Analyzing and modeling spatio-temporal patterns of the New York City office market

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Introduction

This study analyzes spatial patterns of market integration and tests for the existence of fragmented submarkets within a relatively small geographic area. It aims at answering the following questions: Firstly, to what extent do office submarkets constitute economically autonomous entities in a highly diversified and functionally specialized market such as Manhattan? Secondly, are real estate markets best modeled at the metropolitan level? Similarly, is modeling and forecasting of individual submarkets within a metropolitan area yielding significantly better results or is this method simply generating more 'white noise'? Are the statistical determinants of rents of equal significance both cross-sectionally and over time? Finally, do spatial submarkets move across all phases of the market cycle without any systematic lags or deviations from overall market conditions or are there distinct spatial patterns that can be observed?

Real estate markets are characterized by spatial constraints and the distinct physical features and amenities of each individual property. The large degree of product differentiation in commercial real estate gives rise to economically fragmented markets. On the other hand, standard metropolitan forecasting models assume that existing differences in rents and vacancy levels among locations are of subordinate significance compared to the variation observed between metropolitan office markets (i.e. interregional differences). Consequently, these models do not normally differentiate office submarkets within a city.

In contrast to this assumption of a unified market, a number of previous studies have demonstrated that distinct submarkets do exist within urban office markets. 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 not fully 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 typically find that structural and spatial fragmentations are overlapping or interdependent as certain types of properties are more prone to prevail in an area with specific locational characteristics. 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.

The remainder of the paper is organized as follows. The first section reviews previous studies on submarkets and spatial differentiation of commercial real estate markets. Next, the Manhattan office market is examined for signs of spatial fragmentation using descriptive statistics. In a further step, we test if variables reflecting individual characteristics of submarkets such as average age, density and accessibility are able to explain the variation in rental rates of submarkets. Instead of applying a classical fixed-effects model, we focus on the difference between submarket rent and overall market rent. The analytical framework is expanded by estimating a simultaneous equation model for both the overall market and individual submarkets to determine whether such models perform reasonably well at this level of spatial aggregation. In the last step, we test the significance of various characteristics in different phases of the market cycle by using a hedonic model. The stability of parameters is analyzed cross-sectionally to test the independence of submarket observations.

2 Relevant background

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 the prices in all submarkets to converge.

Differentiation of intraurban locations and the evolution of submarkets

Office markets are subject to considerable cyclical movements. Endogenous cycles arguably arise 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). This study addresses these issues in order 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). These intra-urban moves ensure that the locational hierarchy within a city is maintained. 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 to name just one example (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 the mere mechanics of price and rent movements commonly portrayed in market studies.

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 trend 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). Empirical studies supporting this hypothesis also point out that the increasing functional specialization of spatial submarkets has resulted in increasing economic fragmentation of markets (Sivitanidou 1995, 1996, Bollinger et al. 1998).

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 work towards reinforcing 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. While moral hazard structures would be minimal in an efficient market, opportunities for rewarding but ultimately unethical behavior arising from asymmetrical information and other abovementioned factors exacerbate the problem and 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. In contrast to office market research, spatio-temporal models are well established in the housing market literature. 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 locational hierarchies

One of the earliest references to the existence of distinct submarkets 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. In general, there is 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). Typically, 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, 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. But 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 (2000) found evidence that such knowledge spillovers operate almost exclusively at the small-scale level. The authors conclude 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.

Empirical evidence on market fragmentation

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 a spatially homogeneous 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 conclude that further empirical testing for submarket existence is necessary. Sivitanidou (1995) demonstrates that spatial supply-side constraints such as existing zoning regulations are an important factor 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 do not incorporate 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 made to generate new submarkets with the aim of maximizing statistical homogeneity within these markets. 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.

Theoretical considerations of real estate cycles and imperfect markets

Cyclical movements of the real estate markets have been subject to extensive academic research in the past decade (e.g. Clapp, 1993; Barras, 1994; Kummerov, 1999; Wheaton, 1999). Many markets have experienced demand-supply mismatches at a dramatic scale. Out-of-sync markets can partly be explained by the inherent sluggishness of office markets in responding to changes in the demand structure (Cobweb Theorem). 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. Since decision makers on the supply side mostly have either trend line forecasts or no forecasts at their hands it is difficult for them to evaluate their decisions with regard to potential non-linear developments. Faulty predictions are often due to trend extrapolations in times of prosperity and overly optimistic expectations of future market developments. More recently, multiple regression models have been applied to describe the interdependencies of the real estate market. However, most of these models lack the explanatory power necessary to predict future developments reliably since they do not take into account two important principles that determine the development of the built environment and the real estate market. These two principles are asymmetrical information of market agents and the limited rationality of decision makers. One further innovative attempt to grasp more accurately the intangible factor combinations underlying real estate market mechanics are neural network models, genetic algorithms (Bee-Hua, 1998) and cellular automata (Batty, 1998). Mueller (1999) demonstrated that each phase of the cycle is connected to a distinct pattern of rental growth.

However, price convergence can be impeded in a situation of low market transparency and information asymmetries. Market transparency is commonly defined as the ability of market participants to obtain information about the trading process, such as price, rent, transaction volume, terms and conditions of transactions as well as background information on market participants. This study builds on the existing research by examining rental price determinants in the Manhattan office market both cross-sectionally and across time.

Data and methodology

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. Secondly, 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 Wall Street and the Insurance District with well-developed locational profiles. The mosaic of distinct submarkets is reflected in the great degree of heterogeneity of office buildings regarding their vintage, size, technology and amenities. Because of the high density of Manhattan, submarket areas with distinct features can be found within a relatively short distance from one another.

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 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, i.e. west of 9th 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 but remained largely constant except for these cyclical trends. The fact that overall occupied space has increased despite slow growth in employment can be explained by an increase in office space per worker.

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 (Figure 1). The submarket delineation used in this study is based on the definition by Grubb and 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.

Data issues

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 and 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. 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. Submarket data is available from 1992 onwards and building is available from 1999 onwards. 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 and have been smoothed prior to being used in the regression analysis.

Inventory, occupancy and vacancy data

The submarket data obtained from Grubb and Ellis aggregate a fixed 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[1]. A potentially more serious issue is the fact that Grubb and 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.

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 nearly 3,000 Manhattan office buildings but only about 700 buildings of these could be used for the purpose of the hedonic analysis due to missing data for most of the smaller office buildings.

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).

Employment data

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. 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.[2] 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 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.

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. 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.

Methodology

In the first step of the empirical analysis, some basic descriptive measures are used to investigate possible market fragmentation. We examine the neoclassical constant-ratio hypothesis by analyzing quarterly rent changes, standard deviations in submarkets over twelve years. Next, a bivariate correlation matrix of changes in rental and vacancy is generated to test the assumption of simultaneous adjustment. Additionally, cross-correlation diagrams will be examined for systematic lagged adjustment of submarkets.

Analysis of descriptives is not sufficient, however, because it does not permit to conclude whether these similarities are caused by macro-economic factors affect each submarket in a similar way or if rental rates are determined by overall market conditions regardless of individual micro-market conditions. If the former assumption is true, change rates in demand for office space and office employment will be similar in all submarkets. If the latter assumption is true, demand and supply measures may not equilibrate at the submarket level and rental rates will mainly be determined by overall market conditions. To test these assumptions, we consider the deviations of individual submarkets from the Manhattan market and attempt to explain these deviations by incorporating local factors. This is done in three steps: Firstly, we look to explain permanent (spatial) features to explain long-run deviations. Secondly, we are looking at market dynamics and analyze if local factors in submarkets such as employment change or the local vacancy rate are

able to explain a deviating submarket movement. In this step, we use both a pooled time series and cross-sectional regression approach. Thirdly, we estimate completely separate submarket models and look how these models perform.
In order to explore the cross-sectional structure of the Manhattan office market, a regression model is constructed using he long-run average rental rate as a percentage of the overall Manhattan rental rate as the dependent variable. For instance, rents in the Plaza District submarket are an average of 30% higher than overall Manhattan rents. A number of explanatory variables are considered that explain this structural difference. Table 1 gives a description of the variables.

One basic difficulty in estimating the cross-sectional model is the earlier mentioned overlap of structural and spatial characteristics, i.e. the fact that the buildings of the highest quality are typically found in submarkets that exhibit a number of other attractive characteristics. Statistically, this may induce collinearity in the regression model. We therefore present two separate specifications with the first one using the percentage of Class A buildings as the sole predictor to demonstrate the interdependency of submarket and building characteristics. The second specification includes a number of location-specific variables, such as various accessibility measures as well as the average age of office buildings in the district. A full regression model including a series of explanatory variables is not feasible at this level of aggregation, however, because of a lack of sufficient degrees of freedom. A comprehensive hedonic model will be specified at the building level later on in this study.

Econometric modeling at the submarket level

Among the research questions laid out in the beginning of this report was the question whether submarkets are sufficiently autonomous to reliably apply econometric market models which take into account endogenous measures of supply and demand at the submarket level only. If empirical parameter estimations fail to explain the development of the market, it may be concluded that modeling at this aggregation level is not appropriate because submarkets do not constitute a proper market in itself. To this aim, we apply a reduced-form two-stage system of behavioral equations. The first stage incorporates the office space market in terms of occupied space and absorption of new space and the second stage captures the adjustment of office rents to changing market conditions.

Demand for Office Space: Estimating 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 level of occupied space is determined by:

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

(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. 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 attacks in affected submarkets 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.

Rental rate adjustment and vacancy rates

The vacancy rate is the residual of supplied space and demanded space in the following form:

$$V_t = \frac{S_t - OS_t}{S_t}$$

(2)

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. For the purpose of this study, the rent equation is specified as follows:

$$R_t = \mu_0 - \mu_1 V_{t-n} + \mu_2 U_{t-n} \qquad \textit{(3)}$$

In this specification, the routine use of vacancy rates to explain rental rates is supplemented with the amount of sublet space (U_{t-n}) as n additional predictor. The second variable is included because it provides an additional measure for short-term corrections of the space needs of office firms that is not reflected in the overall vacancy rate due to the long-term nature of office leases. The underlying assumption is that 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 an indicator of overall market conditions.

Hedonic analysis

In the next step of the analysis, the rental determinants of office properties will be investigated by estimating a hedonic model for Manhattan office buildings. The quintessential linear hedonic rent model is specified in the following form:

$$\ln R_i = \beta x_i + \phi Z_i + \varepsilon_i \qquad \textbf{(4)}$$

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).

While most hedonic studies of office rents choose a functional form that pools both locational and building-specific variables, two separate models will be estimated in this study, parallel to the method applied at the aggregate submarket level. This allows for a better comparison of location and building attributes with regard to rental price determination.

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, we estimate the parameters of both model specifications for each quarter from 1999 through 2004 individually and compare the resulting parameter estimates over time. Based on the development of aggregate rental rates, we assign each of the quarterly estimates to one of three periods in the market cycle that occurred during the observed period: (1) market recovery, (2) peak, and (3) decline. Finally, we investigate cross-sectional parameter stability of the hedonic estimates across submarkets to reach a conclusion on the existence of submarket fragmentation. The Chow test determines of whether the set of regression parameters (intercepts and slopes) is equal across groups (Chow 1960). If the resulting F statistic is significant, we discard the null hypothesis of structural stability of hedonic regression parameters across submarkets and accept the alternative hypothesis of structural heterogeneity. Accepting the alternative hypothesis would provide additional evidence of submarket fragmentation because equal pricing schemes are expected to prevail in a functionally integrated metropolitan market.[3] The fact that hedonic attributes are valued differently in different submarkets can thus be considered evidence of market fragmentation.

