Inquiries into Real Estate and Macroeconomics: Zoning & Monetary Policy Regimes

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ABSTRACT

DAVID A. LEATHER: Inquiries into Real Estate and Macroeconomics:
Zoning & Monetary Policy Regimes.
(Under the direction of Jacob Sagi and Neville Francis)

In Chapter 1, I take advantage of uncertainty regarding future land use restrictions in order to empirically identify the value of the redevelopment option embedded in real estate prices for New York City (NYC) from 2003-2015. Using a two-stage estimation procedure, ergodic propensities to be zoned to either residential, commercial, or manufacturing land uses are interacted with a proxy for the propensity to be redeveloped. Results show that the interactions provide significantly greater explanatory power than using the intensity proxy alone. And that all option value terms are statistically significant. I estimate the average option value to redevelop in Manhattan & Brooklyn for years 2003-2015 is 20% and 8.5% of total estimated property value in Manhattan and Brooklyn respectively. I also find evidence that manufacturing lots identified as residential by the model sell for a premium of 50% per square foot.

Chapter 2 considers commercial real estate (CRE), a major institutional asset class to which the banking sector has considerable exposure. Because CRE prices tend to be smoothed it is hard to infer their relationship with fundamentals. This is compounded by the presence of complicated underlying dynamics. For instance, inflation acts to increase discount rates but may also be associated with higher rental revenues. Thus it is difficult to sign the impact of inflation on CRE prices, especially given that the dynamics of macro fundamentals periodically undergo regime changes. Similar considerations apply to real economic growth and, by extension, interest rates. We estimate a model, consistent with rational expectations, where regime-dependent macro fundamentals are anticipated in prices. We find that real estate fundamentals and prices vary with macro fundamentals and are highly sensitive to potential regime changes. Correspondingly, information in real estate prices improves the identification macro regimes. Our model allows us to quantify sources

of systematic risk in real estate and price mortgages (which are sensitive to the joint dynamics of interest rates and real estate prices). To the extent that regimes in macro fundamentals arise from shifts in monetary policy, our model may also be used for policy analysis.

To my mother, Jean Evans, papa, Anthony "Tony" Catino, nana, Lenora "Lee" Catino, uncle, Joe Catino, grandmother, Shirley Leather, and grandfather, Stanley Leather. For without their loving support, I would never have had the gall keep my face towards the wind, and set flight towards the Sun.

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This is as much yours as mine.

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CHAPTER 1

THE REDEVELOPMENT OPTION AND LAND USE RESTRICTIONS ACROSS SPACE AND TIME

1.1 Introduction

Few studies focus on zoning regulation's impact on property values through the lens of an options pricing framework. Intuitively, land that is legally allowed to be developed into multiple uses should fetch a higher price than the same plot of land restricted to a single-use. Childs, Riddiough, and Triantis (1996) and Geltner, Riddiough, and Stojanovic (1996) provide a theoretical foundation in the options pricing framework to cement the above intuition. Yet, no studies have attempted to estimate how potential changes in land use restrictions impact the option value to redevelop real estate.

Zoning policy typically regulates two dimensions of property characteristics: intensity and use. Intensity corresponds to the allowed size and dimensions a structure can be built on a given plot of land. One justification for such restrictions is to allow adequate sunlight to penetrate to the street.[1]

The second dimension restricts the allowed use of the built property. The justification for regulating land use is to minimize the external costs that certain building types impose on nearby tenants and to maximize external benefits resulting from agglomeration effects.[2] For example, living next to an industrial factory creates both air and sound pollution, which detracts from the welfare of the neighboring residents. Thus it is optimal to allocate certain areas of land for industrial use far away from residential areas. Similarly, centrally located businesses within an industry can minimize the cost of travel required for face-to-face interaction.

Michael Bloomberg was the mayor of the City of New York from 2002 through 2013. Over

[1] Bliss (2016)

[2] Strange and Rosenthal (2001)

that period, the Bloomberg Administration rezoned approximately 40% of all the properties in the city. As Dan Doctoroff, the former deputy mayor of economic development for the City of New York, noted in an interview:

> We believed New York's economy needed a massive jolt of energy and a push forward to prepare it for the 21st century. If you looked across the city, there were thousands of acres of land that were unused, largely because they were zoned for industrial or manufacturing uses for which could not compete anymore. Many were on some of the most valuable real estate in New York, like along the waterfront, on the West Side of Manhattan, or near Downtown Brooklyn.... In the end, we did 140 separate rezonings during the Bloomberg administration. 40 percent of the city was rezoned.[3]

We take advantage of the numerous rezonings that occurred during the Bloomberg administration to examine how the option value to redevelop real estate fluctuates with changes in zoning designations that correspond to the allowed land use. While many studies in the Urban Economics literature have attempted to disentangle the impact zoning has on property values,[4] the they focus on the impact of changes in the allowed intensity of the building.

To address the question of how changes in the land use component of zoning regulations impact property values, we estimate time-varying propensities of being zoned to each land use designation to proxy for the probabilities of switching zoning designation in the future. We then incorporate these probabilities into the hedonic pricing model of Rosen (1974) to identify how changes in the long-run likelihood of being rezoned impacts the redevelopment option via the framework employed in Clapp and Salavei (2010). Variation in expectations of future zoning designation around major rezoning events is employed in an hedonic estimation to identify the redevelop option component of real estate values.

We find evidence that, on average, the redevelopment option constitutes 20% of total estimated

[3]Florida (2017)

[4]McMillen and McDonald (1991), McMillen and McDonald (2002), Glaeser and Gyourko (2003), Ihlanfeldt (2007)

property value in Manhattan and 8% in Brooklyn. There is also evidence that manufacturing-zoned properties identified by our model as wholly residential sell for a 50% premium per square foot. Lastly, we present evidence that the redevelop option as a percent of the total property value is counter-cyclical with the real estate cycle.

The rest of the paper is organized as follows: Section 1.2 presents the motivation for the research and presents a motivation model to accompany the empirical analysis. Section 1.3 discusses the data sources and summary statistics. Section 1.4 presents the empirical framework and identification strategy. Section 1.5 presents and discusses the results of the estimation. Finally, Section 1.6 concludes.

1.2 Motivation

The value of a property, $PV_{i,t}$, can roughly be separated into the value of the land, $V_{i,t}^{L}$, and the building that sits on the land, $V_{i,t}^{B}$. This relationship holds exactly if the construction industry is assumed to be perfectly competitive:

$$PV_{i,t} = V_{i,t}^{(B)} + V_{i,t}^{(L)}. \tag{1.1}$$

The value of the building, $V_{i,t}^{(B)}$, is the replacement cost to build a structure as similar as possible to the one that already exists on the land. This value tends to decrease with depreciation, $D_{i,t}$, increase with renovations, $I_{i,t}$, and size, $SIZE_{i,t}$. The main driver is the cost of construction, $C_{i,t}$, which includes labor and capital expenses.

$$V_{i,t}^{(B)} = f(I_{i,t}, D_{i,t}, C_{i,t}, SIZE_{i,t}) \tag{1.2}$$

Most of the variation in property values comes from the value of the land that the structure sits on (Davis and Heathcote (2005), Knoll, Schularick, and Steger (2017)). In the urban economics literature, the value of land is thought to represent a call option on development (or redevelopment).[5] When choosing to develop land, the developer must choose both the use of the land and

[5]Titman (1985)

the intensity to which to develop the land. Childs et al. (1996) and Williams (1997) examine the option to continually redevelop a property. Childs et al. (1996) focuses on the option to reconfigure a property between two uses (as well as mixing the two uses), while Williams (1997) focuses on the option to increase the intensity or quality of the property while holding its use constant. Both Childs et al. (1996) and Williams (1997) find that the option to redevelop decreases with an increased correlation between market value of uses and increases with uncertainty regarding future rents.

Zoning restrictions limit both land use and building intensity. Thus a change in zoning designation will have implications for the price of a property. In New York City, a rezoned property can continue to operate under the current use, but significant renovations or redevelopment cannot occur without switching land use to the new designation.[6] When making the redevelopment decision, the developer must consider the expected net payoff of redeveloping the property to its highest and best use today, as well as the net payoff of delaying the redevelopment into the future.

The critical insight of this paper is to recognize that the value of the highest and best use of a property today is limited by the zoning designation today, and the *expected* value of the highest and best use tomorrow is a function of *expected* zoning designation tomorrow. In other words, the zoning designation of any property in the future is uncertain, and the value of the (re)development option should reflect this uncertainty.

Consider a simple two-period example where a landowner is deciding to develop vacant land under uncertainty with regards to the zoning designation. There are two possible zoning designations, $z_t \in \{1, 2\}$. Today the zoning designation is use i, $z_1 = i$. Tomorrow, there is some probability, $\alpha > 0$, of being rezoned to use $j \neq i$, and a probability of $(1 - \alpha) > 0$, of keeping the same zoning designation. From the perspective of the landowner, the choice to develop will depend on weighing the payoff of developing the property to its highest and best use today for property type i, HBU_i, with tomorrow's expected payoff and with the possibility of being able to develop to use j. In this situation, the value of land is

[6] New York City Zoning Resolution, Article 5, Chapter 2, 52-20. https://zr.planning.nyc.gov/article-v/chapter-2/52-20.

$$V_{i,t}^{(L)} = \max\big\{NPV_i, \frac{(1-\alpha)}{(1+r)}NPV_i + \frac{\alpha}{(1+r)}NPV_j\big\}, \tag{1.3}$$

where NPV_i is the net present value of developing to the highest and best use given the zoning designation today is i, and $r > 0$ is the rate of return on the built property (assumed constant across uses). The developer will only choose to wait if

$$NPV_j - NPV_i \geq \big(\frac{r}{\alpha}\big)NPV_i. \tag{1.4}$$

That is, the developer will wait to the later period to develop for the chance event of the zoning designation changing only if the developed property is expected to be more valuable under use j by an amount larger or equal to the rents foregone by waiting a period to develop, $r \cdot NPV_i$, divided by the probability of switching zoning designation, α. This hurdle rate, $\frac{r}{\alpha}$, is decreasing in the probability of switching zoning designations and increasing in the opportunity cost of waiting to develop. For the special case where a zoning change is certain, $\alpha = 1$, the value of the property if it were to be developed to use j must be at least as large as the opportunity cost of waiting. As the probability of being rezoned becomes extremely unlikely, the hurdle value gets larger and the developer will never choose to wait. The key takeaway from this toy model is that the probability of being rezoned, something that occurs with a non-insignificant frequency in New York City from 2003-2015, will impact the option value of redevelopment. The intuition of the toy model above is easily extended to the case of redevelopment.

In many geographies the zoning process is static. In New York City, we find that 2% of all properties in the beginning of the sample switched zoning designation at the end of the sample in 2015. Table 1.1 details the number of zoning changes that occurred for all lots present in the beginning of the sample. Figure 1.1 shows the nature of each transition and where they occurred across space.

Out of 294,040 lots, 5,758 (or roughly 2%) of lots changed land use designation. On net there was an increase in residential and mixed use zoned lots, a small decline in commercial lots, and a 20% decline in manufacturing lots. Yet, there is significant variation in changes conditioning on the initial zoning designation. For example, even though there was a steep decline in manufacturing lots overall, 84 residential and 30 commercial lots were rezoned to be manufacturing.

Out of the 16,149 commercially zoned lots at the beginning of the sample, 14,598 (90%) stayed commercial, 1,466 (9%) switched to residential, and the remaining percent is split relatively evenly between manufacturing and mixed-use manufacturing /residential. For the 13,325 lots zoned manufacturing at the beginning of the sample, where we see the most zoning changes, 10,538 (79%) stayed manufacturing, 865 (6.5%) switched to commercial, 1,922 (14.5%) switched to residential or mixed use manufacturing/residential. Most residential lots stayed residential, but a not insignificant amount of residential lots did switch. Out of the 263,365 lots zoned residential at the beginning of the sample, 595 switched to commercial and 84 switched to manufacturing. The big picture that the data presents to us is that there was a large migration from commercial and manufacturing to residential, with most zoning changes coming from manufacturing zoned lots. However, the changes are not monotonic, and in a given quarter, we may observe a single change from residential to manufacturing.

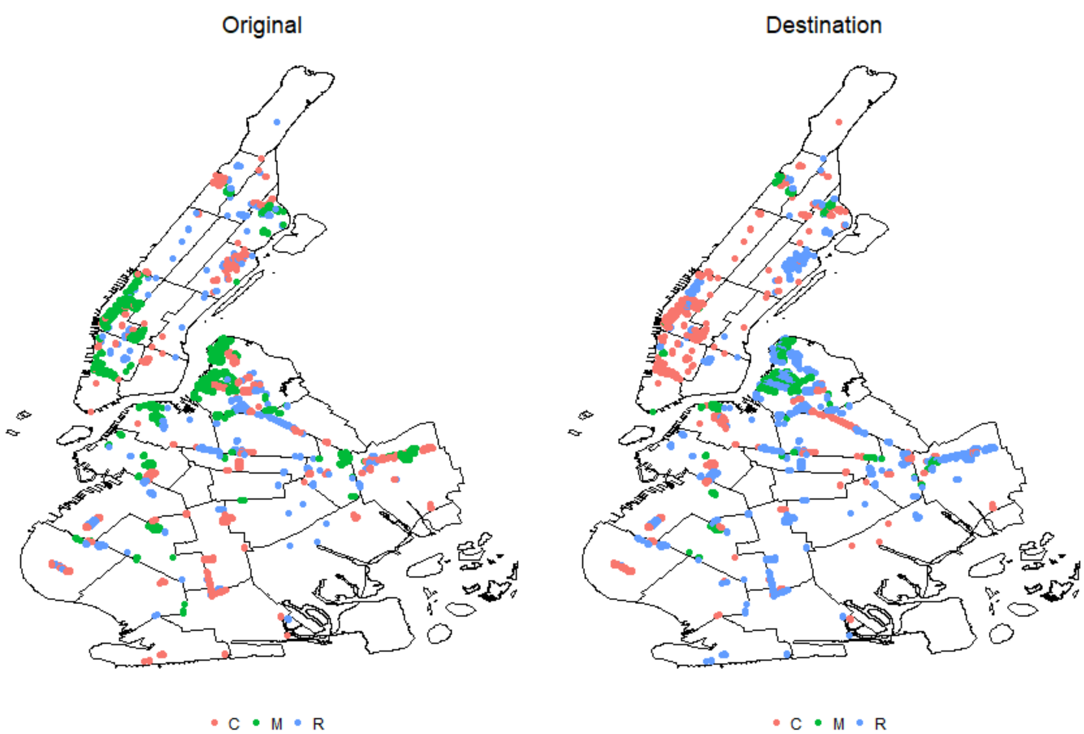
1.2.1 Motivational Model

In reality, the assumption of perfect competition in the construction industry doesn't hold, and we cannot separate the value of land from the structure that sits on the land so easily. A more true-to-life model must take into account uncertainty regarding when the existing structure will be

Table 1.1: Zoning changes that occurred or did not for all lots present in the beginning of the sample from all boroughs from 2003-2017. Res/Man refers to a mixed zoning designation where the property can be used for both residential and manufacturing purposes.

Source	Commercial	Manufacturing	Residential	Res/Man	Total
Commercial	14,598	30	1,466	55	16,149
Manufacturing	865	10,538	935	987	13,325
Residential	595	84	262,683	3	263,365
Res./Man.	24	1	713	463	1,201
Net Change	(-67)	(-2,672)	(2,432)	(307)	

Figure 1.1: Zoning transitions in Brooklyn (bottom) & Manhattan (top) from 2003 -2015. The figure on the left shows the original zoning designation of each property, and the figure on the right shows the zoning designation each property switched to. The dots are colored by zoning designation; red being commercial, green being manufacturing, and blue being residential.



redeveloped and average the net present value of cash flows from the current structure over various redevelopment horizons.

First, assume that macro-fundamentals, X_t, are exogenous and drive dynamics in both the rental market for real estate and the market for selling real estate. Macro-fundamentals also drive time-variation in the zoning process, $Z_{i,t} \in \{C, M, R\}$, and the zoning process follows a time-varying Markov chain conditional on vocational characteristics, $q_{i,t}$:

$$Z_{i,t} \sim \Pi(X_t, q_{i,t}), \tag{1.5}$$

where C represents commercially zoned lots used for office and retail space, M represents manufacturing zoned lots which are typically warehouse structures used for production, storage, or logistic centers, and R represents residential zoned lots which is any structure for which people reside, including apartments.

Each property owner either chooses to redevelop, $R_{i,t} = 0$, or to wait, $R_{i,t} = 0$, with the objective of maximizing the value of his property. If he chooses to wait, his building gets older, which will impact his expected cash flow next period. If he chooses to redevelop, the new use of the building must conform with the current zoning designation, $LU_{i,t} = Z_{i,t}$, where $LU_{i,t}$ is the operational use of the building; he must pay the cost of redevelopment, K, upfront; and he must wait d periods to begin collecting cash flow from the new building,

$$age_{i,t} = \left\{ \begin{array}{ll} age_{i,t-1} + 1, & \text{if } R_{i,t} = 0 \\ -d, & \text{if } R_{i,t} = 1, \end{array} \right\}. \tag{1.6}$$

$$CF_{i,t} = \mathbb{1}(age \geq 0) \exp\{\kappa(X_t, LU_{i,t})q_{i,t} + \gamma(X_t, LU_{i,t})age_{i,t} + \phi(X_t, LU_{i,t})age_{i,t}^2 + w_{i,t}\} - R_t K, \tag{1.7}$$

$$LU_{i,t} = Z_{R_{i,t}^{-1}} \text{ s.t. } R_{i,t}^{-1} := \{\max \tau \leq t : R_{i,\tau} = 1\}. \tag{1.8}$$

In Equation (7), $q_{i,t}$ represents any locational characteristics that may generate a premium or discount on cash flows, as well as building characteristics independent from the age of the structure. The coefficients κ, γ, and ϕ are the implied value of product characteristics as they relate to rents. They are time-varying because rental markets respond to macro-fundamentals, and the implied prices map into current equilibrium rents. Also there are different coefficients for each land use as there are independent rental markets for residential, commercial, and manufacturing properties. Cash flows are log-normally distributed, $w_{i,t} \sim N(0, \sigma_w^2)$.

