sq: within	= **0.0485**	Obs per group:	min =	**3**
between	= **0.8408**		avg =	**10.7**
overall	= **0.6029**		max =	**22**
Random effects u_i	~ **Gaussian**	Wald chi2(9)	=	**43.32**
corr(u_i, X)	= **0** (assumed)	Prob > chi2	=	**0.0000**

ln_rent	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_latitude	81.31256	67.31504	1.21	0.227	-50.62249	213.2476
ln_subway	.0511269	.0398037	1.28	0.199	-.0268869	.1291407
ln_distance 20 bldgs	-.0123613	.088291	-0.14	0.889	-.1854084	.1606858
ln_space within 1500ft	.0545923	.0971972	0.56	0.574	-.1359107	.2450953
ln_building area	.2870436	.0955622	3.00	0.003	.0997452	.4743421
ln_yearbuilt	-2.161858	3.290831	-0.66	0.511	-8.611769	4.288052
ln_stories	.1075023	.1239199	0.87	0.386	-.1353764	.3503809
ln_amenities	-.0613615	.1166992	-0.53	0.599	-.2900877	.1673648
ln_vacancy	-.0224763	.0064326	-3.49	0.000	-.035084	-.0098686
_cons	-286.6238	241.0837	-1.19	0.234	-759.1391	185.8915
sigma_u	.11436392					
sigma_e	.12360667					
rho	.46121862	(fraction of variance due to u_i)				

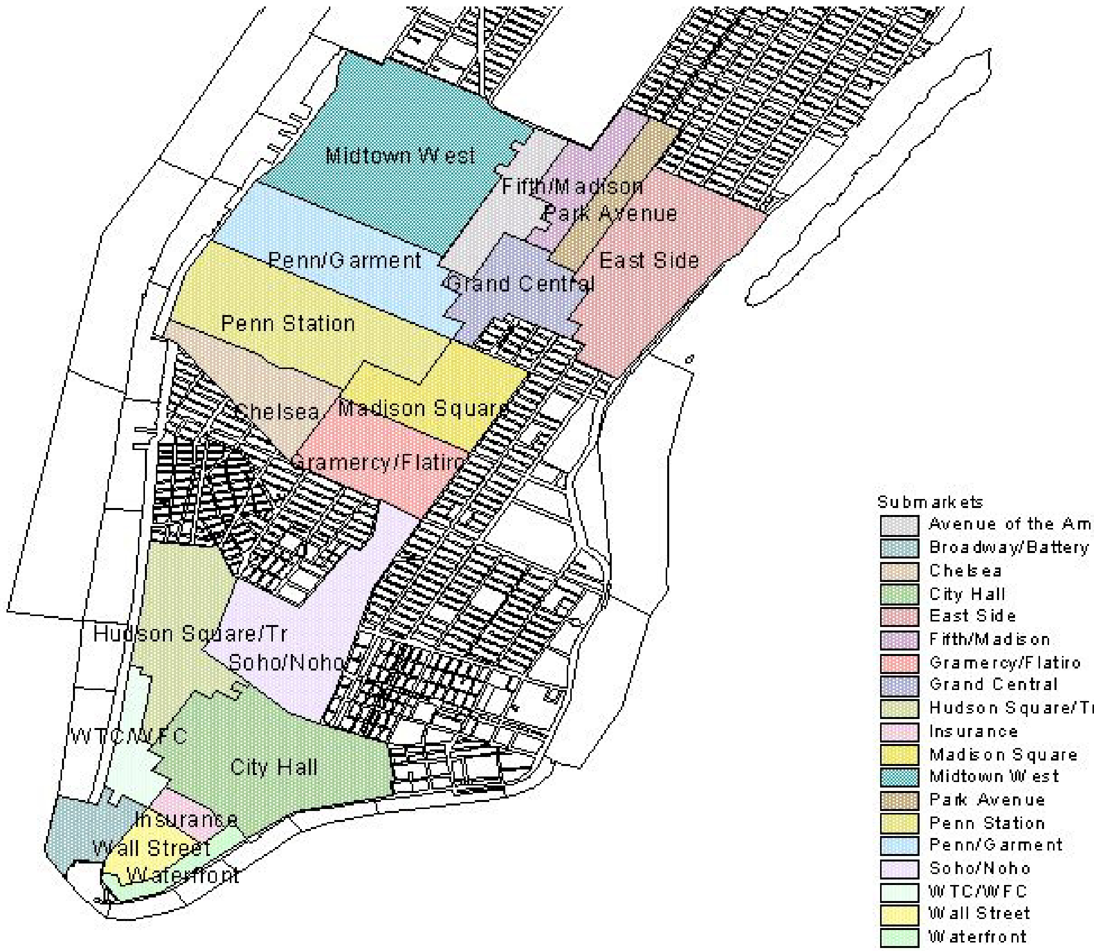


Figure A-1: Definition of Manhattan submarkets (Boundary definition by Grubb & Ellis)