2 Empirical Results

As outlined in the previous section, the structure and development of office market heterogeneity over time is first explored by various descriptive statistics of the Manhattan office market. A boxplot of rental rates (Figure 2) illustrates the basic spatio-temporal pattern of the market, with rental rates bring shown as an index value in comparison to the overall market rate for a time span of roughly 12 years. Submarkets are arranged by spatial proximity from north to south. The boxplot shows the quartiles of the distribution for each submarket where the 25th and 75th percentiles of the rent distribution relative to the Manhattan aggregate are the limits of the respective box. 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. This is likely to be a direct effect of the bubble in the technology sector. 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 ("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 3 displays the distribution of volatility in rental rates in a map of Manhattan and Figure 4 shows changes in office employment at the zip code level illustrating the unequal distribution of employment changes. The graph displayed in Figure 5 demonstrates that submarkets experienced widely different dynamics in office employment from 1992 through 2004. The displayed pattern gives a first indication of distinct submarket cycles which we will explore more formally in the next section.

Moreover, heterogeneity of submarkets may not be identical in all phases of the market cycle. Figure 6 shows the development of rental and vacancy rates of all submarkets market over time and juxtaposes this with average standard deviations. Recalling the constant ratio assumption of neoclassical economic theory, standard deviations would be expected to remain constant over time, which is clearly not confirmed by the empirical data. Instead, the graphs show significant variation in average standard deviations over time and suggest a linear time trend for both rental and vacancy rates from a relatively heterogeneous market at the beginning of the analyzed period towards a more homogeneous pattern in recent years. To test for the existence of this time trend, standard deviations are regressed over a linear time trend variable as the sole predictor. The results reported in Tables 2 and 3 show that there is a clear trend towards a greater degree of market homogeneity regarding both rents and vacancy rates which seems to be independent of the cyclical movement of the market. Whether this trend is caused by a greater degree of market transparency in recent years or by structural changes in the Manhattan market remains to be explored. In general, the convergence in rental rates is more pronounced and clearer than the convergence in vacancy rates as reflected in the amount of variance explained by the time trend variable and the overall R square. However, since twelve years are a relatively short period, a longer time series of reliable submarket data would be needed to firmly establish the existence of a linear convergence trend as opposed to long-run cyclical swings.

Further evidence on cross-sectional rent and vacancy dynamics is provided in a correlation matrix of first-order differences for all submarkets in Tables 4 and 5. Strong integration is found in the two largest submarkets which are neighboring each other (Midtown West and Midtown East/Plaza District). All submarkets exhibit significant correlations with at least one neighboring submarket. The strongest associations are to be observed between changes in rental rates in individual submarkets and in the overall Manhattan market. 4 Correlations of changes in vacancy rates are generally lower but correlate with the overall market with the exception of three submarkets (Penn/Garment, Hudson Square/Tribeca and City Hall).

To explore further whether potential market heterogeneity is caused not only by submarket fragmentation but also by lagged adjustment of submarkets towards a general market equilibrium, we investigate cross-correlation diagrams for possible lags in rental rate adjustment. Figures 7 through 12 show, however, that there are no significant lags in the change rates of the three subareas Midtown, Midtown South and Downtown Manhattan. All three areas demonstrate largely simultaneous shifts in rental rates with no clear spatial lags. Cross-correlation measures at the more disaggregated submarket level did not yield a consistent pattern of lag or lead structures. Regarding changes in vacancy rates, Figures 7 to 12 show that these changes also occur largely simultaneously in all three subareas with no significant lag or lead structures.

Based on the descriptive statistics presented up to this point, it is not possible to draw any conclusions about the existence of submarket fragmentation. In the next step, both cross-sectional and time-series regression analysis is used to detect possible sources of market heterogeneity. First, we test for the relevance of permanent, i.e. spatial and physical, features in explaining the variation of submarket rents. As mentioned earlier, the number of explanatory variables that can enter into the regression analysis is very limited at this aggregation level due to the small number of cross-sectional observations. The first model tests to what extent the overlap of structural and spatial submarkets accounts for the difference in rents. In other words, is there a link between the average rental rate and the physical and spatial features of the buildings in that submarket? As a proxy for structural differences, we choose the percentage of Class A buildings in a submarket.[5] Table 6 reports the results of this basic model. Indeed, the percentage of Class A buildings is a good predictor of the long-run average relative rent level of a submarket (adjusted R square of 0.748). In a second model, we test the predictive power of additional spatial and structural variables with regard to long-run average submarket rental rates. The specification reported in Table 7 includes three independent variables, a compound accessibility index value for all buildings, the amount of square feet of office space within a radius of 1500 feet summed up over all buildings within a submarket (as a proxy for the opportunity of face-to-face interaction) and the average age of buildings in the submarket. With the exception of the compound accessibility measure, the variables reach the desired significance levels and explain the submarket differences reasonably well (adjusted R square of 0.663).

Turning to time series observations, calculate submarket rent and vacancy respectively as a percentage of overall Manhattan rates for all 49 quarterly observations in all 15 submarkets and pool all observations to perform a regression analysis using the relative level of vacancy to predict relative rental rates. Here, all observations are used in the regression model instead of the long-run mean as reported in the previous section. Table 8 shows the parameters and modeling results. Although the basic inverse relationship between both variables is captured by the regression, the model fails to explain submarket heterogeneity. This is probably due to the fact that time-series dynamics between the two variables are not captured well by this simple pooled regression model. To take into account these dynamic relationships, a simultaneous equation model is estimated for Manhattan and a selected number of submarkets.

Simultaneous equation model

The model outlined earlier was estimated empirically using an OLS regression framework. The exogenous shock of the 9/11 attacks was captured with a dummy variable for the overall Manhattan estimations and additionally in those submarkets that were immediately affected by the events. The model is parametrized using quarterly observations from 1992-2004[6].

Estimation of office occupancy

As a first step, the demand for office space was estimated for Manhattan and a number of randomly selected submarkets. Table 9 shows the results of the OLS estimation of 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 were tested and significance levels were 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 continuous increase in occupied space, a time trend variable is included. Moreover, early estimations of the model were not able to fully capture the combined supply and demand shock of the 9/11 attacks. 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 specification of the overall Manhattan market. In the final form of the specification, all variables are significant and show the expected sign (Table 9). 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 (early 1990's) the suggested space use rises to rises to 360 sq. ft. and decreases to 300 square feet per worker during periods of high rents (1999-2001). This specification yields a satisfying fit as indicated by the F-test and R^2. Tables 10 through 17 show the results for each of the seven submarkets selected in this step. All of the models with the exception of one submarket (City Hall) are significant and the variables show the expected signs and significance levels. The results confirm the assumption that office occupancy can be modeled endogenously at the submarket level with the exception of very few submarkets that show data anomalies that have to be explored in depth.

Estimation of rent levels

The second stage of the model estimates rental rates for Manhattan and each of the submarkets. With the help of cross-correlation measures the optimal lag structure of the vacancy variable was determined individually for Manhattan and each of the submarkets. In most cases the lag was three quarters. This means that it takes landlords on average three quarters before they effectively lower asking rents to a level that is in line with prevailing local vacancy rates. Information asymmetries and the persistence of a general market sentiment are further reasons leading to lagged adjustment of rental rates. Table 18 shows the results of the parameter estimation for Manhattan. The model passes the test for autocorrelation, therefore no additional measures to correct for autocorrelation of the residuals are required. Vacancy rates and the amount of sublet space on the market show the expected signs and significance levels. A time trend variable confirms a general trend towards higher rents, even with rental rates that are adjusted for inflation (as is the case for all rental values used in this study). Tables 19 through 25 show the results of rental rate estimations for the submarkets. Since virtually all of the models (except Midtown West/Avenue of the Americas) exhibited autocorrelation of residuals above the specified threshold, the simple OLS model had to be re-estimated using an autoregressive moving average (ARMA) model. The explanatory variables (vacancy rate and sublet rate) do not reach the desired significance levels in many cases, most likely because the included autoregressive terms explain a large part of the existing variation. The overall model fit and explanatory power, however, is quite satisfying as demonstrated by R squares ranging from 0.65 to 0.92 for the submarkets. This may be interpreted as further confirmation that submarkets can indeed be modeled endogenously based solely on submarket-level information.

Estimation of the hedonic regression model

As outlined in the methodology section, two separate hedonic models are estimated at the individual building level to examine rent determinants at various phases of the real estate market cycle. Table 26 shows the variables included in Model I along with the parameter estimates for each quarter. The variables in the final specification of the models are briefly described below.

Vacancy levels are expected to impact asking rents in a building in the same manner described above for the general market, as landlords lower asking rents in response to rising vacancy in a building to attract tenants. The appropriate time lags were estimated for each quarter and subsequently applied in the estimation. The variable is significant in each quarter as indicated by the t-value.

The *building area* variable reflects mainly the 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). In a similar study Bollinger, Ihlanfeldt and Bowes (1998) found average floor area to be a significant variable in determining rents in the Atlanta office market. The results of the estimation confirm these results for the Manhattan market.

Building age is reported to be of relevance in a host of studies on office market rent determinants (Bollinger, Ihlanfeldt and Bowes 1998, Sivitanidou 1998, Slade 2000, Dunse et al 2003). In this study, building age is expressed as year built to the extent that a more recent construction date has a positive impact on rental rates. The age of a building is typically a proxy for the quality of the technological infrastructure and adequacy of the floor layout. The results of this estimation confirm the importance of this factor over the entire estimated period.

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, which is confirmed by the estimates of this study.

The *amenities* variable 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. 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 Model II which measures the location-specific price determinants, we find a number of variables that are significant as rent determinants. Table 27 presents the results of the quarterly rent estimation.

The average *distance of the 20 closest office buildings* was calculated with a nearest neighbor algorithm in a Geographic Information System and reflects ease of access to clients and business services in the immediate vicinity of the building.

Similarly, the *amount of office space located within 1500 feet* of an office building indicated whether a building is located in a major office cluster or not. Therefore, a positive impact of this variable is expected, which is confirmed by the empirical results in Table 27.

The *distance to the nearest subway station* measures ease of access to the public transit which is the most important means of transportation in Manhattan. The estimated parameters confirm the significance of this variable.

Finally, the *latitude and longitude* coordinates were included in the hedonic specification of a building. While not meaningful per se, these variables are potentially apt to capture spatial effects not operationalized in the other variables of the model. The coefficient of the latitude variable is negative which is caused by the effect that the highest-price buildings are located 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 on the eastern part. These estimates are likely to be caused by the fact that the largest office cluster commanding the highest rents is the Plaza District in the northeastern section of Midtown Manhattan.