Equation (8) simply states that the current land use at any building is the zoning designation at time of last redevelopment. This assumption is justified by New York City's zoning policies, which state that when a zoning change occurs, a building can operate under its former use until a redevelopment occurs.

Finally, the price of a property is pinned down by the assumption of no arbitrage in the market for selling real estate, implying prices are equal to risk-adjusted discounted expectations of future cash flows:

$$P_{i,t} = \max_{R(\cdot)} \sum_{s \geq t} \mathbb{E}_t^Q \big[\beta_s CF\big(X_s, Z_{i,s}, LU_{i,s}, q_{i,s}, age_{i,s}(R(\cdot)), R(\cdot)\big)\big]. \tag{1.9}$$

We can then break the price of a property into expected discounted cash flows before the first redevelopment and the expected value of cash flows after the first redevelopment. Let $R_{i,t}^1 := \{\min \tau \geq t : R_{i,\tau} = 1\}$ be defined as the period when the property is first redeveloped after period t. Then,

$$\begin{aligned} P_{i,t} = &\overbrace{\mathbb{E}_t^Q \big[\sum_{t \leq s < R_{i,t}^1} \beta_s CF\big(X_s, LU_{i,s}, q_{i,s}, age_{i,s} = age_{i,s-1} + s - t, R^*(\cdot) = 0\big)\big]}^{V_{i,t}^{(B)}} \\ &+ \underbrace{\mathbb{E}_t^Q \big[\sum_{R_{i,t}^1 \leq s} \beta_s CF\big(X_s, LU_{i,s}, q_{i,s}, age_{i,s}, R^*(\cdot)\big)\big]}_{V_{i,t}^{(L)}}, \end{aligned} \tag{1.10}$$

where

$$R^*(\cdot) := \arg\max_{R(\cdot)} \sum_{s \geq t} \mathbb{E}_t^Q \big[\beta_s CF\big(X_s, Z_{i,s}, LU_{i,s}, q_{i,s}, age_{i,s}(R(\cdot)), R(\cdot)\big)\big]. \tag{1.11}$$

The remaining portion of this paper focuses on empirically separating the first term from Equation (10) - henceforth *current structure value* - representing the expected discounted cash flows from prior to the first future redevelopment, and the second term - henceforth *option value to redevelop* - which is the expected future discounted cash flows post first redevelopment.

1.3 Data

The panel dataset used is constructed from various data sources described below. The final dataset includes 48,929,331 observations. Each observation represents a single lot-quarter from 2002q2 until 2017q4. For each observation, there are a total 109 descriptive variables representing the characteristics of the building, the geographical characteristics of the area around the building, as well as demographic information at the census tract level.

Below, we describe the sources of the data. The Primary Land Use Tax Lot Output dataset is used to track zoning designation as well as a wealth of other property and locational characteristics. It is used in both the estimation of (re)zoning propensities and the hedonic sales model. New York City's Rolling Sales dataset reports all property transactions and is used in the hedonic estimation. The policy dummies in the first stage come from the New York City Department of City Planning's Zoning Application Portal, which was scraped to compile the dataset. Lastly, both the American Community Survey data as well as Bing Maps data is used in post-estimation to decompose option value by location and demographics.

Selected summary statistics are presented in Table 1

1.3.1 Primary Land Use Tax Lot Output

The main dataset employed is the Primary Land Use Tax Lot Output (PLUTO), provided by the New York City Department of City Planning. It contains extensive land use and geographic data for the vast majority of the tax lots in NYC. The panel dataset was released on an annual basis from 2002-2007, but since 2009, it has been released on a semi-annual basis.

PLUTO includes over 70 fields for each tax lot. Of main interest to this paper is extensive information on zoning designations for each property. Zoning is broken down into primary zoning district, overlay district, and special purpose districts. Each category can contain multiple items ordered by the share of the tax lot from largest to smallest.

Other variables of interest include the Floor Area Ratio (FAR) of a building broken down into commercial, residential, office, retail, garage, storage, and factory. There are a number of building descriptors such as number of floors of the building (NumFloors), the area of the lot (LotArea), an identifier for an irregular lot, an identifier for special lot characteristics such as waterfront property, basement type, year built (YearBuilt), the last year the building was significantly altered (LastAlter), and the separately assessed value of the land (AssessLand) and building (AssessBldg) as estimated annually by the Department of Finance for tax purposes.

The process of merging all versions of PLUTO together is no trivial task. The variables included with each release can change from year-to-year, so special care must be taken so that all variables are comparable. The merged dataset contains 48,929,331 million rows, and then we create a quarterly time series from each observation date. For example, if a there is an observation from a property in 2002q1 and 2003q4, I duplicate the 2002q1 row to create observations for 2002q2 -2003q3.

1.3.2 Transaction Data

Property transactions come from the New York City Department of Finance's Rolling Sales data. The Rolling Sales dataset is released on an annual basis from 2003-present. It contains all property transactions that take place in the city. In addition to a subset of variables from the PLUTO dataset, the Rolling Sales data contains the nominal transaction price of the property (SalePrice), as well as the gross square footage (GrossSqFt) of the building and the square footage of the lot the building sits on (LandSqFt). Gross square footage is defined as the total floor area encompassed by the exterior walls of a property. The land area is then the remaining square footage of the lot.

Real estate property transactions are notoriously noisy. In order to remove outliers, for each year and borough I regress the logarithm of sale price on the logarithm of gross square ft. interacted with census tract – a granular measure of geography – along with other building and lot characteristics. I then remove all observations whose studentized-residual is greater than 3.7. Finally, I do a visual inspection for each year and borough to remove all clear outliers that may impact estimation in the hedonic model.

1.3.3 American Community Survey

The American Community Survey (ACS) is an annual survey performed by the US Census Bureau that collects demographic, economic, and housing data for neighborhoods across the US. The survey commenced in 2005, but for smoothing purposes, data is only available from 2009 -present. Each observation represents a 5-year moving average. The data we use is on the census tract level. To get an idea of how granular a census tract is, NYC is broken up into 1,335 individual census tracts; this is far more granular than neighborhoods or even community districts.

Demographic data includes median age (MedAge) and the racial makeup of each neighborhood broken down into white, African-American, Asian, Native American, and other. The "other" designation is largely made up of the Latin American population.

Economic data in the ACS includes the percentage of households with children, the percentage of households that report using public transportation as their main transportation to work, the percentage of those households that primarily walk to work, mean transit time to work, median household income (MedHHIncome), the percentage of those reported being unemployed (%Unemployed), the percentage of households fully covered by health insurance, the percentage of households below the poverty line, and the percentage of households with an annual income greater than $100,000.

The housing portion of the ACS includes the estimated vacancy rate, the percentage of residents who rent (%Rent), the percentage of residents without a vehicle, and the median gross rent of the area (MedGrossRent).

Finally, the education section includes the percentage of those with a less than ninth grade primary school education, the percentage with somewhere between a ninth to twelfth grade education, the percentage of those without a high school diploma, the percentage of those with a bachelor's degree of higher, and lastly, the percentage of residents born in the US.

1.3.4 ULURP Data

Data concerning the Uniform Land Use Review Process was collected by scraping data from the DCP's newly released Zoning Application Portal (ZAP). ZAP is a web tool that allows the public to track the progress of current and past zoning applications through the ULURP process. The information includes the date that each step of the ULURP was cleared, as well as the status of each step.

From the above information I am able to "dummy out" the ULURP process, creating six review-stage legislative dummies: one for the quarter in which the application was certified (CertDum), one for the community board recommended approval or disapproval (ResComDum), one for the approval of the borough president, one for if the DCP has held its public forum, one for if the DCP approved the application, and lastly, and one for if the City Council voted to pass the application into law.

I match each zoning application by its identifier to lot identifiers (BBLs) using the shape files released by the Department of City Planning for zoning map amendments. Using post-GIS and a shape file version of PLUTO called mapPLUTO, I find all properties that intersect the ZMA shape file for each version of MapPLUTO before and after the zoning amendment went into effect. I then check that each intersecting property did indeed change zoning designation and remove those that do not.

1.3.5 Bing Maps Data

Finally, we conjecture that simple network distance to a city center is not sufficient to capture the complexities of NYC's transit system. The subway system is extremely important to getting around in New York City. Mainly, we believe that residents value how easily they are able to travel to midtown Manhattan, from which you can get anywhere else in the city. Yet, transit times will also be correlated with distance to nearest subway or bus station, how many subway lines are in proximity to a property, and the idiosyncrasies of each subway line.

To capture such complexities in the data, we opt to use the Bings Map API to calculate transit time using either the subway or bus to Grand Central Station. In addition to being a central point in New York City's local subway system, it is also the meeting point of other major transportation systems such as New Jersey Transit, Long Island Rail, and the Metro North system.

Lastly, in order to handle the fact that transit times vary across time of day, I average the predicted transit times at 9am, 12pm, 5pm, and 9pm for all weekdays in a fixed week in August 2018. One implicit assumption is that estimated transit times in August of 2018, are representative of the entire sample.

1.3.6 Data Discussion

A brief discussion of the data is presented below.

Selected summary statistics for the full panel dataset are reported in Table 1.2. This sample includes all observations for all boroughs and all years.

Figure 1.2 presents the range of sale price to gross square feet between the 33rd and 66th percentiles in Manhattan and Brooklyn. There appears to be a common cyclical component between the two boroughs, but real estate prices in Manhattan have increased far more than Brooklyn over the sample period.

1.4 Empirical Framework

Clapp and Salavei (2010) develop a method to identify the option value to redevelop a property within the hedonic model. They posit that using the age of a structure as a proxy for structural depreciation produces a biased estimate for net depreciation because structure age might be positively correlated with the option value to redevelop the property. The intuition is that as a building ages, depreciation causes the value of the property to decline. In addition, as the building ages, the difference between the value of the property if it were developed for its highest and best use and the current property value increases, causing the option value to redevelop to increase as a share of total property value. These opposing effects make building age a biased proxy for net depreciation. In order to separate the two effects, Clapp and Salavei (2010) suggest using a proxy for the likelihood of redevelopment. The proxies proposed correspond to various measures of intensity. Examples are the fraction of nearby sales that are teardowns, the ratio of assessed structure value to assessed land value, and the ratio of average floor-area-ratio (FAR) of nearby new construction to FAR of the property considered.

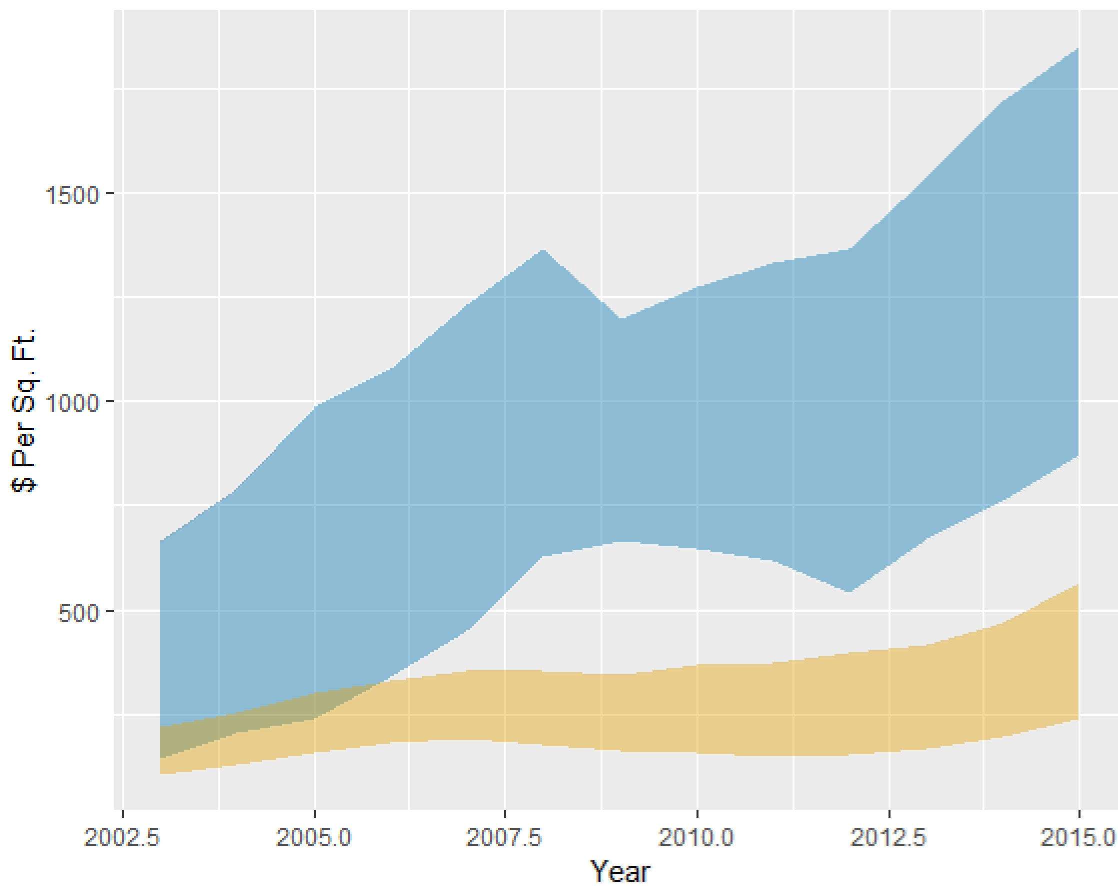


Figure 1.2: This figure shows how sale price per sq. ft. in Manhattan (top) and Brooklyn (bottom) has evolved through time. The lower bound of the range is the 33^{rd} percentile, and the upper bound is the 66^{th} percentile.

Table 1.2: Selected summary statistics.

Statistic	N	Mean	St. Dev.	Min	Max
SalePrice	470,565	1,309,629	16,215,434	10,040	4,111,111,766
GrossSqFt	470,565	4,270	35,125	10	8,942,176
LandSqFt	470,565	3,266	16,202	0	7,649,136
NumFloors	48,929,331	2.4	1.77	0	104
BldgArea	48,929,331	6,469	65,238	0	49,547,830
LotArea	48,929,331	5,165.	71,089	1	29,305,534
YearBuilt	48,861,359	1938	27.42	1661	2017
MetroTimeGCS	48,929,175	18.92	8.39	0.07	51.83
UR	21,951,046	6.286	3.359	0.000	62.700
MedHHIncome	21,939,060	62,398.91	23,743.18	8,694	247,167
%Rent	21,947,586	52.11	25.17	0	100
MedGrossRent	21,413,884	1,294.56	288.22	231	3,479
MedAge	21,949,333	37.22	5.74	17.3	94
HSGradRate	41,108,638	60.85	11.33	27	85.6

In the context of the example above, the proxy of Clapp and Salavei (2010) captures the relationship between the built structure, and the option value to redevelop. The closer to redevelopment a property is, the greater the difference between the rate of return for the property built to its highest and best use, r_{HBU}, and the current rate of return, r. Simultaneously the value from the current structure, $V_{i,t}^{(B)}$, decreases as cash flows are relatively low and redevelopment is expected to commence soon so there are few remaining cash flows from the current structure. The redevelopment value, $V_{i,t}^{(L)}$, increases as redevelopment becomes more likely because the rents foregone by redevelopment, $r \cdot NPV_i$, decrease. In the context of the motivational model above, interacting this paper's land use uncertainty proxy with the proxy of Clapp and Salavei (2010) should increase identification of the option value to redevelopment by capturing both the opportunity cost that works through foregone rents, r, as well as through rezoning probabilities, α. As an additional contribution, identification comes from exogenous variation in the (re)zoning propensities caused by nearby zoning changes.

Munneke and Womack (2017) extend the framework in Clapp and Salavei (2010) by directly estimating the probability of redevelopment in a probit regression, and using those probabilities directly in place of the proxy used by Clapp and Salavei (2010). They make further improvements by addressing selection bias via Lee, Maddala, and Trost (1982).

To address how the uncertainty regarding zoning designation in the future impacts the redevelopment option, I propose a two-stage approach where in the first-stage I estimate a multinomial logistic model to capture the propensity in the future to be restricted to each land use over a two-year horizon. I then interact the generated propensities from the first stages in the hedonic model with the redevelopment proxy as proposed by Clapp and Salavei (2010).

1.4.1 First Stage: Zoning Process

We model the long-run propensities to be (re)zoned as a multinomial logistic model at each time point. In addition, to standard locational and structure characteristics, I incorporate dummy variables in the logistic regression which correspond to the various stages of the Uniform Land Use Review and Procedure. The formal model is

$$\ln \frac{Pr(\Psi_{i,t} = \phi_z | X_{i,t})}{Pr(\Psi_{i,t} = \phi_S | X_{i,t})} = \alpha_z X_{i,t}, \tag{1.12}$$

where $\Psi_{i,t}$ is a categorical variable that identifies the zoning designation lead two years into the future, ϕ_z is the vector whose z^{th} element - which indexes the zoning designation - is equal to unity, and all other elements are equal to zero. $X_{i,t}$ is the vector of explanatory variables. These include individual property and locational characteristics, legislative variables from the ULURP, as well as census tract-specific variables that measure how the land use distribution of the census tract deviates from the community district and borough.