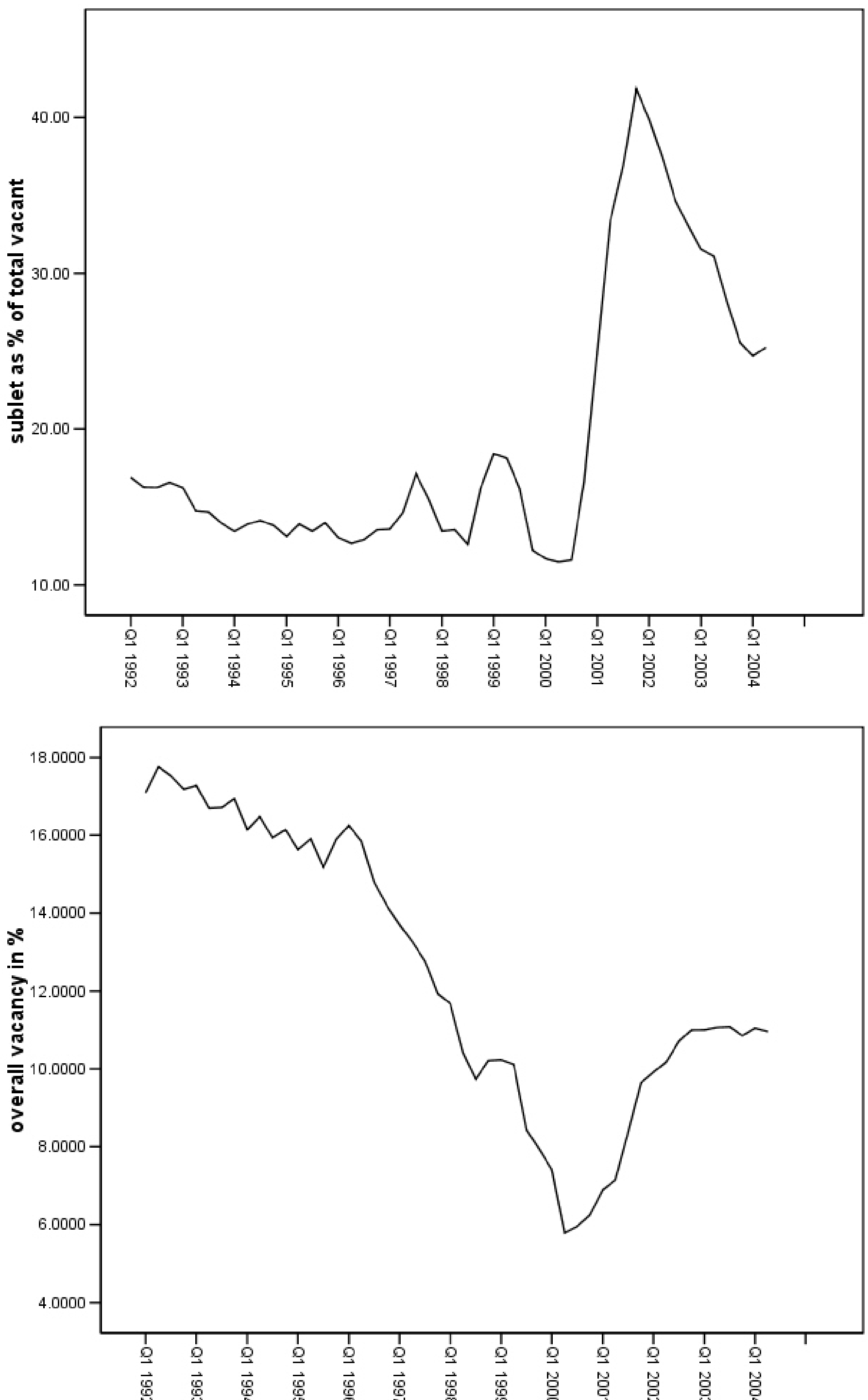


Figure A-2: Sublet space as a percentage of total vacant space (above) and overall vacancy in percent (below). Data: CoStar Group, Grubb & Ellis

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NOTE

The empirical results presented in this dissertation were estimated using the software packages GAUSS 6.0, STATA 9, SPSS 13.0 and the Easyreg econometric package.