Parameter stability and the market cycle

To determine the variability of these rent determinants over time, the time series is divided into three distinct periods of the real estate 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. Figure 13 contains an illustration of the timeline of the three cycles. Next, the two hedonic models were estimated separately for each of the phases. The results are reported in Tables 28 and 29. There are considerable differences in parameter estimates between the peak phase on the one hand and the recovery and decline phases on the other. The results appear counter-intuitive at first sight, however. 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. This 'spillover effect' is demonstrated in Figure 14, which shows that rental rates of Class B buildings approach Class A rents during the peak phase of the market. As a consequence, quality features of buildings as represented by the variables of the two hedonic regression lose some of their explanatory power. 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 rental rates become more polarized.

Parameter stability and submarket fragmentation

Besides the issue of parameter stability over various phases of the cycle, it is pertinent to examine the parameters of the hedonic regression model to test for market fragmentation. To this aim, a Chow test is applied as outlined in the methodology section. Table 30 presents the results for the building-specific and location-specific hedonic models. The Chow values confirm that parameter values are significantly different at each of the phases in the market cycle. Next, to test for fragmentation of submarkets (cross-sectional fragmentation), the parameters of separately estimated hedonic models for Midtown, Midtown South and Downtown Manhattan a Chow test are compared to an estimation with pooled observations (Table 31). Both models exhibit significantly different parameters across submarkets.

Finally, to combine the cross-sectional and time-series analysis, Chow tests are estimated for each of the market phases (Table 32). The F statistics obtained from this calculation confirm the existence of cross-sectional market fragmentation at each of the three phases identified in the market cycle. Again, market fragmentation appears to be weaker during the peak period when there is a relative convergence of all submarkets and spillover effects occur that reach submarkets mainly composed of non-competitive office buildings.

Conclusions

The objective of this study was to test whether submarkets are meaningful entities that can be understood and modeled endogenously using Manhattan as a case study. Moreover, a hedonic approach was applied to investigate rent determinants at various phases of the market cycle.

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.

An initial analysis of descriptive statistical measures reveals a relatively strong integration of the market to the extent that changes in rental and vacancy rates are highly correlated across submarkets. In a further step, the permanent features of submarkets are examined to account for the relative long-run difference of submarket rental rates compared to overall market rents. The study finds that permanent features such as accessibility by public transit, distance of other major office buildings and percentage of Class A properties explain much of the variation in rental rates found between submarkets.

The results of this study support the hypothesis that modeling occupancy and rental rates with submarket-specific variables yields meaningful and significant results. While submarket modeling has to be tested in other metropolitan markets as well, it appears to be a promising approach that could potentially provide additional insight into the economic dynamics of smaller market areas that are not captured by aggregate models operating at the metropolitan market level.

Using a hedonic regression framework, a number of building-specific and spatial variables are identified as major determinants of rents, confirming the results reported in existing studies. An estimation of the hedonic model at various points of the market cycle reveals that parameters vary across the market cycle. The importance of rent determinants varies with the position in the market cycle. Contrary to prior expectations, the hedonic regressions show that most parameter values decrease at the peak phase of the market. Similarly, evidence of submarket fragmentation is found using the Chow test. The lesser degree of submarket fragmentation confirms the assumption of general market convergence during the peak phase of the cycle and a more pronounced divergence of rental rates during the decline and recovery phase.

[1] As far as space accounting of the 9/11 attacks is concerned, all destroyed and damaged building (34.5 million square feet) have been removed from the inventory data in the third quarter and re-inserted as buildings were gradually restored. 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.

[2] 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, we developed 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) we 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.

[3] Absent a direct function to calculate Chow Test statistics in the software used to generate the regression results, an indirect methodology was applied. Tests of between-subjects effects were run including an interaction term for submarkets. The General Linear Model pools the Sums of Squares and degrees of freedom for submarkets and submarkets times the independent variable (X) in question and reports an F-test for submarkets*X. Given a model that includes a term for submarkets and submarkets*X, the group term for submarkets would test differences in intercepts and the submarkets*X term would test differences in slopes. Pooling these terms into a single submarkets*X term has the result that the F-test and the associated p-value for the submarkets*X test is the overall test of whether the full set of regression parameters (i.e., the slopes and intercepts taken together) differ among groups. Hence, the submarkets*X effect in this model is the equivalent of the Chow test. This statistic was computed separately for each of the variables to obtain estimates of the parameter stability of each of the variables used in the regression.

[4] Correlation matrices might be slightly biased towards higher correlations between submarkets and the overall market average because of the fact that each submarket is also contained in the calculation of the average market rate. Therefore, these results have to be interpreted with caution, especially in larger submarkets.

[5] Scientific definitions of Class A space are rare. Archer (2003) outlines at least three distinctive features of Class A space 1) the absence of 'hybrid-use' offices (i.e. retail offices, medical offices, laboratories etc.), 2) a

lesser degree of sensitivity to direct rental expense of its tenants than can be found in Class B and C buildings whose tenants are presumed to be rental cost minimizers, and 3) the dominance of this market as the principal marketplace to the extent that office development and redevelopment is targeted almost exclusively to this market.

6 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.

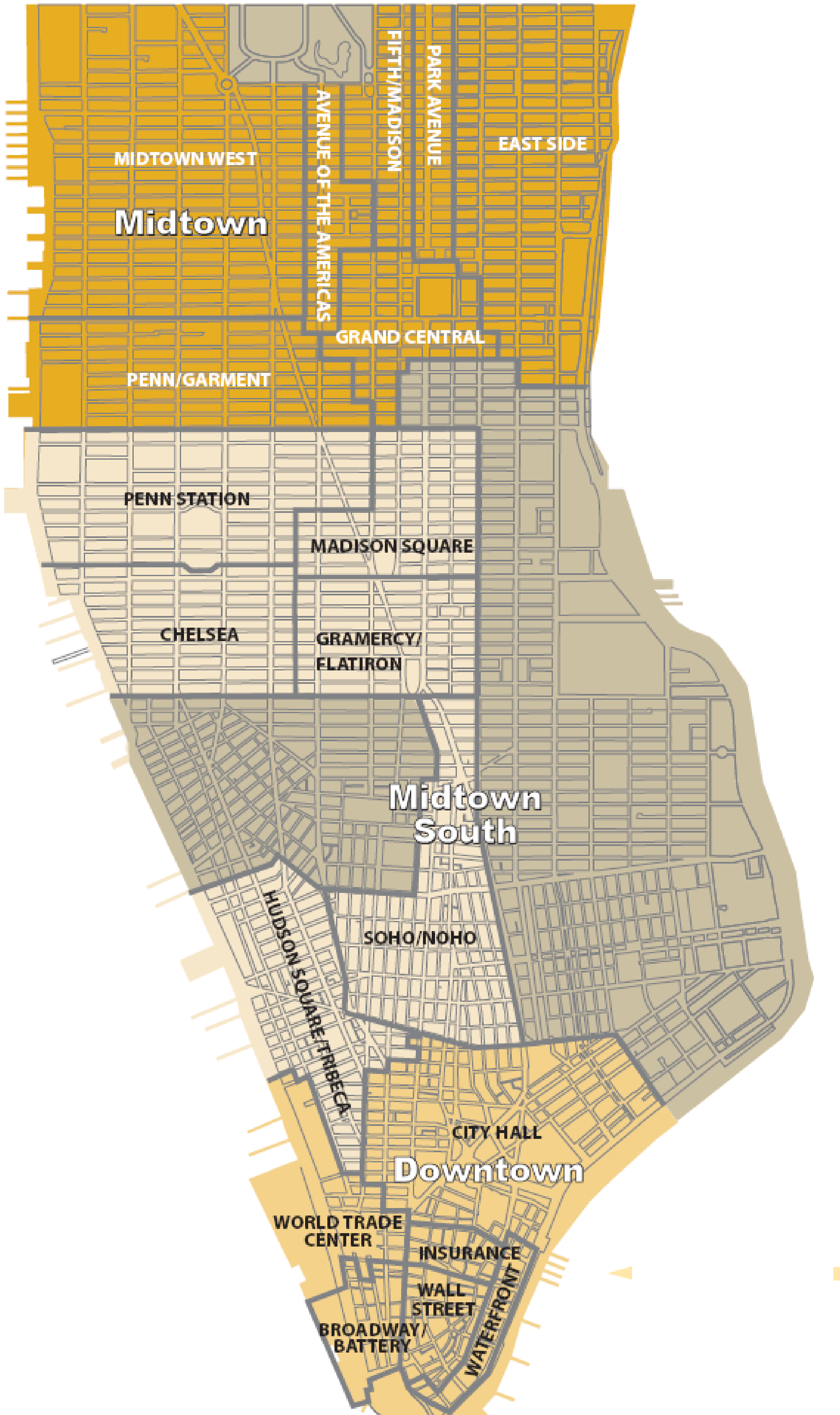

Figure 1: Map of Manhattan subareas and submarkets (Source: Grubb & Ellis)

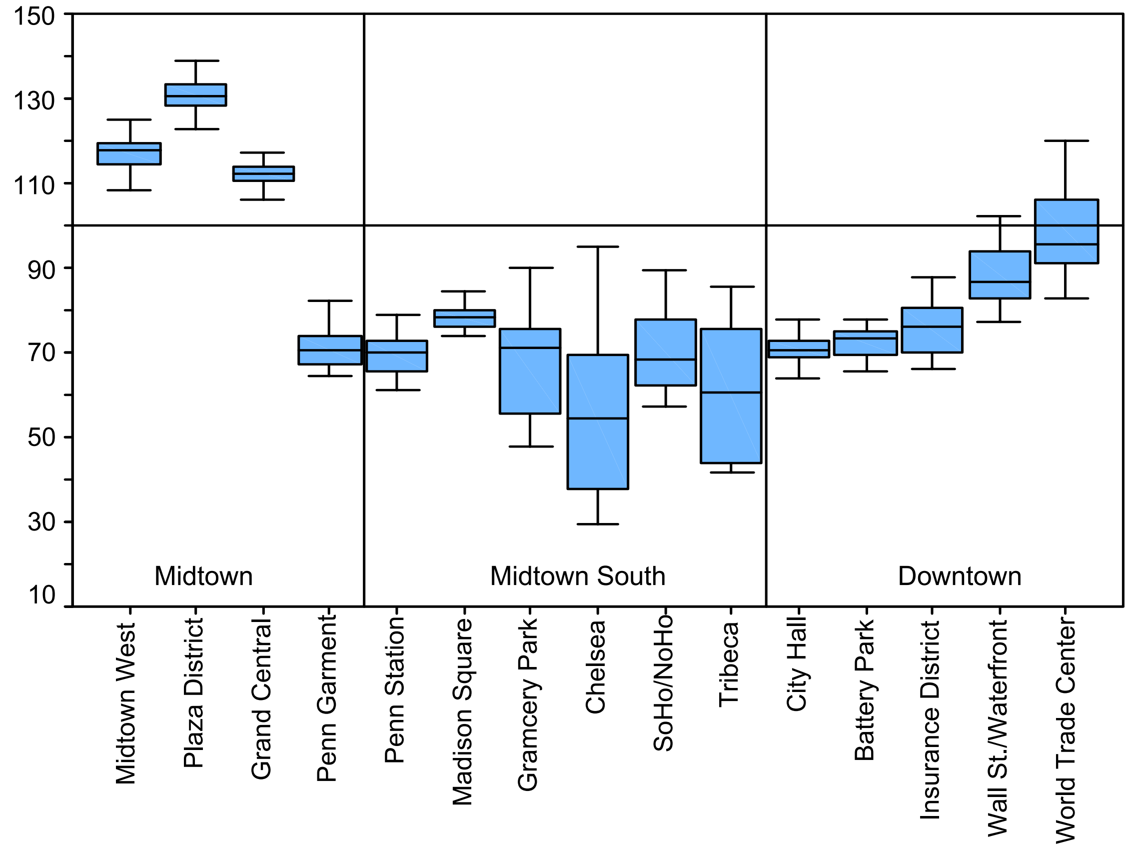

Figure 2: Boxplot of submarket rents relative to the overall Manhattan office market from Q1-1992 through Q1-2004 (index Manhattan=100)