The long-run (re)zoning propensities are non-linear functions of the exogenous parameters:

$$\tilde{\eta}_{i,t,z} := Pr(\Psi_{i,t+2} = \phi_z | X_{i,t}) = \frac{\exp(\alpha_z X_{i,t})}{1 + \sum_{s=1}^{S-1} \exp(\alpha_s X_{i,t})}. \tag{1.13}$$

Note that I call the generated regressors long-run propensities because the model does not include current zoning designation as a regressor. The zoning process is highly persistent, and if one truly wanted to know the zoning designation a process a year from any given date the best predictor would be the current zoning designation. What I attempt to estimate is akin to the ergodic or zoning distribution unconditional of a property's use today. In the context of the presented model, I am not trying to estimate the rows of $\Pi(X_t)$, which correspond to one-step-ahead transitions probabilities, but instead what $\Pi(X_t)$ converges to in its limit,

$$\lim_{t\to\infty} \Pi(X_t, q_{i,t}) = \Pi^*(X_t, q_{i,t}).$$

It can be instructive to think of $\Pi^*(X_t)$ as the optimal land use distribution for the city that moves with underlying market and economic conditions. However, because there are significant frictions associated with rezonings and redevelopments, the city planners are always *chasing* the optimal distribution.

1.4.2 Second Stage: Hedonic Model

The final stage is a linear regression of the logarithm of sale price per square foot on building characteristics, locational characteristics, and the long-run zoning propensities interacted with the redevelopment proxy. The model can be viewed as a hedonic model of real estate prices where propensity to be redeveloped as well as the propensity to be zoned to each use are unobserved building characteristics that are priced.

To go from Equation (12), an infinite sum of expectations of log-normally distributed cash flows, to a log-linear equation for prices, I rely on the Fenton-Wilkinson approximation of Fenton (1960), which states that an infinite series of log-normally distributed random variables approximates a log-normal distribution.

Equation (14) is the measurement equation that is taken to the data:

$$\ln P_{i,t} = a_{i,t} + v_t' q_{i,t} + \sum_z \gamma_z \eta_{i,t,z} LSA_{i,t} + u_{i,t}, \tag{1.14}$$

where $LSA_{i,t}$ is the proxy for redevelopment defined as

$$LSA_{i,t} := \frac{\text{Assessed Land Value}_{i,t}}{\text{Assessed Total Value}_{i,t}}. \tag{1.15}$$

The idea is that redevelopment option consists of an intensity dimension and a potential rezoning dimension. By interacting the probability of being rezoned to each designation next year with the intensity proxy, I can understand how the potential to be rezoned impacts the option to redevelop.

The option value to redevelop property i is then computed as

$$OV_{i,t} := \exp\left(\hat{a}_t + \hat{v}_t' q_{i,t}^0 + \sum_{j=1}^{S} \gamma_{t,j} \hat{\eta}_{i,t,j} LSA_t + \frac{\sigma_{u,i}^2}{2}\right) - \exp\left(\hat{a}_t + \hat{v}_t' q_{i,t}^0 + \frac{\sigma_{u,i}^2}{2}\right). \tag{1.16}$$

I then define the option value associated with the propensity to be zoned use s as

$$OV_{i,t}^{s} := \exp\left(\hat{a}_t + \hat{v}_t' q_{i,t}^{0} + \sum_{j}^{S} \gamma_{t,j} \hat{\eta}_{i,t,j} LSA_{i,t} + \frac{\sigma_{u,i}^2}{2}\right) - \exp\left(\hat{a}_t + \hat{v}_t' q_{i,t}^{0} + \sum_{j \neq s} \gamma_{t,j} \hat{\eta}_{i,t,j} LSA_{i,t} + \frac{\sigma_{u,i}^2}{2}\right). \tag{1.17}$$

1.4.3 Identification

A primary concern with regards to estimation of the hedonic model is potential endogeneity between the land use propensities and prices. It is difficult to disentangle the effect of (re)zoning propensities on prices from the effect that prices might have on (re)zoning propensities themselves.

In order to address such concerns, I focus our estimation in the hedonic model on the subsample of real estate transaction that occur within a year of a nearby major zoning change. I define a zoning change to be major if more than twenty lots changed zoning designation in a given census tract for any given year. I identify 41 such zoning changes throughout the sample.

For each major zoning change event, an area is defined within a mile radius of any lot that changed zoning designation, but not within 1,000 feet of any lot that switched zoning designation. The intuition is that a major zoning change event may very well be endogenous to transaction prices in the area of the rezoning. However, when an area experiences a large rezoning, neighbors that did not experience the rezoning reevaluate their expectations about what their future zoning designation looks like. For example, if the major zoning change made a neighboring area become more like our area, I would not expect a zoning change to occur in the future. However, if the land use distribution of the area that experienced a zoning change becomes more different than ours, I should increase the probability of zoning change in our neighborhood occurring in the future.

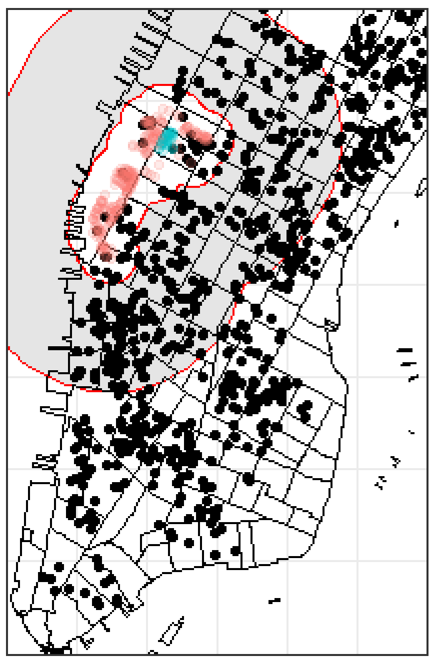
Figure 1.3 illustrates the identification strategy visually for the Hudson Yards rezoning.

1.5 Results

The results of the two-stage estimation procedure are presented below; each is accompanied by a discussion. The entire estimation procedure is run separately for the boroughs of Manhattan and Brooklyn, and each run includes years 2003 -2015.

Before showing the results of the hedonic model, I present evidence that the generated proxy for

Figure 1.3: Identified real estate transactions around the Hudson Yards rezoning. Each black dot represents a property transaction within a year of the Hudson Yards rezoning. The colored dots represent a properties that changed zoning designations to commercial (red) and residential (blue). The shaded area represents the identified zone: within a mile of any property that got rezoned in the Hudson Yards rezoning, but not within 1,000 ft.



land use uncertainty predicts in-sample zoning changes. In addition, I demonstrate that the proxy for redevelopment motivated by Clapp and Salavei (2010) predicts in-sample redevelopments.

1.5.1 First Stage: Estimating Land Use Uncertainty

In the first stage, I run a multinomial logistic regression to capture the uncertainty regarding future zoning designations. Table 1.3 presents summary statistics for the sample used for estimation, while Table 1.4 presents coefficients and significance.

The main drivers of future land use uncertainty are the distributional characteristics of a lot's census tract with respect to land use, and how it differs from the lot's community district (borough). For example, the variable $\%C|CT_{i,t} - \%C|CD_{i,t}$ is defined as the percentage of lots zoned commercial (C) in the census tract (CT) associated with lot i in year t, minus the percentage of lots zoned commercial in the entire community district (CD) associated with lot i. To give a sense of how granular these groupings of geographical area are, there are two hundred and thirty eight census tracts the make up the borough of Manhattan, and fourteen community districts. Figure 1.4 shows the boroughs of Manhattan and Brooklyn broken into community districts (blue border), and census tracts (black border). The idea is if the localized area surrounding a property has more commercial lots than the larger geography, then the current lot is more likely to either be currently commercially zoned or rezoned to commercial in the future. Coefficients of the deviation of both the percentage of lots zoned as commercial or manufacturing in the census tract from the entire borough are significant. Results show if the census tract is either more commercial or manufacturing than the borough, then lots in that tract are more likely to be rezoned as commercial or manufacturing regardless of current zoning. This implies that commercial and manufacturing lots tend to be clumped together away from residential lots.

Table 1.3: Summary statistics from first-stage estimation. $\%C|CT - \%C|CD$ refers to the difference between the percentage of lots zoned to commercial (C) in a lots specific census tract (CT) and the community district (CD). The same notation holds for manufacturing zoned lots (M), and the borough (Boro). LotArea is the area of the lot. Age refers to the age of the building. LastAltered refers to the year the building had its last major alteration. MetroTimeGCS is the estimated transit time to Grand Central Station.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
$\%C\|CT - \%C\|CD$	16,016,931	−0.00000	0.095	−0.813	−0.023	−0.004	0.940
$\%M\|CT - \%M\|CD$	16,016,931	−0.0001	0.123	−0.282	−0.039	−0.003	0.994
$\%C\|CT - \%C\|Boro$	16,016,931	−0.00005	0.123	−0.289	−0.022	−0.006	0.981
$\%M\|CT - \%M\|Boro$	16,016,931	−0.0001	0.133	−0.073	−0.041	−0.034	0.966
LotArea	16,016,931	4,132.826	29,613.590	17	1,914	2,967	9,218,615
Age	16,016,931	80.766	25.529	0.000	73.500	98.500	217.750
LastAltered	16,016,931	72.237	31.558	−0.500	52.500	94.500	216.750
MetroTimeGCS	16,016,931	15.814	5.599	0.070	12.050	19.888	40.207

Other significant variables driving the propensity to be rezoned are the age of the structure, the floor area ratio, the number of floors, the assessed value of the land, and the legislative dummies.

An interpretation can be difficult in the multinomial logit model, in which marginal effects are computed by integrating over the exogenous variables. Results for Manhattan are presented in Table 1.5, and for Brooklyn in Table 1.6.

For Manhattan, each percent deviation of commercial lots in the census tract to the borough increases the propensity to be commercially zoned by almost 0.6% and decreases the probability of being residential by nearly the same amount. It does not appear to have a statistically significant effect on the propensity to be manufacturing. Each percentage point deviation of manufacturing zoned lots from the borough increases the likelihood to be zoned commercial by 0.02%, manufacturing by 0.028%, and residential by 0.05%. Older buildings increase the likelihood of residential or manufacturing and decrease the likelihood of being commercially zoned. Taller buildings are decrease the likelihood of being zoned for manufacturing. A ten percent increase in the assessed value of the land increases the propensity to be commercial by 0.6% and decreases the likelihood of being zoned residential by 0.056%.

The legislative variables have a significant impact. Having a certified ULURP application increased the likelihood of being commercial by 32%, decreased the change of being manufacturing by roughly 3%, and decreased the likelihood of being residentially zoned by 29%. Also how the community board weighs in on the zoning application also has a statistically significant impact. Applications for which the community board is a majority in favor of the proposed zoning change are 21.9% less likely to be commercial in the future, 2.75% more likely to be manufacturing, and 19.2% more likely to be residential.

After running the estimation, the land use propensities are generated by simply taking the model prediction for each classification. Then the base case is simply unity minus the sum of all imputed values.

1.5.2 Do Land Use Propensities Predict Zoning Changes?

Now that land use propensities for each tax lot have been generated, I test whether our generated propensities are predictive of zoning changes. Since I have a limited sample to work with and the

Table 1.4: Results of the first-stage choice model of land use designation two years into the future. The sample includes all lots from both Manhattan & Brooklyn for years 2003-2015. $\%C|CT - \%C|CD$ refers to the deviation of % properties zoned (C)ommercial ((M)anufacturing) in the census tract from the community district $\%C|CT - \%C|Boro$ refers to the respective deviation but from the borough. CertDum is a dummy variable which is one if a ULURP application for a zoning change is in progress and it is certified. ResComDum is a dummy that is equal to one if a ULURP application is in progress and the residential community board approved of the application.

	Land Use	
	C	M
$\%C\|CT - \%C\|CD$	0.225	0.775
$\%M\|CT - \%M\|CD$	-0.449	-5.421***
$\%C\|CT - \%C\|Boro$	6.322***	4.884***
$\%M\|CT - \%M\|Boro$	4.349***	15.69***
LogLotArea	-0.527	0.327
Age	-0.00793***	-0.00341***
LastAltered	-0.0000558	0.000368
FAR	0.0468	0.0950***
LogBldgArea	-0.340	0.0641
LotFrontage	0.00160	0.000630
NumFloors	-0.0200	-0.136***
LogAssessLand	0.608***	0.187
MetroTimeGCS	0.00379	0.0333
CertDum	3.137***	1.002**
ResComDum	-2.106**	-0.215
Constant	-0.443	-9.582***
N	2,118,441	
R_P^2	0.514	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Marginal effects for propensity to be rezoned commercial (C), manufacturing (M), and residential (R) in Manhattan based on the first-stage regression for years 2003-2015. Marginal effects are computed by integrating over observed values of regressors, and the t-statistics are computed using the delta-method. t-statistics in parenthesis.

	C	M	R
$\%C\|CT - \%C\|CD$	0.0119	0.0141	-0.0260
	(0.16)	(1.17)	(-0.32)
$\%M\|CT - \%M\|CD$	0.0357	-0.116***	0.0800
	(0.42)	(-4.14)	(0.90)
$\%C\|CT - \%C\|Boro$	0.593***	0.0135	-0.606***
	(9.81)	(1.35)	(-9.17)
$\%C\|CT - \%M\|Boro$	0.219*	0.288***	-0.507***
	(1.91)	(13.31)	(-4.39)
LogLotArea	-0.0607*	0.0155***	0.0452
	(-1.95)	(4.03)	(1.45)
Age	-0.000785***	0.0000444**	0.000741***
	(-5.58)	(2.12)	(5.77)
LastAltered	-0.0000115	0.00000918	0.00000236
	(-0.14)	(0.55)	(0.03)
FAR	0.00349	0.00143***	-0.00492*
	(1.29)	(2.88)	(-1.68)
LogBldgArea	-0.0369*	0.00668	0.0303
	(-1.75)	(1.61)	(1.40)
NumFloors	-0.0000150	-0.00278***	0.00280
	(-0.01)	(-3.30)	(1.56)
LogAssessLand	0.0614***	-0.00510	-0.0563***
	(7.16)	(-1.10)	(-8.46)
CertDum	0.316***	-0.0255*	-0.291***
	(5.86)	(-1.80)	(-6.44)
ResComDum	-0.219**	0.0275**	0.192**
	(-2.50)	(2.17)	(2.26)

t-statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Marginal effects for propensity to be rezoned commercial (C), manufacturing (M), and residential (R) in Brooklyn based on the first-stage regression for years 2003-2015. Marginal effects are computed by integrating over observed values of regressors, and the *t*-statistics are computed using the delta-method.

	C	M	R
$\%C\|CT - \%C\|CD$	-0.0533	0.0161	0.0372
	(-0.49)	(0.25)	(0.34)
$\%M\|CT - \%M\|CD$	-0.0130	-0.117***	0.130***
	(-0.41)	(-5.46)	(4.78)
$\%C\|CT - \%C\|Boro$	0.251**	0.0262	-0.278***
	(2.41)	(0.39)	(-2.68)
$\%M\|CT - \%M\|Boro$	0.0327	0.269***	-0.302***
	(1.18)	(13.25)	(-11.14)
LogLotArea	-0.0123**	0.00958***	0.00272
	(-2.51)	(4.03)	(0.40)
Age	0.0000464	0.0000970*	-0.000143**
	(1.02)	(1.93)	(-2.11)
LastAltered	-0.0000520**	-0.0000370**	0.0000889***
	(-2.43)	(-2.39)	(3.22)
LotFrontage	0.0000260***	-0.00000757	-0.0000185
	(2.90)	(-0.86)	(-1.31)
NumFloors	-0.00521***	-0.0141***	0.0193***
	(-2.83)	(-7.39)	(5.98)
LogAssessLand	0.0130***	0.00337***	-0.0164***
	(8.70)	(3.01)	(-8.08)
MetroTime	-0.000585***	-0.000137	0.000722***
	(-3.43)	(-1.22)	(3.33)
CertDum	0.00476	-0.0557***	0.0510***
	(0.75)	(-3.29)	(2.66)
ResComDum	-0.00280	-0.0141	0.0169
	(-0.97)	(-0.98)	(1.10)

t-statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

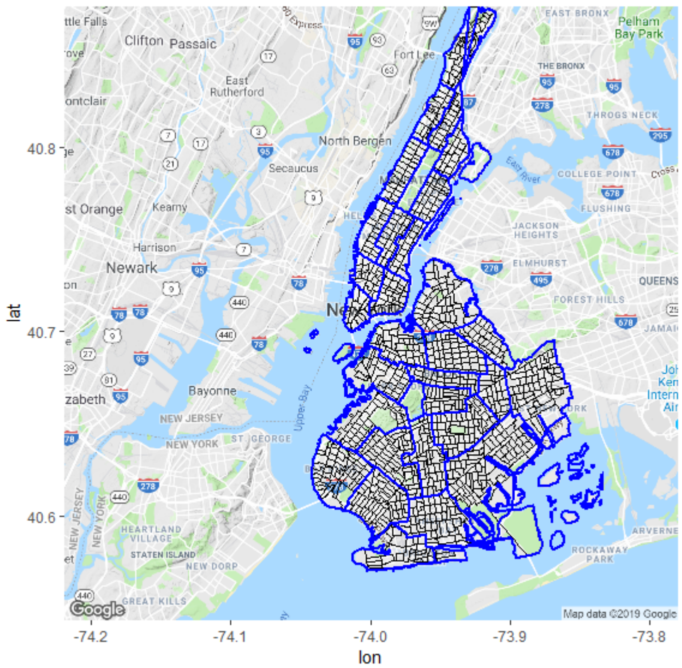


Figure 1.4: The boroughs of Manhattan and Brooklyn with the boundaries that community districts in blue (thick), and census tracts in black (thin). The census tracts are nested in the community districts, and the community districts within the borough. Manhattan is in the north and Brooklyn is in the south, each separated by the East River.

zoning process is highly persistent, I see if I can explain the probability that a zoning change occurs during the sample with zoning propensities at the beginning of the sample.

To determine if our generated land use propensities are actually predictive of zoning changes, I create a dummy variable, D_i, that is equal to unity if a lot has a different zoning designation in 2017 than it did in 2002, and zero otherwise. I remove the few lots that have gone through two or more rezonings over the sample to avoid the case where a lot switched to a new designation and then switched back to their original designation.

We regress $D_{i,t}$ on what I define to be the *transition propensity* at the beginning of the sample, $T_{i,2002}$, as the sum of the propensities to be a land use different from how it is currently zoned.

$$T_{i,2002} := \sum_{z \in \{C,R,M\} \setminus Z_{i,2002}} p(z)_{i,2002}, \tag{1.18}$$

where $Z_{i,2002}$ is the zoning designation of lot i in 2002.

For example, for a manufacturing zoned lot, the transition propensity is the sum of that lot's propensity to be commercial or residential. I run a separate regression for each zoning designation, and also include a specification with census tract fixed effects. Table 1.7 presents results.

Regressions (1) - (3) show the estimation results. All results show that transition propensities are positively correlated with a zoning change occurring throughout our sample, and all results are statistically significant at the 0.1% significance level. For commercial, manufacturing, and residential, respectively, a one percentage point increase in the transition propensity translates into an increased probability of being rezoned by 0.223%, 0.112%, and 0.19%. Including census tract level fixed effects does not hinder the effect, and for commercial and residential, it makes the effect much stronger. This suggests that even within a census-tract, the transition propensities help to distinguish which buildings will transition.

1.5.3 Does Land Share of Assessed Value Predict Redevelopments?

It is imperative that I test if the land share of assessed value, our proposed proxy motivated by Clapp and Salavei (2010), predicts redevelopments in our sample. Since redevelopments occur over a very long cycle, I opt to do an experiment similar to the prior experiment by testing whether propensities predicted observed zoning changes. I create a dummy variable, R_i, indicating whether or not a redevelopment has occurred throughout the entire sample. A redevelopment here is defined as either as a major renovation or a construction project that alters the size or egress of a structure.

We then regress R_i on five dummies representing which quintile of land share of assessed value the property falls into. Results are presented in Table 1.8.

Regression (1), the baseline, shows all coefficients are statistically significant, and there is roughly a 10 percentage point increase in the probability of redevelopment going form the bottom quintile to the top quintile. Controlling for age and the remaining FAR the property owner is legally allowed to add on to the building does not take away the effect of our proxy, although it does dampen it a bit. The difference between the top and bottom quintile decreases to roughly 7 percentage points. Age has a non-linear impact on the probability of redevelopment, reaching an inflection point at around 60 years. This implies that after 60 years of operation, the benefit from having a 'historic' building outweighs redevelopment. Instead, property owners likely invest in the upkeep of their property little-by-little each year to stave off depreciation. Remaining FAR is also

Table 1.7: Regressions (1)-(3) show results from regressing a dummy indicator whether or not a zoning change occurred during the sample on transition propensities at the beginning of the sample defined as the sum or propensities to be a zoning designation other than the lot's current designation, for lots zoned commercial, manufacturing, and residential respectively at the beginning of the sample. Regressions (4)-(6) include census tract fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)
$T^C_{i.2002}$	0.223***			0.362***		
	(0.00632)			(0.0178)		
$T^M_{i,2002}$		0.112***			0.0832***	
		(0.00938)			(0.0118)	
$T^R_{i,2002}$			0.0193***			0.0554***
			(0.000844)			(0.00219)
Constant	-0.0252***	0.140***	0.00128***	-0.0973***	0.153***	-0.000256*
Tract FE	-	-	-	Yes	Yes	Yes
N	15,338	12,508	260,349	15,325	12,498	260,347
adj. R^2	0.075	0.011	0.002	0.575	0.737	0.164

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8: Regressions (1)-(4) predict redevelopment over the sample on quintile dummies of assessed land value as a percentage of assessed total value. Regression (1) presents baseline results. Regression (2) controls for a quadratic term in the age of the structure as well the remaining designated FAR permitted by the New York City Zoning Resolution (FAR Remaining). Regression (3) includes community district fixed effects, and Regression (4) includes census tract fixed effects. The bottom row F-statistics are from a test that the coefficients on all five quintiles are equal to one another.

R_i	(1)	(2)	(3)	(4)
Q1	0.0687***	0.00813*	0.225***	0.0603
	(0.00143)	(0.00340)	(0.0112)	(0.0390)
Q2	0.0733***	0.0115**	0.243***	0.0794*
	(0.00143)	(0.00366)	(0.0113)	(0.0390)
Q3	0.0793***	0.0154***	0.249***	0.0896*
	(0.00143)	(0.00374)	(0.0113)	(0.0390)
Q4	0.102***	0.0331***	0.262***	0.103**
	(0.00143)	(0.00376)	(0.0113)	(0.0390)
Q5	0.165***	0.0785***	0.290***	0.129***
	(0.00143)	(0.00382)	(0.0112)	(0.0390)
Age		0.000718***	0.00104***	0.000910***
		(0.0000928)	(0.0000943)	(0.000102)
Age^2		-0.00000161*	-0.00000823***	-0.00000771***
		(0.000000664)	(0.000000680)	(0.000000719)
CD FE	-	-	Yes	-
Tract FE	-	-	-	Yes
adj. R^2	0.111	0.120	0.141	0.153
F(4,·)	777.56***	377.48***	207.96***	190.44***

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

statistically significant, with each additional floor that is allowed to be added on to the redeveloped building increasing the odds of redevelopment by 2 percentage points. Lastly, regressions (3)-(4) add community district, and census tract fixed effects respectively, and they do not seem to hinder our proxy's ability to predict redevelopment.

1.5.4 Hedonic Regression

Next, a hedonic model is estimated by regressing the logarithm of sale price per square feet on various property characteristics. The advantage of defining intensity as in Equation 14 is that it is increasing in option value; the greater percentage of the total value of the property is due to the land, the higher the option value should be. And when intensity is equal to zero – the land is not valued – it can be interpreted as if there is no option value to redevelop.

For years 2003-2015, I have complete data for 9,853 transactions in Manhattan, excluding condominium sales, which make up the majority of residential transactions in Manhattan. I have 105,047 transactions for Brooklyn. Summary statistics for the estimation sample are presented in Table 1.9 and Table 1.10 respectively.

Table 1.9: Summary statistics for hedonic regression of Manhattan; 2003-2015.

	Mean	Std. Dev.	Min	Max
SaleSqFt	680.92	947.32	1.96	35,416.67
LotArea	3,862.48	4,812.18	320	58,24
Age	95.23	19.23	1.75	119.75
p(C)	.2812	.3353	.0013	.9959
p(M)	.0703	.1952	.0001	.9859
p(R)	.6483	.3868	.0030	.9983
AssessTotalSqFt	49.73	64.94	.490929	2,163
FloorArea	3,509.80	8,691.54	130	359,251
NumFloors	5.104	4.26	1	63
LastAltered	43.94	52.95	-12.25	119.75
ExemptTotalSqFt	2.62	13.55	0	373.60
MetroTimeGCS	9.969675	6.47	.07	26.2
LSA	.4008	.2324	.0121	.9911
Observations	5,276			

Table 1.10: Summary statistics for hedonic regression of Brooklyn; 2003-2015.

	Mean	Std. Dev.	Min	Max
SaleSqFt	290.48	194.77	9.6153	2,854.33
LotArea	2,676.87	4,256.58	340	362,142
Age	88.11	24.04	.5	118
p(C)	.0189	.0726	1.40e-15	.9999
p(M)	.0398	.1491	1.33e-32	.9999
p(R)	.9412	.1650	3.77e-06	1
AssessTotalSqFt	11.80	12.46	.1425	499.36
FloorArea	1,570.58	2,755.36	80	146,300
NumFloors	2.4555	.8697	1	75
ExemptTotalSqFt	1.1238	4.51	0	239.59
MetroTimeGCS	16.3896	4.56	2.81	28.65
LSA	.3985	.2384	.0068	.9906
Observations	35,253			

Regression results from the hedonic model estimation for both Manhattan and Brooklyn are presented in Table 1.11.

The regression specification above regresses the logarithm of the transaction price per gross square foot on land share of assessed value (LSA) interacted with land use propensities, as well as the logarithm of the total assessed value per gross square foot. The LSA terms reflect the option value to redevelop into each use, while the total assessed value terms are interacted to allow for the possibility that changes in the future expected zoning of an area might also impact real estate values through the existing building characteristics.

Ignoring the interaction terms, the elasticity of prices with respect to the land share of assessed value is $\beta_{LSA} - \frac{\beta AV}{LSA}$. As a building depreciates, the land share of assessed value increases. The coefficient on LSA, β_{LSA}, is thus the impact on prices through the option value to redevelop as a building depreciates. This first-order effect is offset by the effect of the building depreciating on the total assessed value inversely proportional to the land share of assessed value. This loss of value from depreciation is most severe when the land share of assessed value is low (or when the building is most valuable).

All coefficients on the LSA term are significant at the 5% level with the exception of the p(r) term for Manhattan (which is significant at the 10% level) and the p(c) term for Brooklyn. For both boroughs, option value is most sensitive to propensities to be zoned commercial, followed by manufacturing and residential.

1.5.5 Discussion: Option Value to Redevelop Across Space

Table 1.12 and Table 1.13 present how option value varies across the entire sample for Manhattan and Brooklyn respectively. The mean option value in Manhattan is 20% of total value, and it is broken down into 28% related to commercial development, 8.5% manufacturing, and 66.3% residential. The option value to redevelop has a standard deviation of 10 percentage points. Lots in Brooklyn have far less option value, with a mean of 8.5% and standard deviation of 4.7 percentage points. Much of Brooklyn's option value is attributed to residential development, with only 1% going to commercial and 4.4% being attributed to manufacturing.

Table 1.11: Hedonic estimation results from Manhattan and Brooklyn from the identified subsample. LSA is the land share of assessed value, and p(z) corresponds to the land use propensities. Standard errors are computed using the Huber-White sandwich estimator and are clustered across census tracts.

	Manhattan	Brooklyn
$\log \frac{SalePrice}{GrossSqFt}$	β / SE	β / SE
p(c) $\times$ LSA	0.851***	0.439
	(0.161)	(0.446)
p(m) $\times$ LSA	0.698***	0.423**
	(0.217)	(0.166)
p(r) $\times$ LSA	0.221*	0.222***
	(0.128)	(0.036)
p(c) $\times \log \frac{AssessTotal}{GrossSqFt}$	0.459***	0.735***
	(0.063)	(0.162)
p(m) $\times \log \frac{AssessTotal}{GrossSqFt}$	0.590***	0.118***
	(0.124)	(0.038)
p(r) $\times \log \frac{AssessTotal}{GrossSqFt}$	0.200***	0.258***
	(0.024)	(0.012)
Controls $\times$ Year	Yes	Yes
CT $\times$ Year FE	Yes	Yes
Observations	4,521	30,215
R^2	0.637	0.549

Table 1.12: Summary statistics for option value in Manhattan

All Properties	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
OV/Total Value	9,853	0.200	0.100	0.007	0.119	0.275	0.455
OV^C/OV	9,853	0.280	0.308	0.00000	0.022	0.438	0.995
OV^M/OV	9,853	0.085	0.207	0.000	0.004	0.037	0.987
OV^R/OV	9,853	0.663	0.364	0.001	0.306	0.976	0.999
Commercial	**N**	**Mean**	**St. Dev.**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
OV/Total Value	3,040	0.191	0.084	0.013	0.123	0.251	0.426
OV^C/OV	3,040	0.599	0.304	0.001	0.318	0.897	0.995
OV^M/OV	3,040	0.085	0.158	0.00001	0.014	0.064	0.969
OV^R/OV	3,040	0.352	0.331	0.001	0.060	0.685	0.993
Manufacturing	**N**	**Mean**	**St. Dev.**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
OV/Total Value	746	0.218	0.092	0.014	0.143	0.288	0.444
OV^C/OV	746	0.259	0.233	0.003	0.084	0.393	0.891
OV^M/OV	746	0.647	0.281	0.005	0.425	0.885	0.987
OV^R/OV	746	0.140	0.183	0.004	0.040	0.139	0.949
Residential	**N**	**Mean**	**St. Dev.**	**Min**	**Pctl(25)**	**Pctl(75)**	**Max**
OV/Total Value	6,067	0.202	0.107	0.007	0.114	0.286	0.455
OV^C/OV	6,067	0.123	0.161	0.00000	0.013	0.184	0.965
OV^M/OV	6,067	0.016	0.063	0.000	0.003	0.011	0.950
OV^R/OV	6,067	0.883	0.162	0.019	0.840	0.985	0.999

Table 1.13: Summary statistics for option value in Brooklyn.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
OV/Total Value	105,047	0.085	0.047	0.002	0.042	0.125	0.305
OV^C/OV	105,047	0.010	0.044	0.000	0.002	0.007	0.793
OV^M/OV	105,047	0.044	0.139	0.000	0.007	0.021	0.994
OV^R/OV	105,047	0.948	0.144	0.001	0.975	0.990	1.000
Commercial	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
OV/Total Value	1,949	0.071	0.044	0.003	0.035	0.102	0.255
OV^C/OV	1,949	0.143	0.214	0.0001	0.012	0.172	0.793
OV^M/OV	1,949	0.073	0.116	0.000	0.015	0.081	0.981
OV^R/OV	1,949	0.792	0.243	0.017	0.712	0.969	1.000
Manufacturing	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
OV/Total Value	3,918	0.105	0.061	0.003	0.055	0.146	0.305
OV^C/OV	3,918	0.013	0.045	0.000	0.002	0.009	0.632
OV^M/OV	3,918	0.529	0.371	0.0004	0.141	0.930	0.994
OV^R/OV	3,918	0.471	0.366	0.001	0.074	0.851	0.999
Residential	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
OV/Total Value	99,180	0.084	0.047	0.002	0.042	0.125	0.274
OV^C/OV	99,180	0.008	0.027	0.000	0.002	0.006	0.766
OV^M/OV	99,180	0.025	0.071	0.000	0.007	0.019	0.974
OV^R/OV	99,180	0.970	0.075	0.025	0.977	0.990	1.000

Table 1.14 and Table 1.15 exhibit how the breakdown of option value varies across demographic factors. On the racial dimension, the higher percent Asian a census tract is, the more the redevelopment option is a fraction of total value in Manhattan. In contrast, the more African-American a neighborhood, the more the option value to redevelop constitutes total property value. Neighborhoods that are the least Asian have option values of 10.64% for commercial, 1.77% manufacturing, and 88.77% residential, while neighborhoods that are the most Asian have redevelopment rates of 57.71% for commercial, 18.75% manufacturing, and 26.43% residential. The distribution of the least African-American census tracts is 40.43% commercial, 9.17% manufacturing, and 54.25% residential. The census tracts which are most African-American have nearly all residential value; the breakdown is 9.51% commercial, 3.73% manufacturing, and 87.72% residential.

One may think the racial breakdown may be related to income. When looking at the same breakdown but for median household income in Manhattan, it is very similar to the breakdown for Asian census tracts. The least Asian neighborhoods have a similar option value to the lowest income census tracts, while the most Asian look very close to the highest income quartile. However, the top quartile of African-American census tracts has more variation than income dynamics might suggest. The top quartile of African-American tracts have more redevelopment option value than the lowest income bracket, and the option value itself is attributed 3% more to residential development. They both have extremely little manufacturing potential.

Table 1.14: A breakdown of option value across various demographics for Manhattan. Q1 refers to the bottom quartile of census tracts, which contains the smallest 25% of values. Q4 is then the quartile of 25% largest of values. The first row shows the percentage of estimated property value that is attributed to total option value. The bottom three rows then break down the distribution of how optional value is related to the propensity of each property to be categorized as each land use. All demographic information is on the census tract level. GCT refers to Grand Central Station.

Percent African American	Q1	Q2	Q3	Q4
Option Value as % of Property Value	20.39	18.96	17.66	16.19
% Commercial	40.43	45.36	39.99	9.51
% Manufacturing	9.17	15.50	8.38	3.73
% Residential	54.25	42.93	54.60	87.72
Percent Asian	Q1	Q2	Q3	Q4
Option Value as % of Property Value	16.02	20.92	18.55	17.58
% Commercial	10.64	24.24	42.36	57.71
% Manufacturing	1.77	7.75	8.74	18.75
% Residential	88.77	71.84	52.23	26.73
Median Age	Q1	Q2	Q3	Q4
Option Value as % of Property Value	16.63	17.11	19.10	20.14
% Commercial	34.28	32.12	31.65	37.33
% Manufacturing	12.04	11.15	8.69	5.49
% Residential	55.95	59.35	63.10	60.37
Median Household Income	Q1	Q2	Q3	Q4
Option Value as % of Property Value	14.92	18.61	19.81	19.68
% Commercial	15.12	31.48	42.52	45.38
% Manufacturing	1.14	8.54	8.46	18.98
% Residential	84.57	62.79	53.21	39.31

Percent Renters	Q1	Q2	Q3	Q4
Option Value as % of Property Value	20.22	19.63	18.31	14.94
% Commercial	37.74	38.37	32.74	26.59
% Manufacturing	12.72	11.73	7.29	5.52
% Residential	53.14	53.58	62.61	69.53
Percent w/ Bachelor's Degree or Higher	**Q1**	**Q2**	**Q3**	**Q4**
Option Value as % of Property Value	14.38	18.52	20.50	19.62
% Commercial	15.12	38.69	37.60	43.52
% Manufacturing	1.21	8.43	15.17	12.28
% Residential	84.44	55.67	51.44	47.95
Metro Time to GCT	**Q1**	**Q2**	**Q3**	**Q4**
Option Value as % of Property Value	21.13	20.91	18.06	19.84
% Commercial	34.80	26.64	20.34	30.25
% Manufacturing	12.01	6.74	5.97	9.38
% Residential	57.05	69.29	75.42	63.41

Education also has similar option value characteristics as median household income. At the top of the income and education bracket, the quartile of tracts with the highest degree earners has 6% more option value associated with residential redevelopment and 10% more residential.