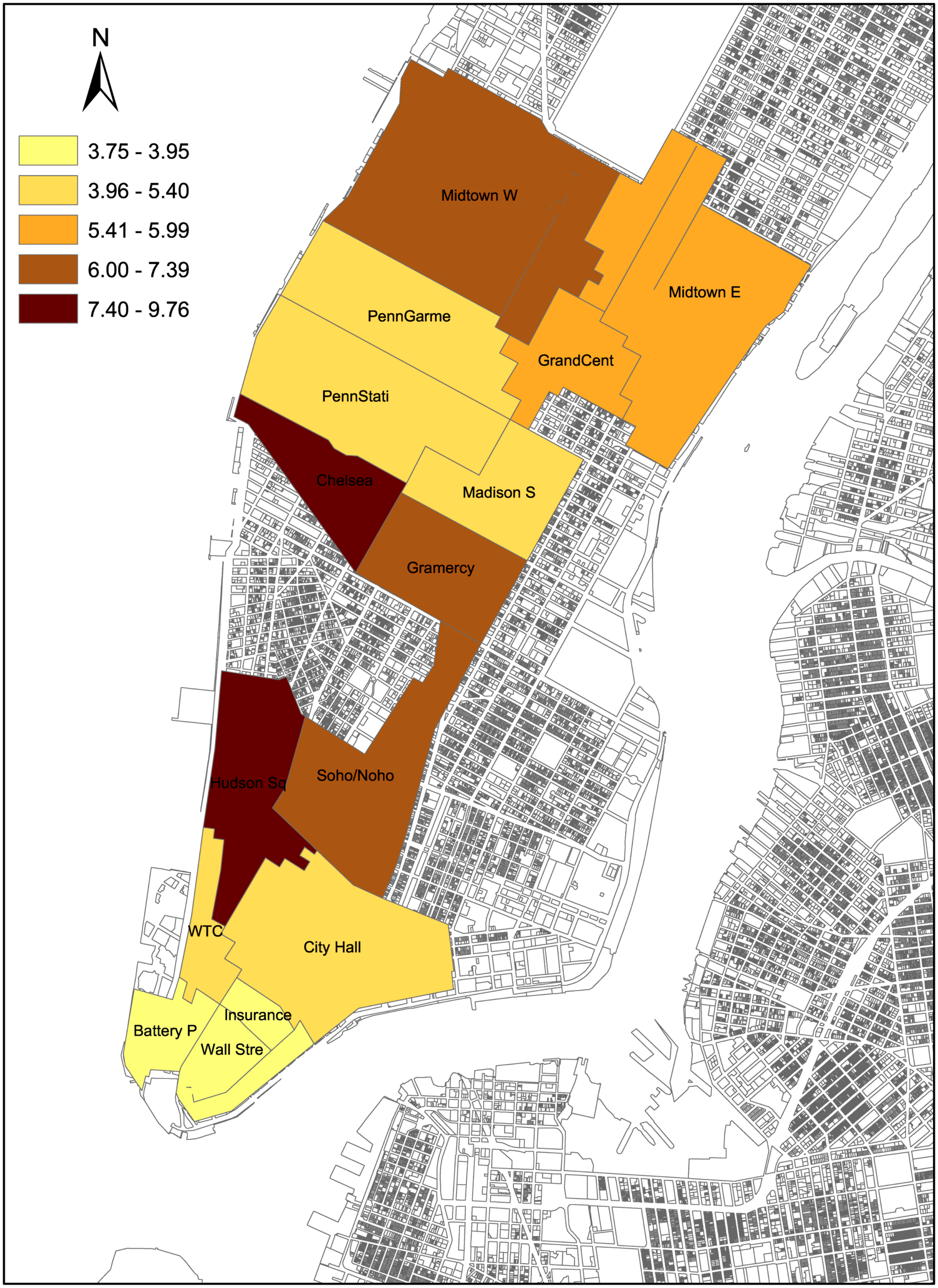

Figure 3: Standard deviations of submarket rents (1992-2004)

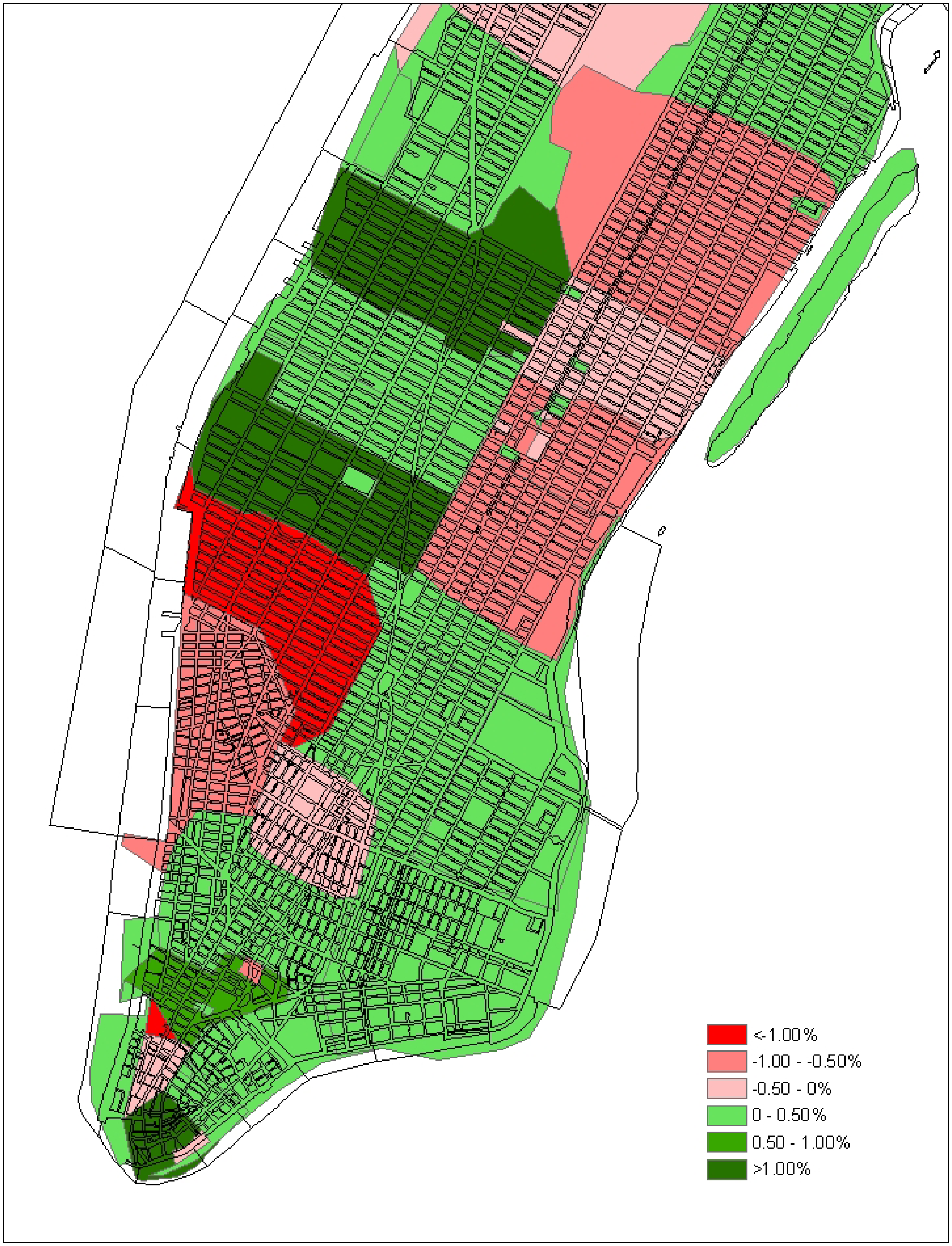

Figure 4: Change of share in Manhattan office employment from 2000 to 2003 for zip code areas (in % of overall share in the total market)

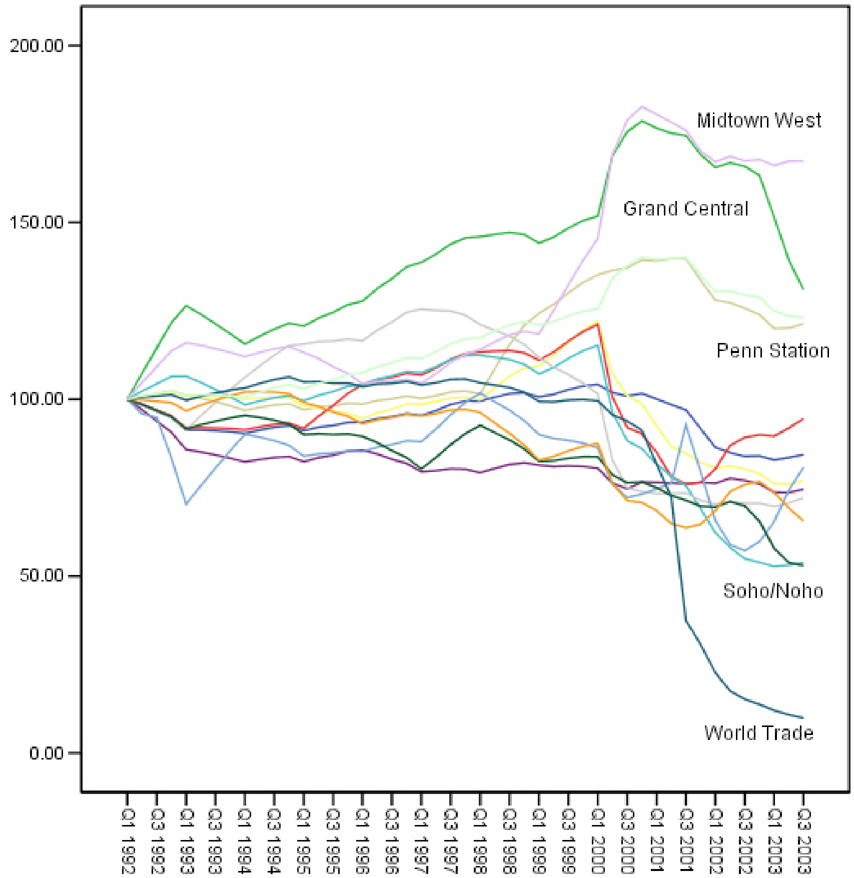

Figure 5: Rental rates in Manhattan submarkets from 1999 until 2004 (index: Q1 1992=100)