Tracts with more renters have a lower amount of option value and have less of the option value devoted to commercial use, less to manufacturing, and more to residential.

Median age of the households in the census tract seems to have a positive correlation with option value. The older the residents of the neighborhood, the more option value there is, likely due to higher incomes.

The changes to option value in Brooklyn are not as drastic as in Manhattan. There is far less variation in option value. This may have to do with the fact that the majority of option value in Brooklyn is associated with residential. More research needs to be done on what is driving the

Table 1.15: A breakdown of option value across various demographics for Brooklyn. Q1 refers to the bottom quartile of census tracts, which contains the smallest 25% of values. Q4 is then the quartile of 25% largest of values. The first row shows the percentage of estimated property value that is attributed to total option value. The bottom three rows then break down the distribution of how optional value is related to the propensity of each property to be categorized as each land use. All demographic information is on the census tract level. GCT refers to Grand Central Station.

Percent African American	Q1	Q2	Q3	Q4
Option Value as % of Property Value	11.46	11.13	11.43	12.09
% Commercial	0.85	1.27	1.36	0.68
% Manufacturing	3.11	7.46	4.38	2.19
% Residential	96.37	91.74	94.60	97.42
Percent Asian	Q1	Q2	Q3	Q4
Option Value as % of Property Value	12.06	11.67	11.20	11.19
% Commercial	1.02	0.91	1.22	1.03
% Manufacturing	3.68	5.07	5.30	3.21
% Residential	95.64	94.36	93.90	96.11
Median Age	Q1	Q2	Q3	Q4
Option Value as % of Property Value	11.70	11.32	11.42	11.66
% Commercial	1.66	1.11	0.75	0.66
% Manufacturing	6.50	5.32	3.70	1.83
% Residential	92.30	93.97	95.87	97.77
Median Household Income	Q1	Q2	Q3	Q4
Option Value as % of Property Value	11.65	11.57	11.66	11.23
% Commercial	1.52	0.84	0.71	1.11
% Manufacturing	4.46	4.54	4.10	4.14
% Residential	94.44	94.99	95.52	95.08

results from Brooklyn.

1.5.6 Discussion: Option Value Across Time

Figure 1.5 and Figure 1.6 show how the option value to redevelop as a percentage of total estimated value has changed each year for Manhattan and Brooklyn respectively. A visual inspection gives creedance to the idea that the option value to redevelop is acyclical. For both Manhattan and Brooklyn, I see option value decrease from 2003-2008, when the great financial crisis hit. From 2008-2010, there is a drastic increase in option value. Once NYC real estate starts to boom again from 2010-2015, I also see a decrease in the option value to redevelop.

This is consistent with Grenadier (1996), which finds that development cascades can occur in periods where there is a downturn in demand for real estate services. As rents from real estate decline during an economic downturn, the opportunity cost introduced from the lost rent during a redevelopment decreases. Landlords then have greater incentive to exercise the redevelopment option, as they can earn even more rents once the recession ends and the property is improved.

1.6 Conclusion

We ask how the option value to redevelop is related to land use restrictions, and how the redevelopment value is related to various demographic and building characteristics. A dataset is constructed that captures land use changes, property transactions, building characteristics, demographics, and economic information for all properties and census tracts in New York City from 2002-2017.

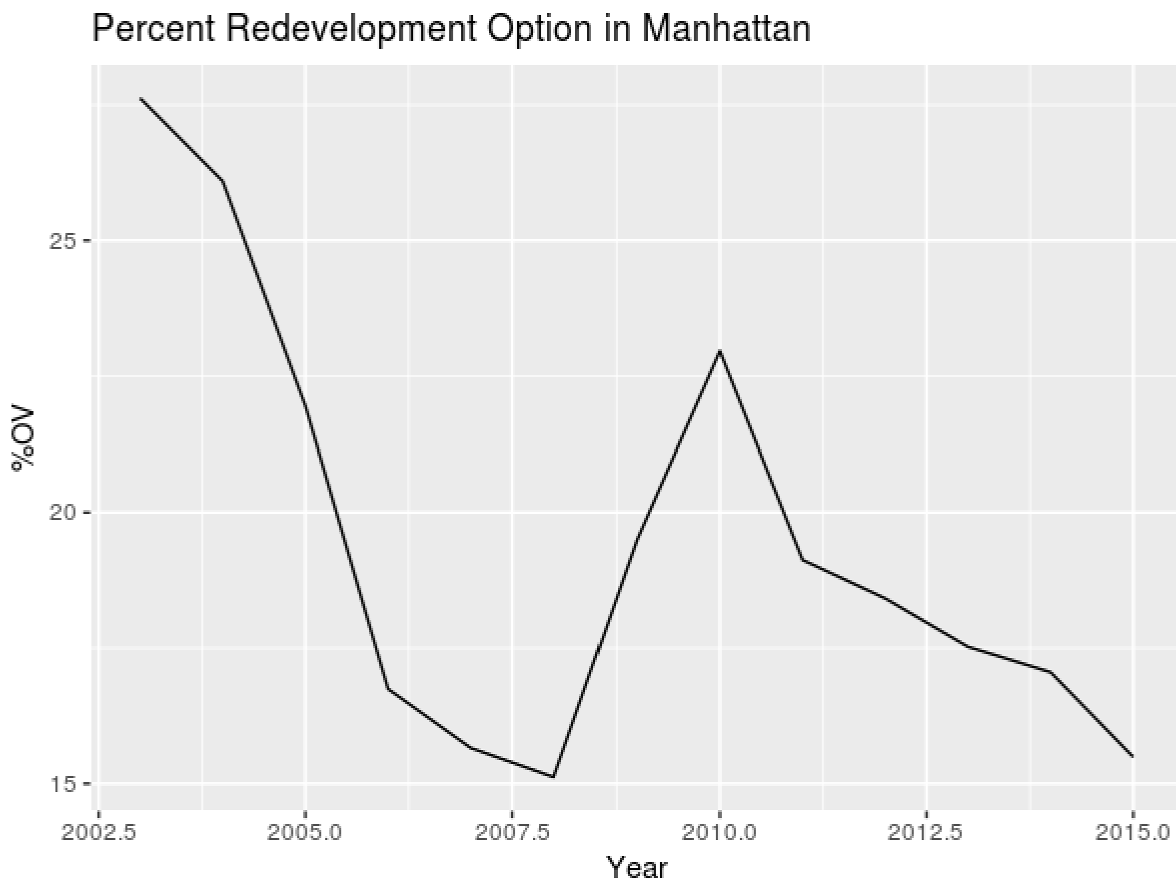


Figure 1.5: Option value to redevelop of a percent of total value over time for Manhattan.

Using a two-stage estimation procedure, propensities to be zoned to either residential, commercial, or manufacturing land uses are interacted with the ratio of assessed land to total assessed value of the property. This ratio proxies for the propensity to be redeveloped.

We find evidence that all option value terms are statistically significant. I estimate the the average option value in Manhattan for years 2003-2015 is 20% of total estimated value, and I estimate that it is 8.5% in Brooklyn. In a sense, Furthermore, the option value broken down by the potential to develop into different land uses shows clear correlations with race, income, and education. Lastly, I present evidence that the option value to redevelop is counter-cyclical with the real estate cycle.

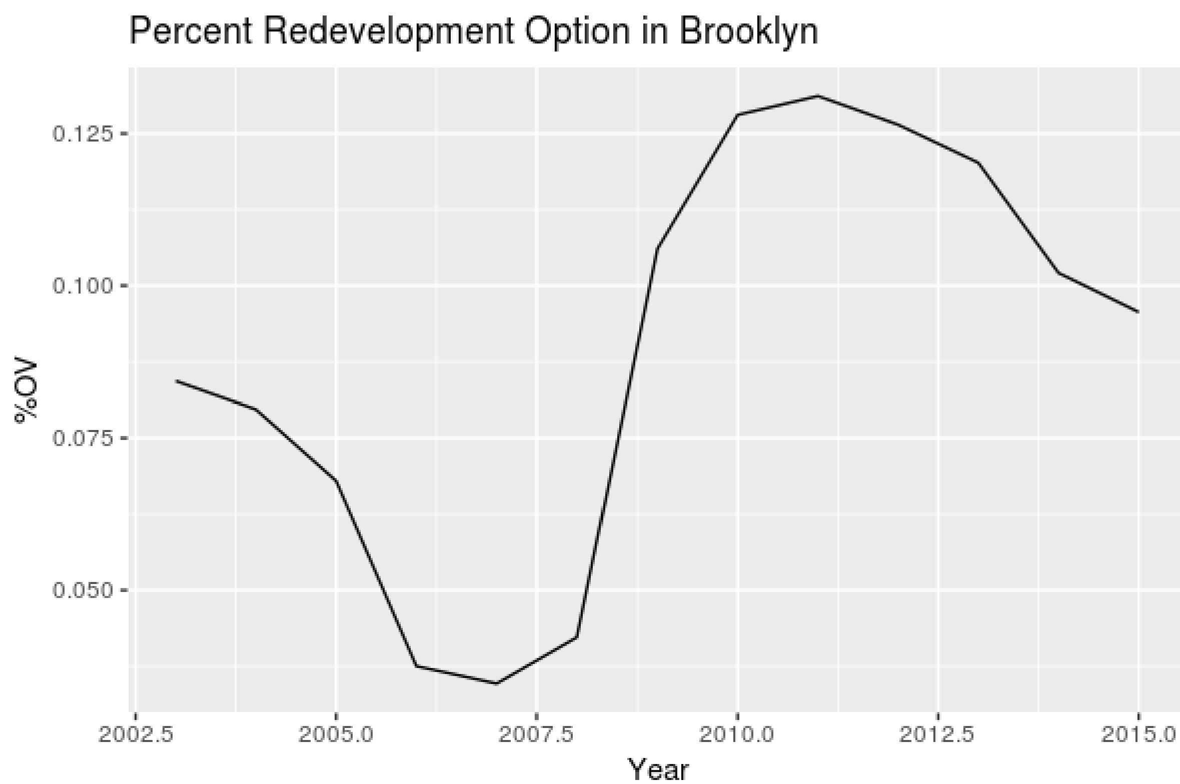


Figure 1.6: Option value to redevelop of a percent of total value over time for Brooklyn.

CHAPTER 2

MACRO FUNDAMENTALS AND COMMERCIAL REAL ESTATE PRICE DYNAMICS

Joint with Jacob Sagi

2.1 Introduction

Commercial real estate (CRE) can be loosely defined as real estate held for the purpose of deriving income (through rental profits) and capital gains. This includes leased space in the residential (apartment), office, industrial, and retail sectors, among others. Although publicly traded portfolios of commercial real estate comprise less than 5% of the overall stock market, the asset class represents roughly 15% of the private equity universe.[1] The latter figure is commensurate with recommendations for "optimal" portfolio allocation and is arguably consistent with its substantial share of the overall economy.[2] Despite its size, the relationship of CRE with macroeconomic fundamentals does not appear to be well-understood. For instance, while the impact of monetary policy on residential real estate prices has been well-studied (Iacoviello 2005), to our knowledge the same is not true of commercial real estate. In this paper, we attempt to better pin-down how commercial real estate prices and fundamentals are influenced by macro fundamentals: growth, inflation, and nominal interest rates. We do this in a structural framework that is consistent with a rational expectations equilibrium (REE) in which investors set prices by attempting to anticipate

[1] The first figure comes from https://www.reit.com/investing/investor-resources/gics-classification-real-estate who cite S&P Dow Jones Indices and MSCI FactSet as the source for the data, and the second figure comes from The rise and rise of private markets: McKinsey Private Markets Review'.

[2] In their 2019 annual release of the Financial Accounts of the United States, the Board of Governors of the Federal Reserve System reports that there is more than $50 Trillion dollars worth of real estate in the United States. Of this, just over 50% correspond to owner-occupied residential assets. Because CRE is primarily held by private actors, it is hard to estimate how much of it there is. A rule of thumb used by some practitioners is that the stock of assets in developed countries that is comparable to CRE held by large institutional investors amounts to roughly half of GDP (see PGIM Real Estate's A Bird's Eye View of Real Estate Markets: 2017 Update). It is further estimated that only one third of that amount is actually held by large institutional investors. In the US, this would amount to a stock of $9 Trillion of which $3 Trillion would already be held by large institutional investors.

the impact of structural changes in macro fundamentals on real estate cash flow fundamentals and discount rates. We find that, based on their cash flow and price characteristics, CRE assets and secured loans are profoundly sensitive to macro fundamentals (both output growth and inflation) and structural breaks in the relationship between these fundamentals. There are multiple reasons why this is important for policy makers, lenders, investors, and consumers.

2.1.1 Why is this research question important?

To understand why a better grasp of the relationship between macro-fundamentals and CRE prices is of keen interest to policy makers, it is useful to recall that a major devaluation in CRE prices played a key role in the Savings and Loan crisis of the late 1980s and early 1990s. The Federal Government's response to the massive systemic bank failures stemming in large measure from non-performing CRE loans was the creation of the Resolution Trust Corporation, whose goal was the orderly liquidation of collateral from non-performing loans. Concern about the risk of similar contagion, and the need for better understanding of CRE price dynamics, recently prompted the President of the Federal Reserve Bank of Boston to say (remarking specifically about CRE) that "...for almost any asset category, positive trends can sometimes evolve into prices that increase more than fundamentals justify. It is very hard to distinguish how much of the price gain is the result of the favorable fundamentals, and how much reflects an abundance of optimism by investors."[3] Because the approach we take to examining relationships between fundamentals and prices is consistent with a REE, we are better able to distinguish prolonged periods when prices are not consistent with fundamentals as well as conduct counterfactual experiments. Indeed, our model estimates imply a historically large departure of commercial real estate prices from fundamentals starting in early 2006 and peaking around mid-2007.

Correspondingly, lending institutions whose financing is heavily influenced by regulatory and monetary policy hold a great deal of debt collateralized by CRE (either explicitly or implicitly). The relationship of this collateral value to funding costs is clearly of vital interest to such institutions, especially when it comes to assessing portfolio risk. Our modeling framework can be used

[3]The quote is taken from a May 9, 2017 speech by Eric S. Rosengren, "Trends in Commercial Real Estate", addressing conference attendees at NYU.

to quantify the risk associated with well-diversified CRE portfolios over arbitrary horizons. For more context, consider that roughly $4 Trillion of lending is directly secured to CRE.[4] This only accounts for loans directly secured to CRE and likely understates the lending market's exposure to CRE because real estate forms the bulk of many business entities' tangible assets, and senior unsecured lending has an implicit claim on the unencumbered portion of such assets.[5]. It is also worth mentioning that CRE mortgages are disproportionately held by regional banks — CRE loans represent 35% (8%) of all loans for banks with assets under $10B (greater than $1T) — suggesting that shocks to this asset class could propagate quickly in the real economy.[6]

It is likely self-evident that investors care about the above-discussed issues facing policy makers and lenders . Beyond that, some practitioners view real estate investments as hybrid fixed-income securities. A particularly vivid yet somewhat anecdotal example for this is the so-called "taper tantrum" episode in the late Spring of 2013, when the US Federal Reserve Chairman Ben Bernanke announced the Fed's intention to unwind quantitative easing. The announcement is alleged to have affected real estate investment trusts (REITs) more negatively than other stocks, and REITs lost more ground relative to non-REIT stocks as the economy continued to improve that Summer and the Fed re-iterated its intentions.[7] Some practitioners also argue that real estate investments provide a good hedge against inflation. The argument typically given is that as overall prices are increased, rents too will be escalated. Academics, on the other hand, have struggled to find a simple relationship between real estate prices and interest rates or inflation (E.g., see Hartzell, Hekman, and Miles 1987; Liu, Hartzell, and Hoesli 1997; Peyton 2009). Efforts to link

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[4]This figure comes from Table L.217 of the Financial Accounts Guide published by the Board of Governors of the Federal Reserve System. It includes "non-residential commercial" and multi-family (rental apartment) real estate assets.

[5]See Tuzel (2010); Cvijanović (2014).

[6]This figure comes from an industry publication, the Yardi Matrix Bulletin (July 2018), titled "Regional/Local Banks Eat More of the Commercial Mortgage Pie: When is Enough?".

[7]To our knowledge, there is no definitive proof of a causal link between the Fed announcements and REIT returns over this period. One attempt at this is Lee (2016).

these variables have been confined to linear regressions without economic constraints on how fundamentals interrelate. Our paper contributes to this literature by re-visiting these questions within a REE-consistent framework that is able to reflect structural changes in the relationship between CRE prices and macro fundamentals.

In equilibrium, residential housing values are linked to the rental market, and thus commercial real estate. This is because renting and owning are (imperfect) substitutes for satisfying demand for housing services. The implication is that valuations in the two markets cannot be decoupled. Thus an understanding of CRE price dynamics does carry over to helping understand housing price dynamics, and consequently consumer household wealth. An important challenge in this literature, however, is the lack of key data. While an impressively large time-series panel of house prices is readily available, such data cannot be easily complemented with underlying cash flows.[8] An advantage of working with CRE is the potential availability of both cash flow and prices. By using cash flow data to help pin down price movements, one may be better able to tie down the relationship between prices and fundamentals. To the extent that such relationships qualitatively carry over from residential CRE to owner-occupied homes, our work is also relevant to the literature on consumer and household finance.

2.1.2 Paper synopsis

We estimate a model that combines two important economic features: (i) The feedback between short-term interest rates, inflation, expected inflation, and the output gap; and (ii) "No-arbitrage" dynamic asset-pricing in which current prices correspond to discounted future cash flow. In the model, the discount rate varies with the nominal rate and time-varying risk premium, while cash flow growth rates vary with inflation and the output gap. Prices combine the two in a highly non-linear and forward-looking fashion. In particular, the relationship between the three macro variables can structurally change and such changes are anticipated in prices. Finally, time-varying cash flow volatility influences prices through Jensen's inequality.

To model structural shocks that could (but need not be) interpreted as monetary policy shifts,

[8] Researchers may use "imputed rent" to substitute for actual cash flow but, even beyond the obvious measurement error, this does not net out renovations and additions.

we employ a variant of the model used by Bikbov and Chernov (2013). They reason that combining a REE-consistent monetary policy model with observed bond prices can lead to improved identification of both model parameters and monetary policy regimes.[9] By adding other asset prices to the estimation, together with corresponding cash flows, we are able to simultaneously estimate structural regimes, cash flow (and price) sensitivity to macro variables across regimes, and pricing errors. The linking of prices to fundamentals (macro variables and cash flow) permits an analysis where one can point to periods where the former depart from the latter.

We are led to the suspicion that structural regime changes might be important to understanding CRE prices by the following fact. A regression of the ten-year treasury yield on inflation exhibits a regime break between data from the 1990's and the following period (the regression coefficient roughly halves in going from the earlier to the later period). Moreover, average CRE income yields, known as capitalization rates or "cap rates", co-moved very little with treasury bond yields and inflation in the earlier period, but the co-movement became large and highly significant afterwards (positive for bond yields and negative for inflation).[10] In a Gordon-Williams growth model, cap rates are equal to the difference between discount and income growth rates. If real estate income growth co-moves strongly with inflation then whenever discount rates are also highly sensitive to inflation (e.g., a "Hawkish" monetary policy regime) the discount and growth effects wash out and cap rates would be less sensitive to moves in inflation or yields. When discount rates are relatively insensitive to inflation (e.g., a "Dovish" monetary policy regime), the same reasoning would predict for cap rates a positive sensitivity to interest rates and a negative sensitivity to inflation. While the former intuition may be appealing in explaining why cap rates were insensitive to interest rates and inflation before 2000 and highly sensitive afterwards, it is somewhat ad-hoc in selecting only a single regime break-point. Another cause for concern is that the intuition above builds on the Gordon-Williams growth model which is inherently static, while a structural break process is

[9]Clarida, Gali, and Gertler (2000) and Bianchi (2013) also find strong evidence of regimes in monetary policy.

[10]A break point can be found in 2000q4 via a supremum Wald test. Bianchi (2013) estimates a more sophisticated model that suggests a monetary policy regime change in 1999Q3. The two dates yield similar results for the relationship between treasury bond yields, inflation, and cap rates.

dynamic. If CRE prices react to monetary policy, then it must be that investors also anticipate monetary policy and that this feeds back into CRE prices (i.e., cap rates). The only way to test and measure this is to estimate a dynamic model of macro fundamentals and asset prices in which investors anticipate future structural changes. This is what we attempt to do in this paper.

The model of macro fundamentals that we use can be viewed as a regime-switching VAR with constraints on the coefficients that arise from REE considerations.[11] We allow for structural changes in the sensitivity of interest rates to inflation and the output gap. Likewise, we allow interest rate volatility to exhibit regimes.

We model real estate income fundamentals as depending contemporaneously on inflation, the output gap, and lagged income. Given such a dependence, the monetary policy model pins down discount rate dynamics and therefore the present value of cash flows (i.e., prices). We use income and price data from three large real state asset portfolios consisting of apartment, office, and industrial assets. In addition, as in Bikbov and Chernov (2013), we use price data on 2-, 5-, and 10-year treasury strips. Our maximum likelihood estimation finds the set of model parameters that best links prices to fundamentals while fitting the joint dynamics of macro fundamentals.

Our model is able to fit bond prices with an error roughly comparable to that found in Bikbov and Chernov (2013).[12] Real estate asset pricing errors vary from 5% to 7%. Generally, we find significant positive sensitivities to the output gap and inflation across all real estate asset cash flow. An OLS analysis of real estate cash flow dependence on macro fundamentals yields similar results for the output gap, but insignificant loadings on inflation. This highlights the disadvantage of analyzing cash flow growth fundamentals without also including price information. It is important to add that real estate income is generally positively associated with inflation using univariate

[11] In a REE, the output gap, inflation, and nominal rates depend on the expectations of consumers and market participants for future output gap, inflation, and nominal rates. In other words, the VAR structure is augmented with forward-looking components which must be integrated out. An arbitrary VAR will not necessarily correspond to a REE, hence the need for constraints.

[12] Treasury bond pricing errors under the model that includes information from real estate portfolios are around 0.40%. Without the real estate portfolios ((i.e., the Bikbov and Chernov 2013, model)) the pricing error is around 0.26%. As seen in similar studies (e.g., Chiang, Hughen, and Sagi 2015), the fit to prices tends to erode with the addition of more assets in the estimation. This is because, despite the addition of more model parameters, the same basic fundamentals are required to explain a greater range of dynamics.

measures of association but, because inflation and the output gap are positively correlated, in a multivariate analysis the loading on inflation declines and may even turn negative.

In the estimated interest rate regimes, the sensitivity of rates to inflation and the output gap are simultaneously positive and high or positive and low. These have natural interpretations as monetary policy regimes where in one regime the Fed actively targets inflation and an overheated economy, while in the other regime the Fed abstains from such targeting. The former regime can be viewed as "active" (or "hawkish") while the latter regime as "passive" (or "dovish"). Correspondingly, we identify high and low interest rate volatility regimes which could represent, following Bikbov and Chernov (2013), shifts between a flexible (or "loose") versus "rigid" (or "tight") implementations of monetary policy.

If the estimated regimes are interpreted as monetary policy shifts, then one can use the model to study the impact of monetary policy on real estate prices. Consistent with the intuition given earlier, an active (passive) monetary policy would be associated with higher (lower) cap rates. In the estimated model, real estate prices are lowest when monetary policy actively targets inflation and an overheated economy, but the policy is only loosely or "flexibly" applied (leading to above-average interest rate volatility). The mirror image situation — a passive regime targeting a low rate and low rate volatility — exhibits the highest real estate prices. Model estimates are consistent with the view that the last decade has been, on average, characterized by such a passive-rigid regime. Thus a key model insight is that well-defined regime shocks can dramatically impact prices. For instance, in expectation, moving from an active-flexible to a passive-rigid regime leads to a 100-150 basis point decline in cap rates (and a corresponding large increase in prices). Moving the other way leads to higher cap rates although the effect is (on average) a bit more muted.

Finally, we study the impact of regimes changes on mortgage spreads. Here too we find that the most pronounced impact comes from a well-defined active/passive policy change, associated with as much as a 100 basis point change in spreads of newly originated instruments and a 20%-30% change in the value of existing loan portfolios. In summary, changes in regime, both those anticipated and those that actually occur, appear to have a profound impact on CRE and CRE derivatives (e.g., mortgages).

2.2 Literature Review

2.2.1 Regime changes in monetary policy

Identifying structural breaks in macro fundamentals is not an easy task. Sims (2001) argues that by checking for parameter instability in single-equation models or reduced-form regressions, economists are less likely to gain valuable economic insights because they are attempting to draw inference from a misspecified model. Said differently, a well-specified model should include the anticipatory influences. On the other hand, when estimating structural MS-DSGE models that employs the rational expectations (RE) assumption, the estimated parameters tend to be poorly identified.

There exists a large literature that attempts to answer the question, "did a change in the way monetary policy was conducted during the 1980s contribute to the reduction in volatility of inflation, & economic growth during that same period". Clarida et al. (2000) (hence CGG) test for instability of a forward-looking monetary policy rule in the spirit of Taylor (1993). The authors find that prior to 1979:Q3, the US monetary authority's response to changing inflation expectations to be less than unity. During the the Volcker-Greenspan era, the authors find that the central bank raised interest rate more than one-for-one with inflation expectations. Their findings suggest that during Arthur Burns' reign of chairman of the Fed was characterized by destabilizing monetary policy that coincides with a period of a high volatility of economic fundamentals. In contrast to the Burns era, the Volcker-Greenspan era was stabilizing and coincides with a period of low volatility of economic fundamentals.

This paper is related to studies in the vein of CGG, that opt to use structural multivariate DGSE models to capture monetary policy regime changes, as opposed to the single-equation used by CGG. Early examples include Lubik and Schorfheide (2004) and Sims and Zha (2006).[13]

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[13] In support of employing stochastic monetary policy regime changes, Sims and Zha (2006) write that "policy changes, if they have occurred, have not been monotonic, and they have been difficult to detect. Both the rational public in our models and econometricians must treat the changes in policy probabilistically, with a model of how and when the shifts occur and with recognition of the uncertainty about their nature & timing."

2.2.2 Asset pricing and monetary policy

Rudebusch and Wu (2008) as well as Bekaert, Cho, and Moreno (2010) connect an affine no-arbitrage model of the term structure of interest rates to a hybrid small-scale New-Keynesian model similar to the one used in this paper but without allowing for multiple independent regimes. Similarly, Bikbov and Chernov (2013) attempt to employ the term structure of interest rates to get sharper estimates on a Markov-Switching New-Keynesian model allowing for the monetary policy rule parameters, the volatility of the output gap & inflation, and the volatility of short-term nominal interest rates to all switch independently of each other. The authors find the econometrician's ex-post probability of being in a given monetary policy regime is much sharper in the model that includes select terms of the yield curve. Theirs is used as a starting point for our model, as it addresses Sims (2001)'s concern that models of monetary policy that ignore heteroskedasticity while allowing for parameter instability are prone to be spurious.

Also clearly related are recent attempts to connect bond and equity market price dynamics to monetary policy. Campbell, Pflueger, and Viceira (2014) employ a New-Keynesian model to explain the time-variation in correlations between stock market and bond market returns. In their model, agents do not anticipate possible regime changes in monetary policy. Song (2017) undertakes a similar analysis by estimating a rational expectations model in which the monetary authority changes between two policy regimes (active versus passive). While we, like Song (2017), work in a REE framework, our model is reduced-form and additionally considers changes in the volatility of interest rates (e.g., a rigid versus flexible policy regime).

2.2.3 Real estate and macro fundamentals

Plazzi, Torous, and Valkanov (2010) test predictions about CRE cap rate implied by the Dynamic Gordon model of Campbell and Shiller (1988), which posits that the cap rate is a function of the future expected path of returns, or future expected path of rental growth rates (i.e., cap rates should predict future returns or future rent growth). In a cross-sectional analysis Plazzi et al. (2010) find that certain classes of cap rates do predict either rental growths or future returns, but the predictability is dependent on how returns co-vary with rental growth rates. In a related study, Plazzi, Torous, and Valkanov (2008) find that the cross-sectional dispersion of CRE cap rates is related to macro fundamentals.

Using data from a US CRE fund, Hartzell et al. (1987) find that imputed quarterly portfolio returns are positively related to both expected inflation and inflation shocks over the (highly inflationary) period 1974-1983. Perversely, securitized real estate (i.e., REITs) appear to have the opposite relationship with inflation and there is some evidence that this difference is linked to feedback with monetary policy (Liu et al. 1997).

2.3 Data & Basic Statistics

2.3.1 Data

We employ data from the US from years 1992:Q1 to 2014:Q2. The output gap is constructed from a quadratic detrending of log real GDP per capita from FRED. We use the annual log-change of personal consumption expenditure (PCE) obtained from FRED to instrument for inflation because it is widely believed that the FED targets this measures in setting its monetary policy.[14] The continuously compounded annualized Fama-Bliss return on a 3-month ZCB is used for the short-term rate of interest (the "short rate").

Real estate (unlevered) property value and net operating income (NOI) growth data is from the National Counsel of Real Estate Investment Fiduciaries (NCREIF) and corresponds to constituent properties of the NCREIF Property Index. Each quarter, the NCREIF property data is aggregated for three distinct real estate asset categories: Apartments, Industrial, and Office.[15] Cap rates are calculated for each quarter-category by dividing the aggregated property values reported for the end of that quarter by the trailing four quarters of NOI (including the current quarter's NOI). Although cap rates are supposed to be forward-looking (i.e., employing expectations for next year's NOI), this number is not available and the discrepancy can be viewed as part of the estimated

[14]See https://www.federalreserve.gov/newsevents/pressreleases/monetary20120125c.htm.

[15]Data for retail CRE properties are also available from the NCREIF. Because of highly variable standard errors in estimates of the average NOI growth across the NCREIF retail properties portfolio, we elect not to use it in our estimation.

measurement error. Income growth is calculated from quarterly NOI.[16] Although NCREIF data is available as early as 1978q1, the number of properties is significantly smaller in the earlier period. Figure 2.1 demonstrates that the data is quite noisy prior to the early 1990s. In our analysis we employ data starting in 1992q1.

Figure 2.2 provides visual evidence for the substantial co-movement of cap rates across asset categories. It is also clear that the cross-sectional dispersion of cap rates is time-varying suggesting that the different asset categories have different sensitivities to macro-economic factors. Table 2.1 documents summary statistics for the panel variables before and after the monetary policy regime break identified in Bianchi (2013). The ν_i's denote income growth rates while the c_i's denote cap rates (i.e., earnings yields). The subscripts A, I, and O respectively denote "apartments", "industrial", and "office". The short rate, ten-year strip rate, inflation, and output gap are denoted as r, r_{10}, π, and g. Asterisks correspond to cases in which the post-1999q3 mean or standard deviation of a variable is significantly different from the corresponding statistic pre-1999q3. While there is no clear evidence that cash flow variables underwent a significant change, real estate cap rates have declined across the board in the post-1999q3 period. As mentioned in the introduction, this decline in cap rates has been accompanied by a decline in interest rates, while inflation has remained more or less steady (though perhaps more volatile).

Table 2.2 documents the correlations of the panel variables before and after 1999q3. The second panel identifies correlation coefficients that are significantly different from those in the first. Several patterns emerge. The relationship between real estate prices (as represented by cap rates) and macro fundamentals seems to have undergone a significant change. This is especially pronounced for the ten-year rate. Earning growths also experienced a change in their relationship with macro fundamentals, but this seems to be primarily mediated through the output gap. Finally, as expected with a persistent shift from an active to a passive monetary policy regime, the relationship between long-term rates and inflation declined significantly.

The summary statistics provide suggestive evidence that the dynamics of both cash flow and

[16]Seasonality in the income growth series is not, overall, statistically significant.

prices underwent a regime change along with macro fundamentals. Moreover, given that prices correspond to discounted cash flow, the documented changes in the summary statistics were likely mediated through both the cash flow growth and discount rate channels. However, the summary statistics on their own do not provide a sense of whether/when prices reflect fundamentals and through what channel. To address such questions one must employ some sort of model that ties fundamentals to prices. To fit the data well, a model would also have to capture the changing relationships between the price and fundamental variables. In the next section we describe such a model.

2.4 Model

We employ an extension/variant of the Markov-switching rational expectations model proposed in Bikbov and Chernov (2013). The model connects a small-scale New-Keynesian framework to asset prices. Henceforth, to fix intuition and ease of exposition, we refer to the structural changes in the relationship between macro fundamentals as arising from monetary policy (MP). As mentioned earlier, regime changes in practice may be the result of other influences.

2.4.1 Macroeconomic Dynamics

Our specification of the macroeconomic dynamics allow for a simultaneous system of equations that are both forward- and backward-looking. The former provide consistency with a rational expectations paradigm (see discussion in Bikbov and Chernov 2013). The variables of interest are the output gap (g_t), the inflation rate (π_t), and short-term interest rate (r_t). To match the granularity of the time-series panel we choose the continuously compounded annualized yield on the 3-month risk-free bond to proxy for r_t.

$$
\begin{aligned}
&\text{(IS)} \qquad && g_t = m_g + (1-\mu_g)g_{t-1} + \mu_g \mathbb{E}_t g_{t+1} - \phi(r_t - \mathbb{E}_t \pi_{t+1}) + \sigma_g \epsilon_t^g \\
&\text{(PC)} \qquad && \pi_t = (1-\mu_\pi)\pi_{t-1} + \mu_\pi \mathbb{E}_t \pi_{t+1} + \delta g_t + \sigma_\pi \epsilon_t^\pi \\
&\text{(MP)} \qquad && r_t = m_r(s_t^m) + \rho(s_t^m) r_{t-1} + \hat{\alpha}(s_t^m)\mathbb{E}_t \pi_{t+1} + \hat{\beta}(s_t^m) g_t + \sigma_r(s_t^d)\epsilon_t^r
\end{aligned}
\tag{2.1}
$$

Where $\varepsilon_t^i \sim^{iid} N(0,1)\ \forall i \in \{g, \pi, r\},\ \forall t \in \{1, \ldots, T\}$.