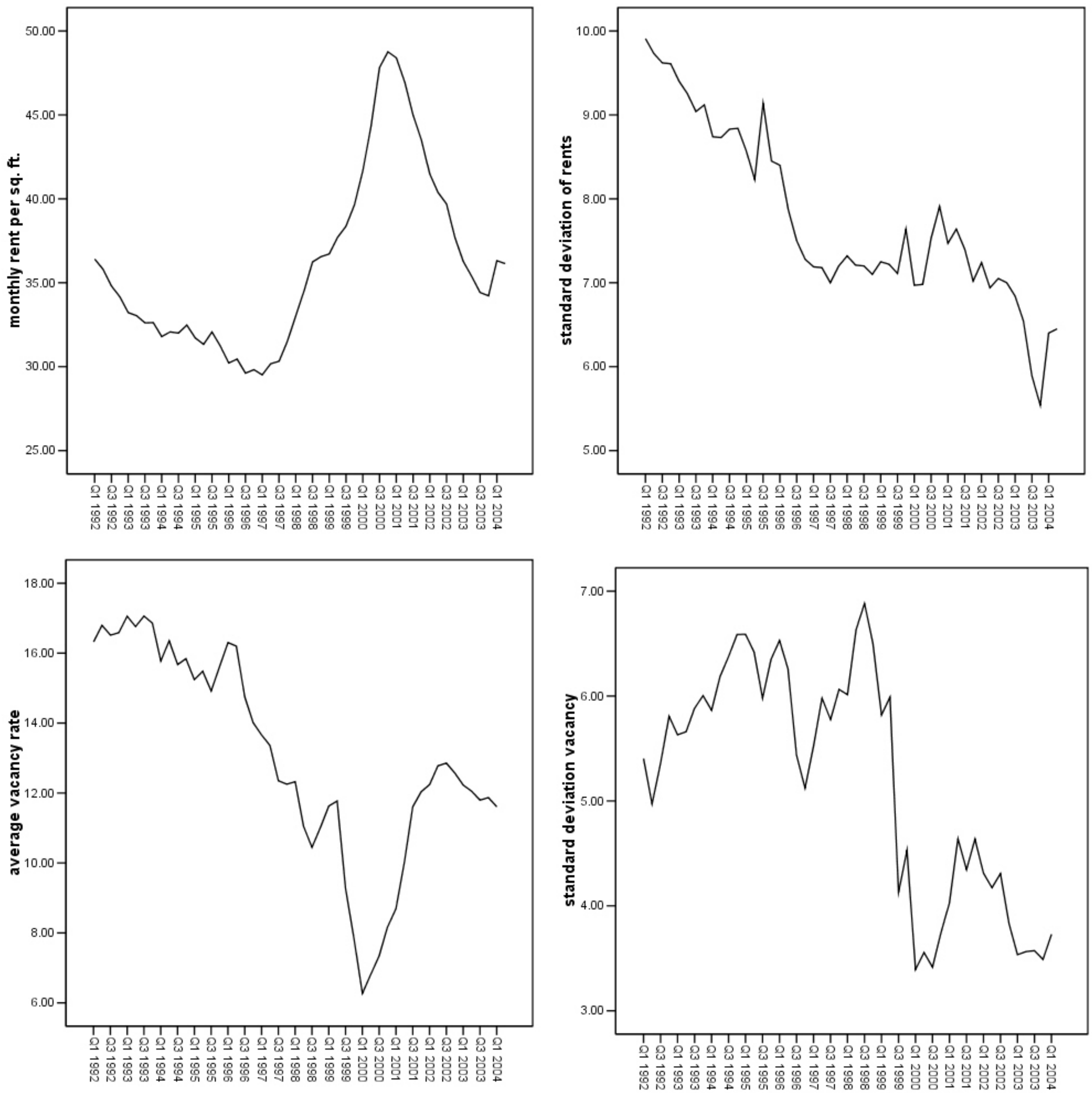

Figure 6: Average rental and vacancy rates and standard deviations of Manhattan submarkets from 1992 through 2004

Table 1: Linear time trend and rental rate variability across submarkets

Variable name	Data	Source
S	Inventory of office space (in sq. ft.)	Grubb and Ellis (1992-2004), CoStar
OS	Occupied office space (in sq.ft.)	
A	Quarterly net absorption	
R	Asking rent (in $ per sq. ft.), Class A/B/C	
V	Vacancy (in sq.ft.), sublet and direct	
SL	Sublet space (in % of total vacant space)	
E	Office employment by zip-code area and NAICS code (ES 202)	New York State Bureau of Labor Statistics
Z_n	9/11 dummy variable	

Table 2: Linear time trend and rental rate variability across submarkets

Dependent variable: rental rate standard deviation of submarkets				
Variable	**Coefficient**	**t-value (S.E.)**	**H.C. (S.E.)**	**probability**
intercept	9.40237	69.447 (0.13539)	79.237 (0.11866)	0.00
time trend	-0.06465	-13.991 (0.00462)	-15.921 (0.00406)	0.00
R^2 = 0.8031; Adjusted R^2 = 0.7990 Jarque-Bera/Salmon-Kiefer test = 2.880699 (accept at 5%) Breusch-Pagan test = 0.119889 (accept at 5%) Standard error of residuals: 0.47151 Note: H.C. = Heteroskedasticity consistent t-value. These t-values and standard errors are based on White's heteroskedasticity consistent variance matrix				

Table 3: Linear time trend and vacancy rate variability across submarkets

Dependent variable: vacancy rate standard deviation of submarkets				
Variable	**Coefficient**	**t-value (S.E.)**	**H.C. T-VALUE (S.E.)**	**probability**
intercept	6.58416	29.361 (0.13539)	29.722 (0.11866)	0.00
time trend	-0.05559	-7.121 (0.00781)	-8.065 (0.00689)	0.00
R^2 = 0.5190; Adjusted R^2 = 0.50870 Jarque-Bera/Salmon-Kiefer test = 2.880699 (accept at 5%) Breusch-Pagan test = 0.119889 (accept at 5%) Standard error of residuals: 0.772884				

Table 4: Correlation matrix of percentage changes in rental rates

	Midtown West/	Midtown East/Plaza	Grand Central	Penn/Garment	Penn Station	Madison Square	Gramercy /Flatiron	Chelsea	Soho/Noho	Hudson Sq	City Hall	Broadway	Insurance	Wall Street	World Trade	**Manhattan**
MidtownWest/	1	.802(**)	.323(*)	.690(**)	.610(**)	.624(**)	.407(**)	.579(**)	.436(**)	.434(**)	.268	.361(*)	.555(**)	.540(**)	.506(**)	.872(**)
Midtown East/Plaza	.802(**)	1	.301(*)	.636(**)	.659(**)	.595(**)	.455(**)	.462(**)	.216	.417(**)	.367(*)	.522(**)	.674(**)	.566(**)	.380(*)	.847(**)
Grand Central	.323(*)	.301(*)	1	.402(**)	.336(*)	.329(*)	.129	.600(**)	.160	.159	.265	.191	.276	.482(**)	.188	.584(**)
Penn/Garment	.690(**)	.636(**)	.402(**)	1	.716(**)	.743(**)	.405(**)	.562(**)	.474(**)	.407(**)	.160	.284	.633(**)	.610(**)	.410(**)	.799(**)
Penn Station	.610(**)	.659(**)	.336(*)	.716(**)	1	.616(**)	.391(**)	.301(*)	.528(**)	.408(**)	.259	.390(**)	.587(**)	.511(**)	.411(**)	.740(**)
Madison Square	.624(**)	.595(**)	.329(*)	.743(**)	.616(**)	1	.355(*)	.597(**)	.447(**)	.448(**)	.143	.321(*)	.552(**)	.460(**)	.391(*)	.729(**)
Gramercy/Flatiron	.407(**)	.455(**)	.129	.405(**)	.391(**)	.355(*)	1	.346(*)	.229	.338(*)	.288	.295	.471(**)	.439(**)	.279	.489(**)
Chelsea	.579(**)	.462(**)	.600(**)	.562(**)	.301(*)	.597(**)	.346(*)	1	.352(*)	.405(**)	.144	.198	.355(*)	.547(**)	.288	.675(**)
Soho/Noho	.436(**)	.216	.160	.474(**)	.528(**)	.447(**)	.229	.352(*)	1	.380(*)	.332(*)	.273	.055	.409(**)	.188	.400(**)
Hudson Sq	.434(**)	.417(**)	.159	.407(**)	.408(**)	.448(**)	.338(*)	.405(**)	.380(*)	1	.044	.292	.305(*)	.310(*)	.084	.434(**)
City Hall	.268	.367(*)	.265	.160	.259	.143	.288	.144	.332(*)	.044	1	.446(**)	.080	.444(**)	.340(*)	.352(*)
Broadway	.361(*)	.522(**)	.191	.284	.390(**)	.321(*)	.295	.198	.273	.292	.446(**)	1	.413(**)	.589(**)	.130	.503(**)
Insurance	.555(**)	.674(**)	.276	.633(**)	.587(**)	.552(**)	.471(**)	.355(*)	.055	.305(*)	.080	.413(**)	1	.445(**)	.324(*)	.685(**)
Wall Street	.540(**)	.566(**)	.482(**)	.610(**)	.511(**)	.460(**)	.439(**)	.547(**)	.409(**)	.310(*)	.444(**)	.589(**)	.445(**)	1	.203	.724(**)
World Trade	.506(**)	.380(*)	.188	.410(**)	.411(**)	.391(*)	.279	.288	.188	.084	.340(*)	.130	.324(*)	.203	1	.562(**)
Manhattan	.872(**)	.847(**)	.584(**)	.799(**)	.740(**)	.729(**)	.489(**)	.675(**)	.400(**)	.434(**)	.352(*)	.503(**)	.685(**)	.724(**)	.562(**)	1

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 5: Correlation matrix of percentage changes in vacancy rates

	Midtown West/	Midtown East/Plaza	Grand Central	Penn/Garment	Penn Station	Madison Square	Gramercy/Flatiron	Chelsea	Soho/Noho	Hudson Sq	City Hall	Broadway	Insurance	Wall Street	World Trade	**Manhattan**
MidtownWest/	1	.174	-.018	-.036	.150	.198	.230	.318(*)	.113	.065	-.340(*)	.225	.053	.225	.230	.504(**)
Midtown East/Plaza	.174	1	.193	.175	-.120	.267	.047	.392(**)	.297(*)	.288	.028	.102	.212	.225	.103	.575(**)
Grand Central	-.018	.193	1	.077	.077	-.140	.566(**)	.351(*)	.301(*)	.048	.018	.333(*)	.301(*)	.478(**)	.181	.540(**)
Penn/Garment	-.036	.175	.077	1	-.002	-.049	.160	-.266	-.162	.411(**)	.140	.158	.033	-.018	-.060	.084
Penn Station	.150	-.120	.077	-.002	1	.005	.259	.265	.036	.081	.034	.278	.120	.184	.138	.351(*)
Madison Square	.198	.267	-.140	-.049	.005	1	-.162	.130	.016	.048	.124	-.261	-.029	.117	.253	.372(*)
Gramercy/Flatiron	.230	.047	.566(**)	.160	.259	-.162	1	.380(*)	.176	.226	-.221	.363(*)	.362(*)	.571(**)	.110	.526(**)
Chelsea	.318(*)	.392(**)	.351(*)	-.266	.265	.130	.380(*)	1	.110	.005	-.144	.235	.114	.539(**)	.197	.615(**)
Soho/Noho	.113	.297(*)	.301(*)	-.162	.036	.016	.176	.110	1	.144	.058	.360(*)	.124	.084	.023	.348(*)
Hudson Sq	.065	.288	.048	.411(**)	.081	.048	.226	.005	.144	1	.066	.179	.299(*)	.209	-.151	.293
City Hall	-.340(*)	.028	.018	.140	.034	.124	-.221	-.144	.058	.066	1	-.084	-.265	-.159	.046	-.027
Broadway	.225	.102	.333(*)	.158	.278	-.261	.363(*)	.235	.360(*)	.179	-.084	1	.158	.199	-.127	.323(*)
Insurance	.053	.212	.301(*)	.033	.120	-.029	.362(*)	.114	.124	.299(*)	-.265	.158	1	.189	.241	.374(*)
Wall Street	.225	.225	.478(**)	-.018	.184	.117	.571(**)	.539(**)	.084	.209	-.159	.199	.189	1	.235	.699(**)
World Trade	.230	.103	.181	-.060	.138	.253	.110	.197	.023	-.151	.046	-.127	.241	.235	1	.529(**)
Manhattan	.504(**)	.575(**)	.540(**)	.084	.351(*)	.372(*)	.526(**)	.615(**)	.348(*)	.293	-.027	.323(*)	.374(*)	.699(**)	.529(**)	1