The investment/savings (IS) relationship tells us current economic growth is a function of prior economic growth, agents' expectations for future economic growth (conditional on today's information set), and the expected effective real rate next period. This captures the widely held notion from macroeconomic theory, that a high cost of capital decreases economic growth through lower investment. The Phillip's curve (PC) reflects the persistence of price growth (through lagged inflation), the influence of an economy below its potential (negative output gap) is to reduce inflation through higher unemployment, and the notion that current prices anticipate higher future prices. Note that this equation implies that the unconditional expected value of g_t is zero. The monetary policy rule (MP), similar to that used in Clarida et al. (2000), assumes that the monetary authority responds to inflation expectations and economic growth.

We assume the presence of two types of regime state variables, s_t^m and s_t^d, where $s_t^i \in \{0, 1\}$ for $i \in \{d, m\}$. Thus, at each point in time the macro-economy can be in one of four regimes corresponding to the pair, $S_t = (s_t^m, s_t^d)$. The regime driving changes to the monetary policy response, s_t^m, allows for the simultaneous change of the short-rate drift, $m_r(s_t^m)$, the interest-rate smoothing parameter, $\rho(s_t^m)$, the response to inflation expectations, $\hat{\alpha}(s_t^m)$, and the response to the output gap, $\hat{\beta}(s_t^m)$. The regimes associated with s_t^d only impact $\sigma(s_t^d)$ and correspond to changes in the *discretionary* component to monetary policy by capturing different possible levels of tolerance by the monetary authority for deviations from its rule.[17] We assume that each of s_t^m and s_t^d follows an independent (but not identical) 2-state Markov chain.

All macro-economic dynamics in the model are driven by the state vector $x_t = (g_t, \pi_t, r_t)$, and the Markov regime S_t. Assuming a transversality condition, Cho (2016) establishes that the system of equations in (2.1) can be expressed in VAR form as

$$x_t = m(S_t) + \Phi(S_t)x_{t-1} + \Sigma(S_t)\varepsilon_{t+1}, \tag{2.2}$$

where for each realization of S_t the VAR parameters ($m(S_t)$, $\Phi(S_t)$, and $\Sigma(S_t)$) satisfy non-linear

[17]To capture the period before the so-called "Great Moderation", Bikbov and Chernov (2013) also include a third regime state variable that impacts the volatility of the output gap and inflation. None of our data precedes the Great Moderation. Moreover, a White Test on the volatility of the output gap and inflation during our sample cannot reject the null hypothesis of homoskedasticity at the 10% significance level. We therefore dispense with this third regime.

restrictions.[18] The non-linear restrictions arise through the forward-looking components when one plugs (2.2) in (2.1).

To price assets that depend on x_t, one must also specify the dynamics of a risk-adjusted (i.e., "risk-neutral") version of (2.2). Following Bikbov and Chernov (2013) and the literature on affine term-structure models (e.g., Duffee 2002), we assume that risk premia can be a time-varying linear function of x_t and the risk adjusted dynamics of (2.2) are given by

$$x_t^{\mathbb{Q}} = m^{\mathbb{Q}}(S_t) + \Phi^{\mathbb{Q}}(S_t)x_{t-1} + \Sigma(S_t)\varepsilon_t^{\mathbb{Q}}, \tag{2.3}$$

where

$$\begin{aligned} m^{\mathbb{Q}}(S_t) =& m(S_t) - \Sigma(S_t)\Sigma'(S_t)\Pi_0 \\ \Phi^{\mathbb{Q}}(S_t) =& \Phi(S_t) - \Sigma(S_t)\Sigma'(S_t)\Pi_x, \end{aligned}$$

The vector Π_0 and matrix Π_x are constant, while $\varepsilon_t^{\mathbb{Q}}$ is standard Normal under the risk-neutral measure, $\mathbb{Q}$.

2.4.2 Asset Pricing

Consider a payoff of D_τ in quarter τ. Denote the present value of D_τ at period $t < \tau$ as

$$\text{PV}_t[D_\tau] = \mathbb{E}_t[M_{\tau,t}D_\tau] \equiv \mathbb{E}_t^{\mathbb{Q}}[e^{-\sum_{s=t}^{\tau-1} r_s} D_\tau],$$

where $\mathbb{E}_t[\cdot]$ denotes the expectation operator conditional on information at t, $M_{\tau,t}$ is the state-price deflator at t for payoffs at $\tau \geq t$, and $\mathbb{E}_t^{\mathbb{Q}}[\cdot]$ is the expectation operator under the equivalent martingale measure (i.e., risk-neutral expectations).

Consider now a sequence of payoffs, $\{D_\tau\}_{\tau=t+1}^{N}$ such that

$$\mathbb{E}_t[\frac{D_{t+1}}{D_t}] = \mathbb{E}_t^{\mathbb{Q}}[\frac{D_{t+1}}{D_t}] = e^{\nu_t}.$$

[18]See also discussions in Bikbov and Chernov (2013) and Cho (2016).

Here, ν_t can be interpreted as the growth rate of cash flow. This assumption in the equation above implies that investors do not require compensation to level shocks of cash flows. Thus risk premia can only be associated with shocks to the expected growth rates of cash flows.[19] It follows that an asset paying $\{D_\tau\}_{\tau=t+1}^N$ will have present value of

$$\text{PV}_t[\{D_\tau\}_{\tau=t+1}^N] = D_t \sum_{\tau=t+1}^{N} \mathbb{E}_t^{\mathbb{Q}}\left[e^{\sum_{s=t}^{\tau-1}(\nu_s - r_s)}\right].$$

Hence, the price-earnings ratio of this asset becomes

$$Q_t \equiv \frac{\text{PV}_t[\{D_\tau\}_{\tau=t+1}^N]}{D_t} = \sum_{\tau=t+1}^{N} \mathbb{E}_t^{\mathbb{Q}}\left[e^{\sum_{s=t}^{\tau-1}(\nu_s - r_s)}\right]. \tag{2.4}$$

In the formalism above, the price of a zero-coupon bond (ZCB) paying \$1 at period $\tau > t$ is

$$B_{t,\tau} = \mathbb{E}_t^{\mathbb{Q}}\left[e^{-\sum_{s=t}^{\tau-1} r_s}\right], \tag{2.5}$$

and the corresponding annual yield (assuming quarterly periods) is

$$y_{t,\tau} = -\frac{4}{\tau - t}\log(B_{t,\tau}). \tag{2.6}$$

Let $\ln \xi_s^{\mathbb{Q}} = \nu_s^{\mathbb{Q}} - r_s^{\mathbb{Q}}$ denote the distribution of $\nu_s - r_s$ under the risk-neutral measure, $\mathbb{Q}$. In an appendix to their paper, Bikbov and Chernov (2013) suggest a way of calculating expectations of the form appearing in (2.4) whenever $\ln \xi_s$ is Normally distributed conditional on the path of Markov-switching variables. Their method is accurate up to about 40 periods (i.e., ten years). Because r_s satisfies this conditional Normality requirement, one can apply their method to pricing bonds (which they do). One can also apply the same methodology to other assets as long as $\nu_s^{\mathbb{Q}}$ also preserves this conditional Normality assumption. To stay within this computational constraint, we

[19]This is consistent with the findings of the so-called "long-run risk" literature (starting with Bansal and Yaron 2004) where dominant sources of risk premia are shocks to expectations of growth rates rather than level shocks. We make this assumptions to reduce the number of priced shocks in the model.

assume the following structure for real estate asset income. For a given sequence of asset payoffs, identified by the subscript j, we assume that

$$\nu_{j,t} = a_j + \gamma_{j,\pi}\pi_t + \gamma_{j,g}g_t + \rho_j \nu_{j,t-1} + u_{j,t},$$

The shock $u_{j,t}$ is independent of the macro-fundamental shocks (the ε_{t+1}'s), is Normally distributed, serially uncorrelated, and has conditional variance $\sigma^2_{j,u}$.

We further assume that the risk-neutral dynamics of $\nu_{j,t}$ are given by

$$\nu^{\mathbb{Q}}_{j,t} = a_j + \gamma_{j,\pi}\pi^{\mathbb{Q}}_t + \gamma_{j,g}g^{\mathbb{Q}}_t + \rho_j \nu^{\mathbb{Q}}_{j,t-1} - \ell_j + u^{\mathbb{Q}}_{j,t},$$

where $\ell_{j,g}$ is a risk-premium and $u^{\mathbb{Q}}_{j,t}$ is Normally distributed with variance $\sigma^2_{j,u}$. These assumptions guarantee that both $\ln \xi_s$ and $\ln \xi^{\mathbb{Q}}_s$ are Normally distributed conditional on the path of Markov-switching variables.

While the assets in which we're interested (real estate and stocks) have an infinite payoff horizon, we are only able to reliably compute $\mathbb{E}^{\mathbb{Q}}_t\left[e^{\sum_{s=t}^{\tau-1}(\nu_{j,s}-r_s)}\right]$ up to about 40 quarters. To overcome this additional difficulty, we borrow from the approach investors commonly take when calculating present values of long-lived assets. Specifically, note that one can write,

$$Q_{j,t} = \sum_{\tau=t+1}^{K} \mathbb{E}^{\mathbb{Q}}_t\left[e^{\sum_{s=t}^{\tau-1}(\nu_s - r_s)}\right] + \mathbb{E}^{\mathbb{Q}}_t\left[e^{\sum_{s=t}^{K-1}(\nu_s - r_s)} Q_{j,K}\right].$$

One can view $Q_{j,K}$ as a continuation value for $Q_{j,t}$, $K-$periods in the future. We approximate $Q_{j,t}$ by setting $K = 39$ (ten years out) and $Q_{j,K} \equiv Q^*_j$ (a constant) in the second term. The constant, Q^*_j is calculated by solving

$$Q^*_j = \sum_{\tau=t+1}^{K} \mathbb{E}^{\mathbb{Q}}\left[e^{\sum_{s=t}^{\tau-1}(\nu_s - r_s)}\right] + \mathbb{E}^{\mathbb{Q}}\left[e^{\sum_{s=t}^{K-1}(\nu_s - r_s)}\right] Q^*_j,$$

where $\mathbb{E}^{\mathbb{Q}}[]$ corresponds to an unconditional expectation.

2.4.3 Additional model details and estimation procedure

The data set includes proxies for the state variables, $x_t = (g_t, \pi_t, r_t)$, a vector y_t of longer-maturity treasury strips (2-year, 5-year, & 10-year), the observed (rather than expected) asset growth rates $\nu^g_{j,t}$, and asset cap rates $c_{j,t}$ (with $j = A, I$ and O). We assume that the short-term interest rate is observed without measurement error, while the longer-term strip yields, earning growths, and cap rates are observed with standard normal i.i.d. measurement error. We estimate the model via maximum likelihood. For the macroeconomic state variables and regimes, and the treasury securities, the approach loosely adheres to Bikbov and Chernov (2013).[20] The estimation procedure is constrained to parameterizations such that the forward solution exists, and the process conditional on any regime is stable in the mean-square sense under both the physical, and risk-neutral measure. Following Bikbov and Chernov (2013) we restrict $\delta, \phi \geq 0$.

We assume that the correlations between the three real estate income growth rates can be modeled via a loading on a single systematic factor:

$$u_{j,t} = w_{j,t} + \sigma_{j,Z} Z_t, \qquad j \in \{A, I, O\},$$

where Z_t is a standard iid Normal variable that is independent of all other shocks in the model, $w_{j,t}$ is an idiosyncratic component with variance $\sigma^2 j, W$, and real-estate risk premium is $\ell_j = \lambda_Z \sigma_{j,W}$.

Because expected growth rates and earnings yields (the $\nu_{j,t}$'s and $Q_{j,t}$'s, respectively) can only be approximately observed, adding Normally distributed iid measurement error to this expression results in

$$\begin{aligned} \nu^g_{j,t} - \Big(a_j + \gamma_{j,\pi}\pi_t + \gamma_{j,g} g_t + \rho_j \nu_{j,t-1}\Big) &= \sigma^2_{j,\nu}\epsilon^\nu_{j,t} + u_{j,t} \\ -\ln c_{j,t} - \ln Q_{j,t} &= \sigma^2_{j,Q}\epsilon^Q_{j,t}, \end{aligned}$$

where the ϵ's correspond to iid standard Normal measurement errors and j ranges over A, I and

[20] See also, Dai, Singleton, and Yang (2007) and Ang, Bekaert, and Wei (2008).

O. These expressions can be incorporated into the log-likelihood function in the usual way. Note that to estimate the model we do not have to observe or filter $u_{j,t}$ as only its variance enters into the likelihood function as described. Moreover, the variances of the $u_{j,t}$'s (or subcomponents, in the case of the real estate assets) can be identified because they appear in the covariance matrix as well as the price levels through a Jensen's inequality term.

Table 2.3 summarizes the model parameters. Due to the likelihood being highly non-linear, we perform a search for the global maximum, constraining the VAR coefficient matrices (under the physical and risk-neutral measures, respectively) to have eigenvalues smaller than one. We generate a quasi-random Sobol grid of 1,000,000 nodes over a reasonable parameter space. We then evaluate the likelihood of each point. An optimization procedure is then run using the nodes with the highest 1000 likelihood values. The highest resulting likelihood is then the final parameter estimate. Confidence intervals are then computed by simulating 1000 panels of the data using the model parameter and re-estimating the parameters for each of the panels. This results in a distribution of parameter that can be used to calculate a confidence interval.

2.5 Model Estimation Results

We estimate two versions of the model. The first version, similar to the exercise undertaken by Bikbov and Chernov (2013) only includes zero coupon bonds among the asset prices incorporated into the estimation procedure (the TSM model). We then incorporate the three real estate portfolio income and price series to the estimation (the CAP model).

Figure 2.3 depicts the latent regime variables in the TSM and CAP models. The most striking element of the comparison between the two estimates is that the CAP model regimes are much more persistent. The added stability can be attributed to the fact that the regimes now have to explain both bond and real estate prices. One way to explain this is that in estimating the TSM model the likelihood function introduces "spurious" regimes to better fit to bond prices. In the CAP model, howver, these spurious regimes would signal dramatic shifts in real estate prices that are not observed in practice. Thus, one may conclude that, beyond being influenced by monetary policy regimes, real estate prices can be instrumental in identifying them.

Figures 2.4 and 2.5 provide a visual sense of the CAP model fit. Specifically, the macro state variables (g_t, π_t and r) are tracked well by their one-step ahead forecasts. The fit to bond prices is adequate (measurement errors of 40), but not as good as under the TSM model (not depicted in the figure). This is consistent with other studies (e.g., Chiang et al. 2015) in which the fit to prices erodes with the addition of more assets in the estimation. This happens because, despite the addition of more model parameters, the same basic fundamentals are required to explain a greater range of dynamics.

The real estate income growth series on the right side of 2.5 (i.e., the ν^g's) are closely tracked by their forecasts conditional on π_t, g_t and lagged ν_t^g (i.e., the ν's). The fit to real estate cap rates (left) is generally good, ignoring 2006q1-2008q4. The plots depict several periods during which the data persistently departs from the model. This can be because some persistent factor is missing from the model. For instance, it might be that during the recent prolonged episode of quantitative easing (2015-2017), interest rate dynamics were unlike anything seen before and beyond the ability of our model to capture.[21] Alternatively, prolonged departures between the model and prices might arise whenever prices exhibit a more tenuous connection with fundamentals. Indeed, the most pronounced example of this is furnished by the period between 2005-2010 when prices across all asset categories were above their model values. While it is difficult to attribute a direct cause for a difference between actual prices and prices generated by fundamentals through a model, examining such differences can contribute to a discussion (e.g., among policy makers) that contemplates the various influences at play.

Tables 2.4-2.7 report on the estimated model parameters for the TSM and CAP models. Estimates of macro fundamental parameters are roughly in agreement across the two models. Interestingly, the monetary policy coefficients, $\hat{\alpha}$ and $\hat{\beta}$, are more distinct across regimes in the CAP model estimation. Generally, based on the bootstrapped confidence intervals, we find positive and significant sensitivity to the output gap and inflation across the cash flow time series of the real estate assets. An OLS analysis of real estate cash flow dependence on macro fundamentals yields

[21]There is no "zero lower bound" in our model, where the short-term interest rate, conditional on the regime path, has a Gaussian distribution.

similar results for the output gap, but insignificant loadings on inflation. This highlights the disadvantage of analyzing cash flow growth fundamentals without also including price information. It is important to add that real estate income is generally positively associated with inflation using univariate measures of association but, because inflation and the output gap are positively correlated, in a multivariate OLS analysis the loading on inflation declines and may even be negative.

Risk premium specific to real estate cash flow (i.e., net of the premium assessed via exposure to inflation and the output gap) corresponds to $\sigma_{i,Z}\lambda_Z$. Across the three assets, the quarterly systematic volatility, $\sigma_{i,Z}$, is close to 30 basis points. The real estate risk premiu, $\lambda_Z = 0.42$, amounts to a quarterly risk premium of about 15 basis points, or roughly 0.6% per annum. It is possible that some portion of this risk premium is associated with the liquidity risk associated with investing in physical real estate.