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

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

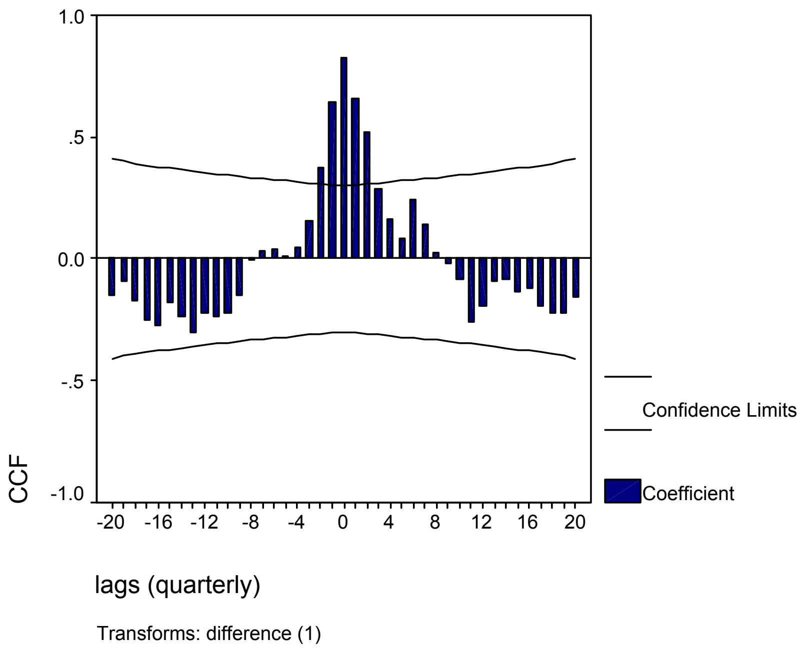

Figure 7: Rent Midtown and Midtown South

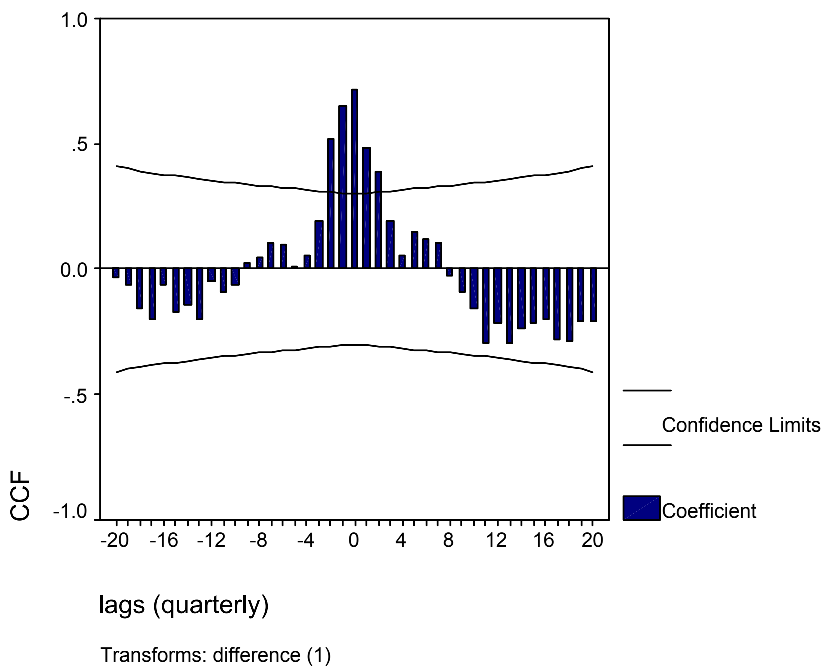

Figure 8: Rent Downtown and Midtown

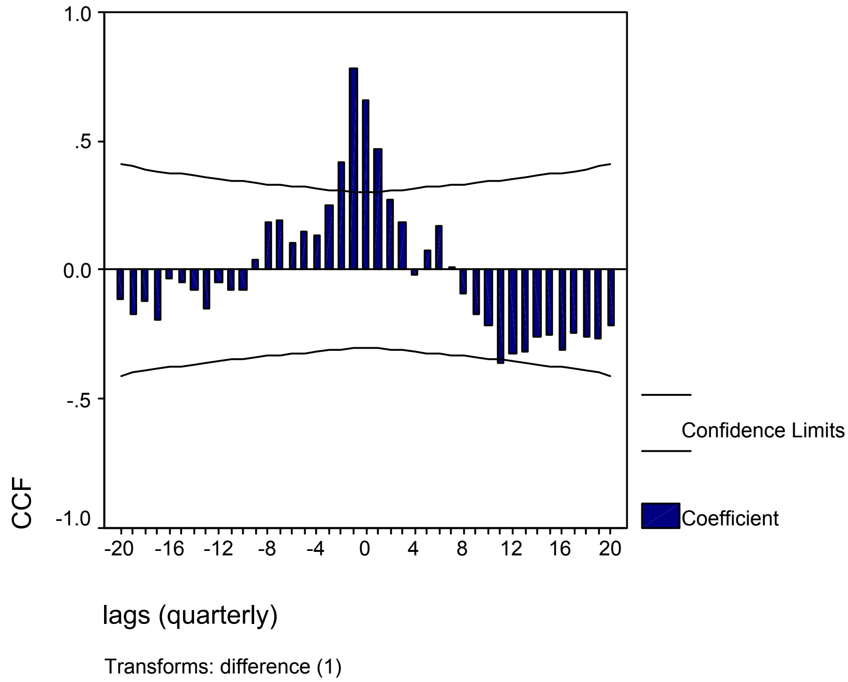

Figure 9: Rent Downtown and Midtown South

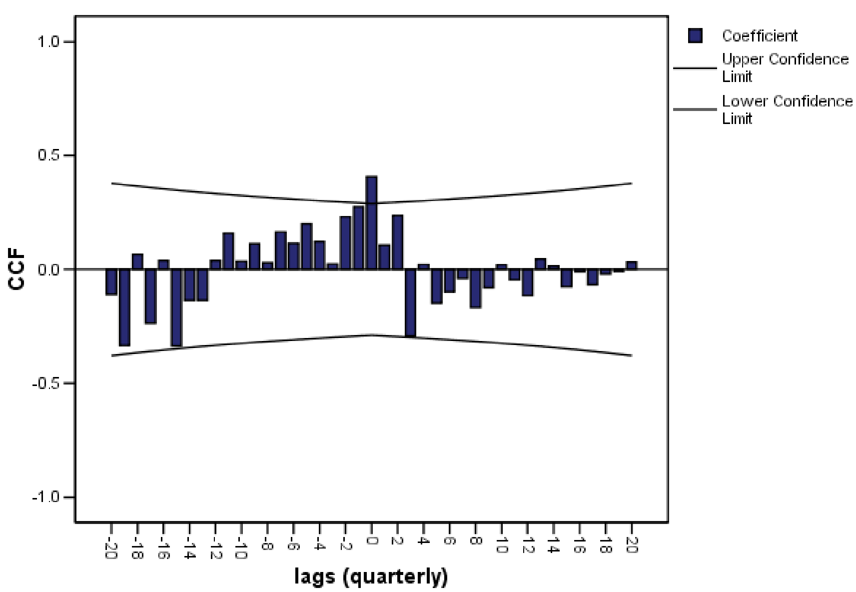

Figure 10: Vacancy Midtown and Midtown South

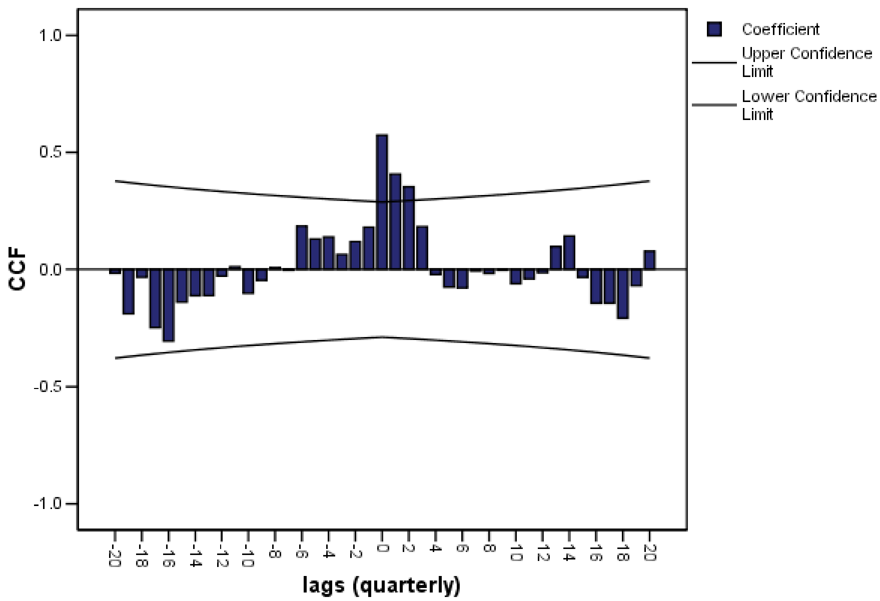

Figure 11: Vacancy Midtown and Downtown

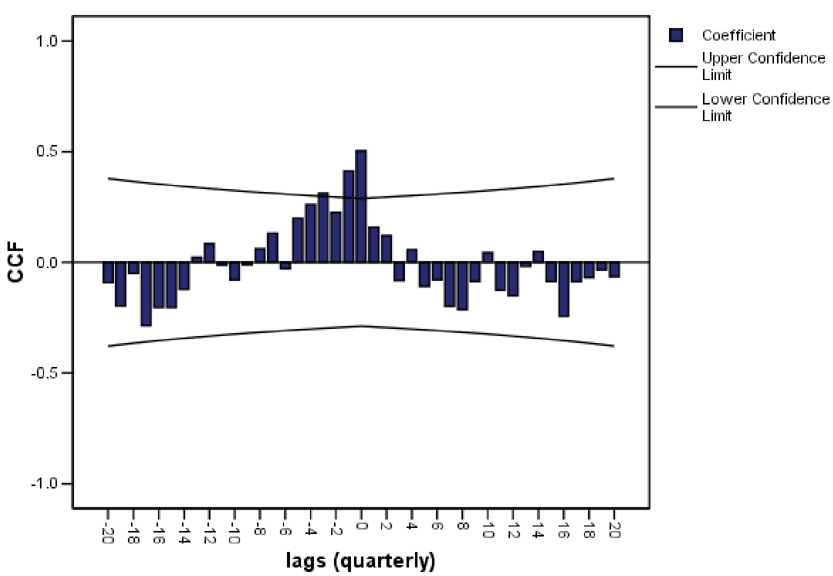

Figure 12: Vacancy Midtown South and Downtown

Table 6: Variation of submarket rents and percentage of Class A buildings

Dependent variable SMR (submarket rent as a percentage of market rent)				
Variable	**Coefficient**	**t-value (S.E.)**	**H.C. T-VALUE (S.E.)**	**probability**
Intercept	0.72311	6.213 (0.11639)	5.540 (0.13054)	0.00
Percentage Class A	64.51883	15.510 (4.15982)	23.730 (2.71892)	0.00
R^2 = 0.748; Adjusted R^2 = . 0.729 Jarque-Bera/Salmon-Kiefer test = 0.771 (accept at 5%) Breusch-Pagan test = 0.059 (accept at 5%) F test = 38.60 Standard error = 11.262				

Table 7: Variation of submarket rents and aggregate spatial characteristics

Dependent variable SMR (submarket rent as a percentage of market rent)				
Variable	**Coefficient**	**t-value (S.E.)**	**H.C. T-VALUE (S.E.)**	**probability**
Combined accessibility	2.94490	1.110 (2.65203)	1.356 (2.17130)	0.17
Space within 1500 feet	0.000871	3.021 (0.000563)	3.425 (0.000477)	0.00
Year built	0.05234	3.311 (0.01581)	3.758 (0.01393)	0.00
R^2 = 0.711; Adjusted R^2 = 0.663 Jarque-Bera/Salmon-Kiefer test = 0.90305 (accept at 5%) Standard error = 12.543				

Table 8: Pooled time series model

Dependent variable: Rent ratio Manhattan to Submarket N				
Variable	Coefficient	t-value	St.Error	Probability
Intercept	.942	43.433	.022	.000
α_1 (basic sq.ft./worker)	434.503	43.826	9.914	.000
R_{t-1}	-1.183	-4.198	.282	.000
T (time trend)	-2.490	-16.404	.152	.000
R^2 = 0.042; Adjusted R^2 = 0.041 **F test = 33.138**				

Table 9: Estimation of occupied space (Manhattan)

Dependent variable OS Manhattan				
Variable	**Coefficient**	**t-value**	**H.C. t-valuei**	**Probability**
α_0 (intercept of OS*-OSt-1)	-2,200,000	-11.212	-14.435	.000
α_1 (basic sq.ft./worker)	339.54245	64.042 (5.30185)	71.242 (4.76607)	.000
R_{t-1}	-0.83845	-5.141 (0.16639)	-5.039 (0.16310)	.000
Z_1	-29.62176	-5.915 (5.00759)	-24.840 (1.19248)	.000
Z_2	-18.02937	-3.663 (4.92166)	-16.911 (1.06612)	.000
Z_3	-8.18453	-1.769 (4.87454)	-7.651 (1.06977)	.000
T (time trend)	-0.22253	-3.721 (0.05981)	-2.713(0.08202)	.000

R^2 = 0.835; Adjusted R^2 = . 0.815
F test = 42.62
Standard error = 4.564
Jarque-Bera/Salmon-Kiefer test[ii] = 3.038184 (accept at 5%)
Breusch-Pagan test = 7.381228, p-value = 0.19380 (accept at 5%)
Collinearity: highest VIF = 1.1, lowest eigenvalue = .907

Table 10: Estimation of occupied space

Dependent variable OS(Midtown West/Avenue of the Americas)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	13841347	3.780	3661644	.000
α_1 (basic sq.ft./worker)	434.503	43.826	9.914	.000
R_{t-1}	-1.183	-4.198	.282	.000
T (time trend)	-2.490	-16.404	.152	.000
R2 = 0.941; Adjusted R2 = . 0. 939				
F test: = 352.258				
Collinearity: highest VIF = 17.457, lowest eigenvalue = .009				

Table 11: Estimation of occupied space

Dependent variable OS(Midtown East/Plaza District)				
Variable	Coefficient	t-value	St. error	Probability
α_0 (intercept of OS*-OSt-$_1$)	44260722	8.555	5173457	.000
α_1 (basic sq.ft./worker)	356.115	17.286	20.601	.000
R_{t-1}	-1.447	-2.922	.495	.005
T (time trend)	1.674	7.555	.222	.000
R^2 = 0.585; Adjusted R^2 = 0.567				
F test: = 31.062				
Collinearity: highest VIF = , lowest eigenvalue =				

Table 12: Estimation of occupied space

Dependent variable OS(Grand Central)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	20222028	8.199.	2466392	.000
α_1 (basic sq.ft./worker)	364.163	19.408	18.763	.000
R_{t-1}	-1.311	-2.499	.525	.016
T (time trend)	-1.374	-5.983	.230	.000
R^2 = 0.667; Adjusted R^2 = 0.652 **F test: = 44.699** **Collinearity: highest VIF = , lowest eigenvalue =**				

Table 13: Estimation of occupied space

Dependent variable OS(Penn Station)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	6348999	3.432	1849937	.000
α1 (basic sq.ft./worker)	269.626	26.451	10.193	.000
R_{t-1}	-1.755	-3.529	.497	.001
T (time trend)	1.902	10.202	.186	.000
R^2 =.876 **; Adjusted R^2 =** .871 **F test: =** 155.974 **Collinearity: highest VIF =**1.881 **, lowest eigenvalue =** .139				

Table 14: Estimation of occupied space

Dependent variable OS(SoHo/NoHo)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	2972933	13.326	223095	.000
α_1 (basic sq.ft./worker)	79.078	3.467	22.811	.001

R_{t-1}	-4.911	-4.198	1.170	.000
T (time trend)	2.130	3.558	.598	.001
R^2 = .712; **Adjusted R^2 =** .699				
F test: = 54.449				
Collinearity: highest VIF = 11.737, **lowest eigenvalue =** .021				

Table 15: Estimation of occupied space

Dependent variable OS(City Hall)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	5695353	44.471	128070	.000
α_1 (basic sq.ft./worker)	3.279	.067	.947	.000
R_{t-1}	-9.364	-4.420	.000	.000
T (time trend)	.291	.338	.737	.000
R^2 = .395 ; **Adjusted R^2 =** .367				
F test: = 14.352				
Collinearity: highest VIF = 1.355, **lowest eigenvalue =** .019				

Table 16: Estimation of occupied space

Dependent variable OS(Insurance District)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	4563087	5.836	781899	.000
α_1 (basic sq.ft./worker)	53.692	3.424	15.682	.001
R_{t-1}	-4.153	-7.315	.568	.000
T (time trend)	2.375	14.247	.167	.000
R^2 = .870; **Adjusted R^2 =** .864				
F test: = 147.676				
Collinearity: highest VIF = 1.024, **lowest eigenvalue =** .010				

Table 17: Estimation of occupied space

Dependent variable OS(Wall Street/Waterfront)				
Variable	Coefficient	t-value	St.Error	Probability
α_0 (intercept of OS*-OSt-1)	14926910	4.560	3273650	.000
α_1 (basic sq.ft./worker)	392.896	16.482	23.838	.000
R_{t-1}	-3.969	-5.244	.757	.000
T (time trend)	-1.298	-6.170	.210	.000
R^2 = .646; **Adjusted R^2 =** .630 **F test: =** 40.125 **Collinearity: highest VIF =** 1.035**, lowest eigenvalue =** .007				

Table 18: Estimation of rental rates

Dependent variable ΔRENT (Manhattan)				
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
SL_{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 = 42.62 Standard error = 4.564 Jarque-Bera/Salmon-Kiefer test = 0.257 (critical 5.99, accept at 5%) Collinearity: highest VIF = 1.1, lowest eigenvalue = .907 Test for ARCH u(t) is Gaussian white noise (accepted)[iii]				

Table 19: Estimation of rental rates

Dependent variable: ΔRENT (Midtown West/Avenue of the Americas)				
Variable	**Coefficient**	**t-value (S.E:)**	**H.C. T-VALUE (S.E.)**	**p-value**
Intercept	0.66047	19.912 (0.03317)	15.897 (0.04154)	0.00000
Vr	-1.73447	-9.446 (0.18361)	-8.555 (0.20274)	0.00000
SL	-0.25628	-3.389 (0.07563)	-2.710 (0.09456)	0.00070
R^2 = 0.6702; Adjusted R^2 = 0.6552 Durbin-Watson = 1.319358 Jarque-Bera/Salmon-Kiefer test = 2.213855 (accept at 5%) Breusch-Pagan test = 1.936736 (accept at 5%) F test: = 44.70 (significant at 5%) Breusch-Pagan test = 66.48 (reject at 5%) Standard error of the residuals (SER): 0.0431				

Table 20: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (Midtown East/Plaza District)				
Variable	**Coefficient**	**t-value (p value)**	**H.C. T-VALUE (p value)**	
Intercept	0.369239	2.605 [0.00919]	1.438 [0.15036]	
Vr	0.127714	1.213 [0.22530]	2.240 [0.02512]	
SL	0.369239	2.605 (0.00919)	1.438 (0.15036)	

a(1,1)	0.879436	8.866 (0.00000)	13.031 [0.00000]	
c(1,1)	-0.175969	-1.014 [0.31038]	-1.350 [0.17707]	
R^2 = 0.9189 RSS = 51.792133271E-02 s.e. = 10.497429601E-02				

Table 21: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (Grand Central)				
Variable	**Coefficient**	**t-value (p value)**	**H.C. T-VALUE (p value)**	
Intercept	0.146592	0.917 [0.35926]	0.781 [0.43480]	
Vr	-0.014633	-0.087 [0.93069]	-0.192 [0.84809]	
SL	-0.031039	-0.323 [0.74648]	-1.170 [0.24191]	
a(1,1)	0.984692	9.087 [0.00000]	40.407 [0.00000]	
c(1,1)	0.588167	1.087 [0.27707]	1.746 [0.08076]	
R^2 = 0.6834 RSS = 16.930463414E-01 s.e. = 18.979531760E-02				

Table 22: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (Penn Station)				
Variable	**Coefficient**	**t-value (p value)**	**H.C. T-VALUE (p value)**	
intercept	0.127714	1.213 (0.22530)	2.240 (0.02512)	
Vr	0.497489	9.457 [0.00000]	3.067 [0.00216]	
SL	0.369239	2.605 (0.00919)	1.438 (0.15036)	
a(1,1)	0.879436	8.866 (0.00000)	13.031 [0.00000]	
c(1,1)	-0.175969	-1.014 [0.31038]	-1.350 [0.17707]	
R^2 = 0.9189 RSS = 51.792133271E-02 s.e. = 10.497429601E-02				

Table 23: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (Insurance District)				
Variable	**Coefficient**	**t-value (p value)**	**H.C. T-VALUE (p value)**	
intercept	0.856515	8.650 [0.00000]	23.847 [0.00000]	
Vr	0.034983	0.729 [0.46607]	1.196 [0.23189]	
SL	0.057221	1.643 [0.10031]	0.804 [0.42111]	

a(1,1)	1.047866	25.017 [0.00000]	40.825 [0.00000]	
c(1,1)	-0.179513	-0.135 [0.89262]	-0.282 [0.77830]	
R^2 = 0.8054 RSS = 45.96 s.e. = 10.497429601E-02				

Table 24:: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (Wall Street/Waterfront)				
Variable	**Coefficient**	**t-value** **(p value)**	**H.C. T-VALUE** **(p value)**	
intercept	1.075142	15.461 [0.00000]	14.354 [0.00000]	
Vr	-0.146638	-2.226 [0.02599]	-1.928 [0.05390]	
SL	-0.085772	-3.006 [0.00265]	2.840 [0.00451]	
a(1,1)	) 0.965847	12.604 [0.00000]	24.269 [0.00000]	
c(1,1)	1.183879	9.217 [0.00000]	6.778 [0.00000]	
R^2 = 0.9043 RSS = 30.06 s.e. = 79.145682921E-03				

Table 25:: OLS-ARMA model of submarket rental rates

Dependent variable: ΔRENT (City Hall)				
Variable	**Coefficient**	**t-value (p value)**	**H.C. T-VALUE (p value)**	
intercept	0.639616	441.083 [0.00000]	689.726 [0.00000]	
Vr	0.101381	42.512 [0.00000]	57.015 [0.00000]	
SL	0.003169	5.826 [0.00000]	8.655 [0.00000]	
a(1,1)	0.947176	7.620 [0.00000]	19.402 [0.00000]	
c(1,1)	-0.083960	-0.324 [0.74601]	-0.234 [0.81537]	
R^2 = 0.8676 RSS = 27.043783763E-02 s.e. = 79.304804633E-03				

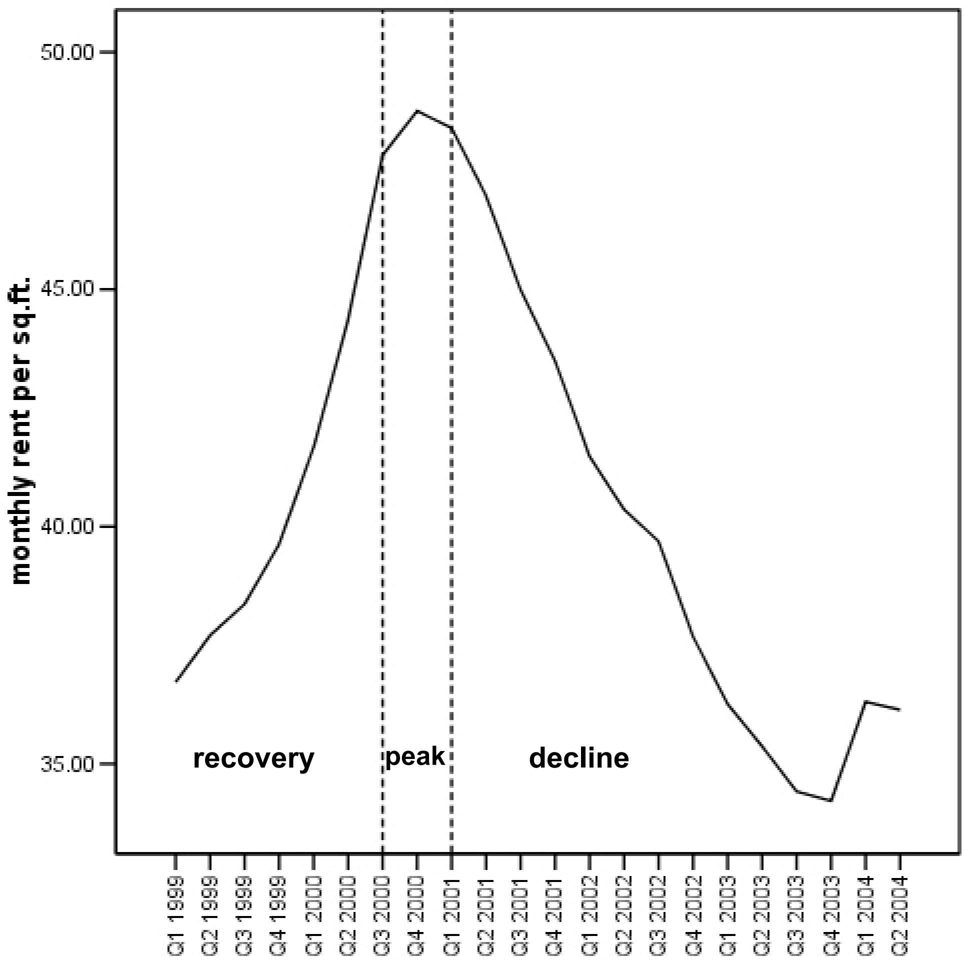

Figure 13: Phases of the Manhattan office market cycle

Table 26: Hedonic regression model I: building-specific price determinants

	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)	.06 (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

continued

	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	0.408	0.396	0.393

Table 27:: Hedonic regression model II: location-specific price determinants

	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

continued

	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

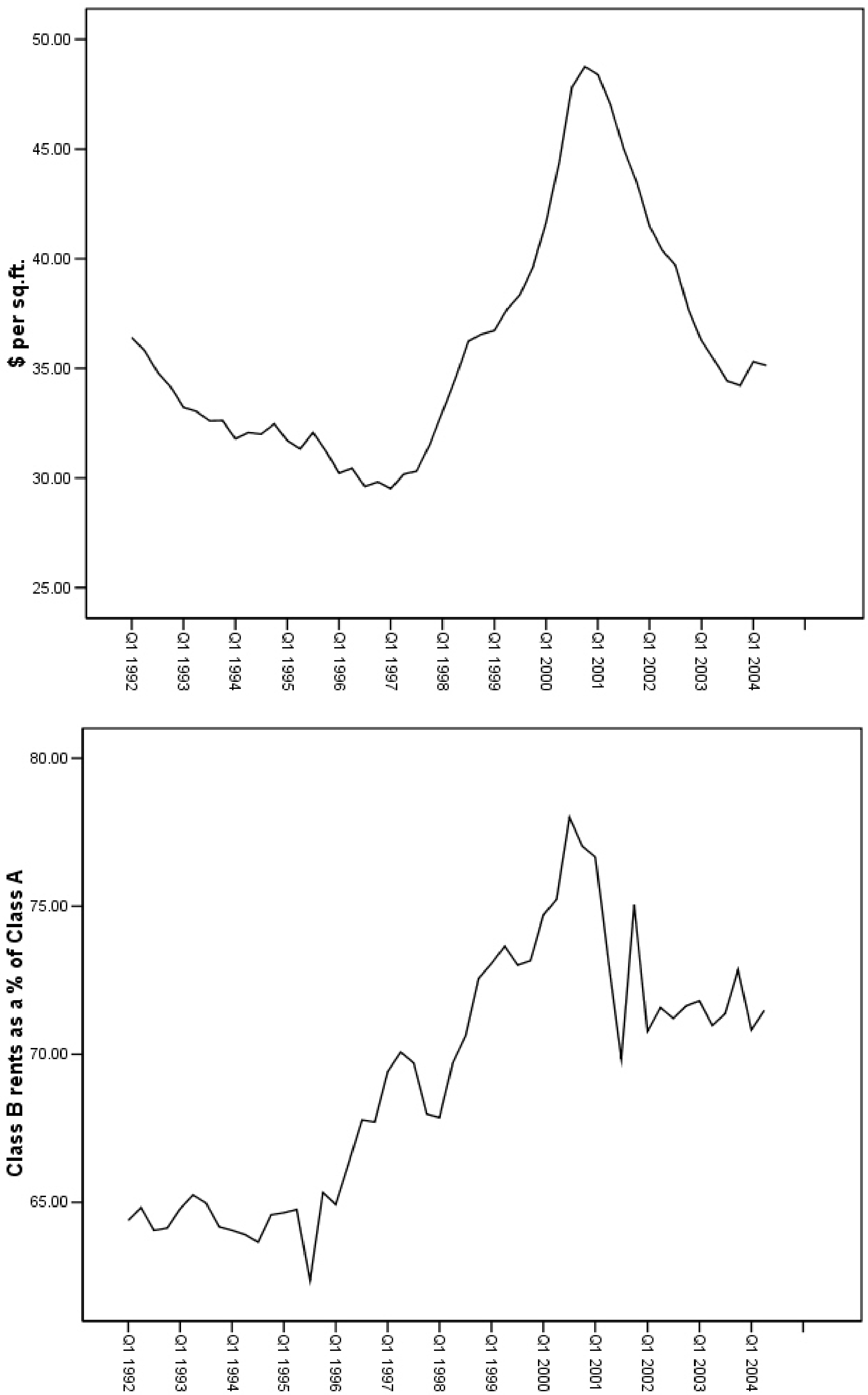

Figure 14: Convergence of rental rates during the peak phase in the market cycle: average rental rates (above) and rental rates in Class B buildings as a percentage of Class A rental rates

Table 28: Hedonic regression (Model I) at various phases in the market cycle

	recovery	*peak*	*decline*
Intercept	-75.466	-55.8657	-70.0031
Ln vacancy	-0.02317	-0.00967	-0.01423
Ln building area	0.0605	0.043	0.045692
Ln year built	9.814333	7.741667	9.393154
Ln stories	0.1365	0.167	0.168538
Ln amenities	0.043333	-0.013	0.073154
Adjusted R^2	0.353833	0.295	0.377

Table 29: Hedonic regression (Model II) at various phases in the market cycle

	recovery	peak	decline
Intercept	11063.67	7291.037	9116.156
Ln distance 20 buildings	0.228167	0.184	0.207846
Ln space 1500 feet	0.115	0.046667	0.100385
Ln distance subway	-0.0945	-0.07067	-0.09615
Ln longitude	-2176.86	-1510.49	-1840.22
Ln latitude	-457.003	-212.574	-322.374
Adjusted R^2	0.429167	0.35	0.429308

Table 30: Chow test of parameter stability of hedonic models during recovery, peak and decline of the market

	Model 1 (building-specific)	Model 2 (location-specific)
Chow test	**17.483****	**27.494****

** Significant at the 1 percent level

Table 31: Chow test of cross-sectional parameter stability over submarkets

	Model 1 (building-specific)	Model 2 (location-specific)
Chow test	**9.866****	**13.589****

** Significant at the 1 percent level

Table 32: Chow Chow test of cross-sectional submarket parameter stability at different phases of the market cycle

	Model 1 (building-specific)	Model 2 (location-specific)
Recovery	**9.39****	**15.48****
Peak	**8.39****	**10.63****
Decline	**13.24****	**15.92****

** Significant at the 1 percent level

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

ii The Jarque-Bera/Salmon-Kiefer test of the null hypothesis that the model errors u_j are $N(0,\sigma^2)$ distributed. This test 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.