Finally, we conduct several tests to assess the extent to which it is important to jointly estimate the macro and (real estate) asset pricing components of the model. First, we ask whether the data can distinguish between CAP model estimates of the macro fundamental parameters and their TSM counterparts. To that end, we compare the maximum likelihood of the TSM model with the TSM-model likelihood calculated when the TSM parameters equal the CAP model estimates. The resulting likelihood ratio test (Chi-Squared, with 34 degrees of freedom) rejects the null hypothesis that the models estimates are the same with $p < 10^{-10}$. In other words, including real estate prices in a joint estimation profoundly changes the inference of the macroeconomic parameters. Next, we constrain the macro fundamental parameters in the CAP model to their values under the TSM model. We then estimate only the real estate asset fundamental parameters (listed in Table 2.3) and compare the likelihood of the constrained and unconstrained CAP model estimates. This likelihood ratio test (Chi-Squared, with 34 degrees of freedom) also rejects the null hypothesis that the models estimates are the same with $p < 10^{-10}$. In other words, real estate prices contain information about macro fundamentals. This is consistent with the observation made earlier about the smoothed empirically observed monetary policy regime in Figure 2.3. Indeed, while one cannot reject the hypothesis that the dynamic discretionary (i.e., rigid/flxible — the two red-dashed lines in the figure) regime variables inferred by the two models are equivalent, it is possible to reject

($p < 0.005$) that this is so for the monetary policy regime (i.e., active/passive — the two blue solid lines in the figure).

2.6 Real Estate Sensitivity to Macroeconomic Regimes

2.6.1 Price dynamics and regime "impulse response"

The model estimates can be used to study the impact of monetary policy regimes and their changes on asset prices. Figures 2.6-2.8 depict the model behavior of expected cap rates based on the estimated model parameters. Each period represents one quarter. In Quarter 0, the cap rate is initialized to the expected value of macro-fundamentals conditional one of four regime combinations (Active/Flexible, Active/Rigid, Passive/Flexible and Passive/Rigid). For each such combination, the blue circles correspond to a baseline evolution. The red pluses and yellow stars correspond to experiments in which at quarter 1 there is a single regime change. For instance, if in Quarter 0 the regimes correspond to an Active/Flexible combination of states (top right panel in the figure), then the plot with red pluses denotes the evolution of cap rates if in Quarter 1 there is a change to a Passive/Flexible combination of states. This type of experiment is akin to an impulse response function for cap rates.[22]

To obtain the plots, we first calculate the expected value of the macro state variables in each of the eight combinations of regimes: $\{$Passive, Active$\} \times \{$ Flexible, Rigid$\}$. This is used to initialize economy at Quarter 0. From this initial point, we simulate 40 quarters of data from the model data generating process (under the physical measure) and plot the average cap rate. The impulse response functions are generated by forcing the regime to change in Quarter 1.

The lowest cap rates across all asset types is associated with a Passive/Rigid regime where monetary policy does not target inflation nor aim to curtail growth by increasing interest rates, and the policy implementation is disciplined (exhibiting low rate volatility). According to Figure 2.3, this regime combination has been in place since roughly 2012. The regime combinations, Passive/Flexible and Active/Rigid, are largely "stable" in that cap rate forecasts are similar to current cap rates. The regime combination, Active/Flexible, corresponds to a loose inflation-fighting

[22]While there are possible regime changes, changing more than one of the s_t^i's at a time is a very low probability event given the persistence of the independent regimes.

regime in which Fed rate decisions are less predictable and overall rates are above average. Sudden regime changes can lead to cap rate changes of 100-150 basis points, corresponding to valuation changes of 15%-20%. Such sharp regime changes would be a rare occurrence as in practice (and in the model) regime changes are probabilistic.[23] Still, such jumps denote the impact on prices that a clear and persistent policy chance is credibly communicated to markets. What this exercise demonstrates is that monetary policy can have a large impact on real CRE prices.

2.6.2 Risk premia

The risk premia reported in Tables 2.5 and 2.7 directly apply to real estate income growth (e.g., the risk of a $1 "bond" that delivers the income from a real estate investment held for one year). Real estate assets can be viewed as a perpetuity of stochastic income and, just as long-maturity bonds coupon may be riskier than short maturity bonds, real estate assets may be riskier than might indicated by their time-series of income .

One way to measure the risk premium associated with a real estate asset is to compare the cap rate using the physical measure ($\mathbb{P}$-measure) with its actual value as calculated using the $\mathbb{Q}$-measure. Table **??** reports on this cap rate spread in the different regimes. The table documents the results of simulating the macroeconomic state vector, x_t, conditional only on being in a fixed regime. For each simulated value of x_t we calculate the corresponding cap rates under the $\mathbb{Q}$ and $\mathbb{P}$ measures and calculate their differences. The mean and 95% "confidence interval" of the resulting distribution of cap rate spreads is reported in Table **??**. The real estate risk premia are lowest (highest) in the Passive-Rigid (Active-Flexible) regime, consistent with the observation that this is also the highest (lowest) price regime. Within regime, the risk premium may exhibit substantial variation, with the greatest degree of variation present in the Active-Flexible regime.

Figure 2.9 plots the model implied time-series of cap rate spreads (i.e., risk-premia). Each quarter, x_t and its corresponding cap rate spread is calculated in each regime, and then the filtered probabilities at date t are used to weight the plotted risk premia. The plot depicts a secular decline

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[23]The regimes in Figure 2.3 are smoothed, meaning that they represent what the policy would most likely have been at any date in the sample given what we know about the entire sample. The prices calculated to fit the model and in the estimation correspond to the filtered probability which represents investors' best guess as to the current regime (which is unobservable to both investors and the econometrician).

in the real estate risk premium across all asset types. The most pronounced changes appear to have taken place after 2000. The dramatic results of quantitative easing, which in the model corresponds to the onset of a Passive-Rigid regime, are observed in the post-2011 period.

2.6.3 Macroeconomic regimes and mortgage spreads

As mentioned in the Introduction, CRE mortgages represent a large proportion of regional and local banks' loan portfolios. Given that the underlying collateral has substantial exposure to monetary policy shocks, it seems natural to ask how the loan portfolios themselves might behave. We examine separately loans secured by real estate portfolios corresponding to each of the three CRE asset types studied earlier, and assume that each such portfolio has the same characteristics as our aggregate time series. For instance, the apartment portfolio collateral has time series price governed by the model dynamics in Section 2.5.

Consider a ten-year interest-only (IO) non-prepayable mortgage on a property that pays according to the following rules: (i) An interest coupon of $r_m/4$ is paid each quarter on the original principal borrowed as long as it is less than NOI produced by the property that quarter. (ii) If the NOI cannot cover the interest payment, all income is paid that quarter to the lender and the principal owed is increased by the difference between $r_m/4$ and NOI (i.e., negative ammortization). (iii) In Year 10, the lender is paid the lesser of the principal owed plus the last coupon payment, or property value plus last NOI.

We solve for $r_m/4$ by simulating and averaging payoff paths under the $\mathbb{Q}$-measure and discounting by the compounded risk-free short-term rate. The solution is obtained by setting the average equal to the loan amount (a fraction of the asset value as determined by the initial loan-to-value). We compare r_m to the value of a 10-year treasury par bond to calculate the corresponding "default" spread.

For each regime combination, we initialize the economy at contract inception to the mean state variables conditional on the regime combination. The resulting mortgage spreads are plotted in Figure 2.10. With mortgage pricing, there is a tension between the size of the risk premium (high in the "A/F" compound regime and low in the "P/R" compound regime) versus forecasted asset value (increasing in the "A/F" compound regime and decreasing in the "P/R" compound regime).

In the case of the "A/F" (currently low prices and high risk-premium) regime, the anticipation of increasing prices and therefore lower default risk is the more dominant effect, and the mortgage spread is low. In the "P/R" regime (or low-price and high risk-premium) compound regime, the lower risk premia is balanced against the anticipation of increasing prices and this leads to higher mortgage spreads.

At high LTVs, the difference in spreads across extreme policy scenarios is over 100 basis points. Consistent with documented evidence for CRE mortgages (see, for example, Downing, Stanton, and Wallace 2008), apartment properties exhibit the smallest mortgage spread. It is important to emphasize that assessment arises strictly from calculating the present value using cash flow fundamentals for apartment properties. In addition, it is also important to keep in mind the dominant role played by the Government Sponsored Enterprises (GSEs) in underwriting apartment property mortgages. This may additionally lower apartment mortgage spreads relative to "fundamentals" (i.e., what they would be without an effective government "subsidy"). Thus, another role for the model could be in modeling the impact of privatizing the GSEs on commercial real estate mortgages.

The magnitudes of the spreads we calculate are roughly commensurate with the pricing of investment-grade CMBS fixed-rate bonds, which are essentially loans that only default if a large and well-diversified portfolio of CRE substantially declines in value. For instance, AAA CMBS bonds subordinated by roughly 30% of more junior tranches typically traded at a spread of close to 100 bps to treasuries in 2013. By contrast, BBB bonds around the same time might have only enjoyed subordination levels between 5% and 10% and traded around 250 bps above treasuries. To provide a better sense of how CRE mortgage spreads might vary with the macroeconomic environment we depict them as a time series in Figure 2.11 at 65% and 80% LTV. Similar to Figure 2.9, the plotted mortgage spread at date t weights the various regime spreads using the filtered probabilities at date t. Here we see that, holding constant historical subordination levels, CMBS bonds issued since 2011 are likely "riskier".

To obtain a sense for how a regime change can impact existing mortgages, first calculate the mortgage price in a given regime (at the average of the state variables) for a fixed LTV. Then, as with the "impulse response" experiment discussed earlier, we force the economy into another regime the following quarter. The plots in Figure 2.12 depict the corresponding price impact as a function of LTV. Here too, there are two forces. A change in regime impacts both the collateral value as well as income growth rates.

A shift into the "A/F" regime from any other regime tends to result in substantive losses (as much as 30% if the origination regime is "P/R"). Correspondingly, existing loans can dramatically increase in value, especially when entering a "F/R" regime. Interpreting the recent episode of quantitative easing as a "F/R" regime suggests that monetary policy succeeded in shoring up bank balance sheets by increasing the value of banks' loans. On the flip side, it is easy to see how a protracted "F/R" regime might lead to fragility in the banking sector. As old CRE debt is retired or refinanced it is replaced with debt that is more susceptible to being marked down in value (as seen by the higher default spreads in Figure 2.10). The top-right panel in Figure 2.12 demonstrates that a regime change will result in a double digit loss in banks' CRE loan portfolio.

2.7 Conclusions

There is a great deal of evidence that the structural relationship between macro-fundamentals changes through time. Intuitively, this can have a profound impact on commercial real estate assets, whose cash flow positively depend on both inflation and real output. By estimating a model of regime changes in macro-fundamentals, together with how they are related to discount rates and asset cash flow, we are able to quantify the impact of macreconomic regime changes (like monetary policy) on real estate asset prices. Our model may be used to both forecast real estate cap rates as well as conduct experiments to assess the future impact of a monetary policy change on property and mortgage portfolios.

We are able to identify four regimes distinguished by high/low interest rate volatility and high/low sensitivity to both inflation and the real output gap. A high volatility regime in which interest rates are sensitive to inflation and output is characterized by high cost of capital (and risk premia), and low asset prices. A low volatility regime in which interest rates are insensitive to inflation and output features low cost of capital (and risk premia), and high asset prices. According to our estimate, the U.S. economy has been in the latter state since roughly 2011. A sudden change in policy can result in a substantial decline in prices of commercial real estate (and associate existing mortgages).

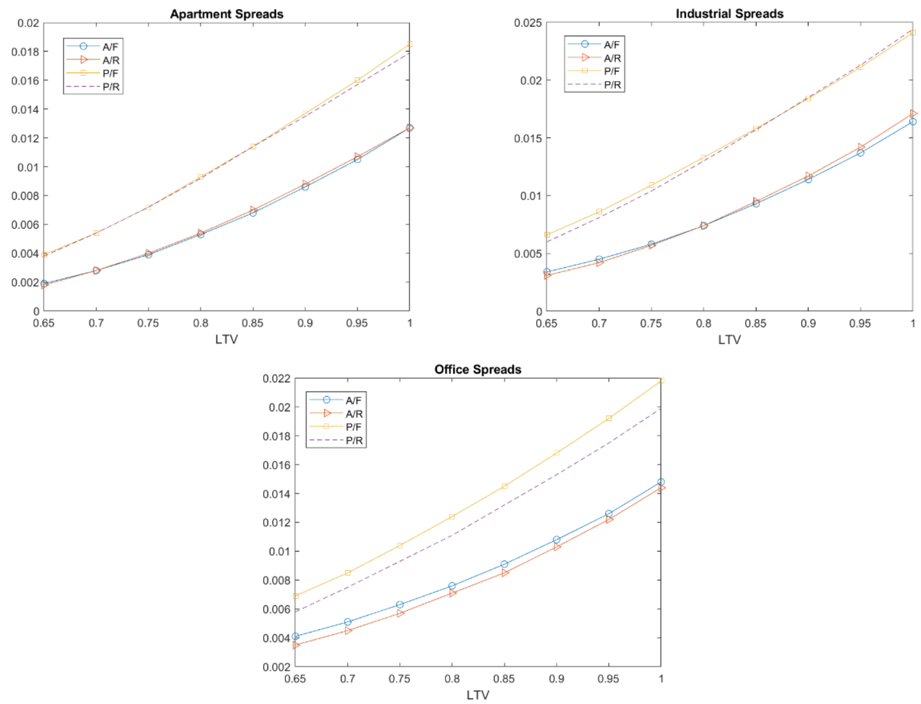

Figure 2.1: NCREIF Apartment (a) cap rates and (b) NOI growth rates.

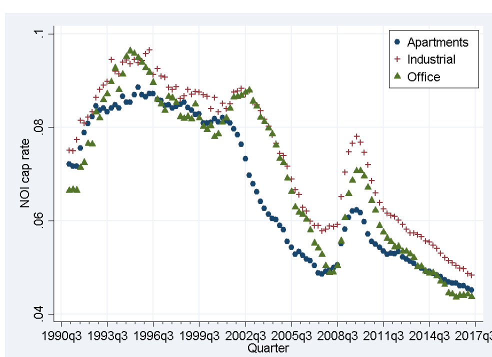

Figure 2.2: NCREIF cap rates for the real estate investment categories studied.

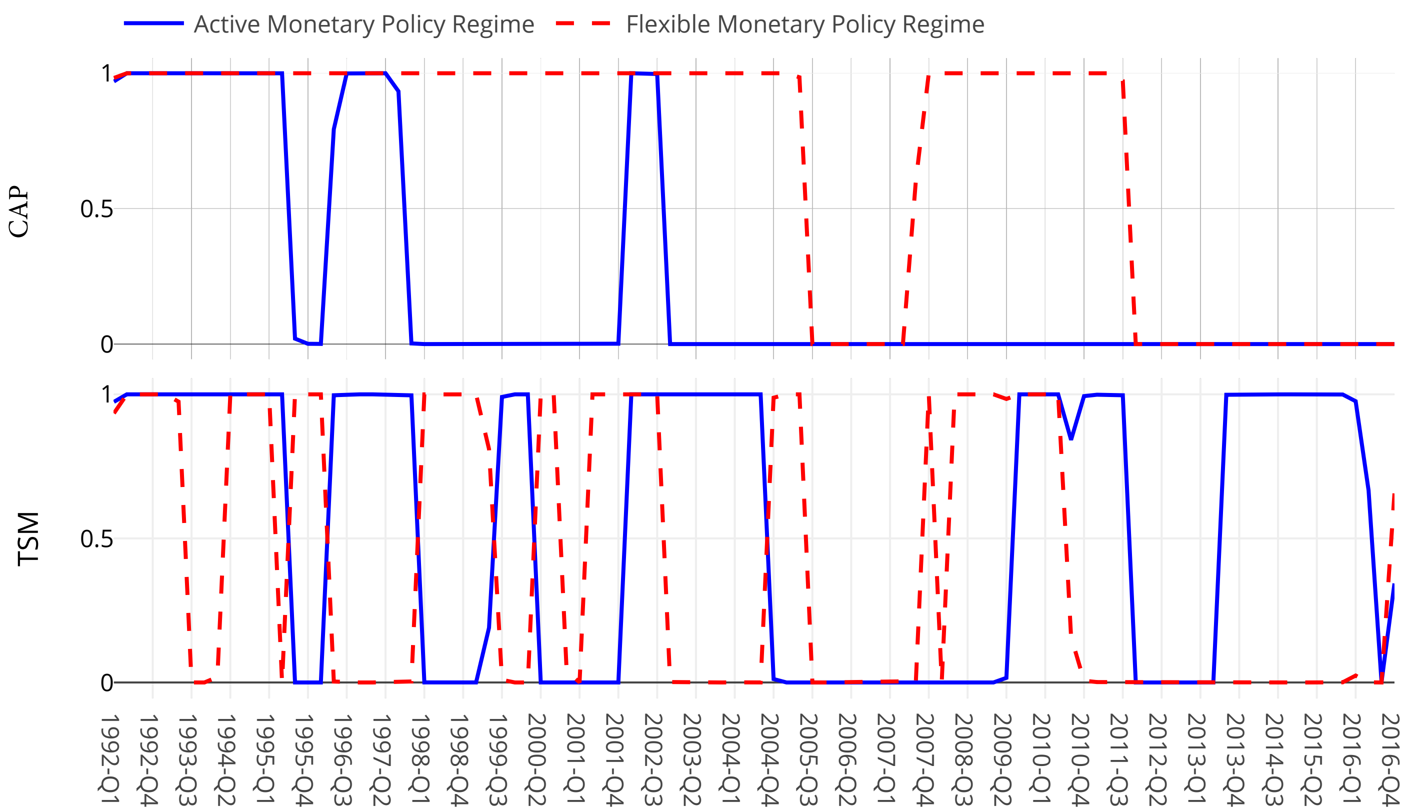

Figure 2.3: Smoothed regime probabilities for the estimated TSM and full model.

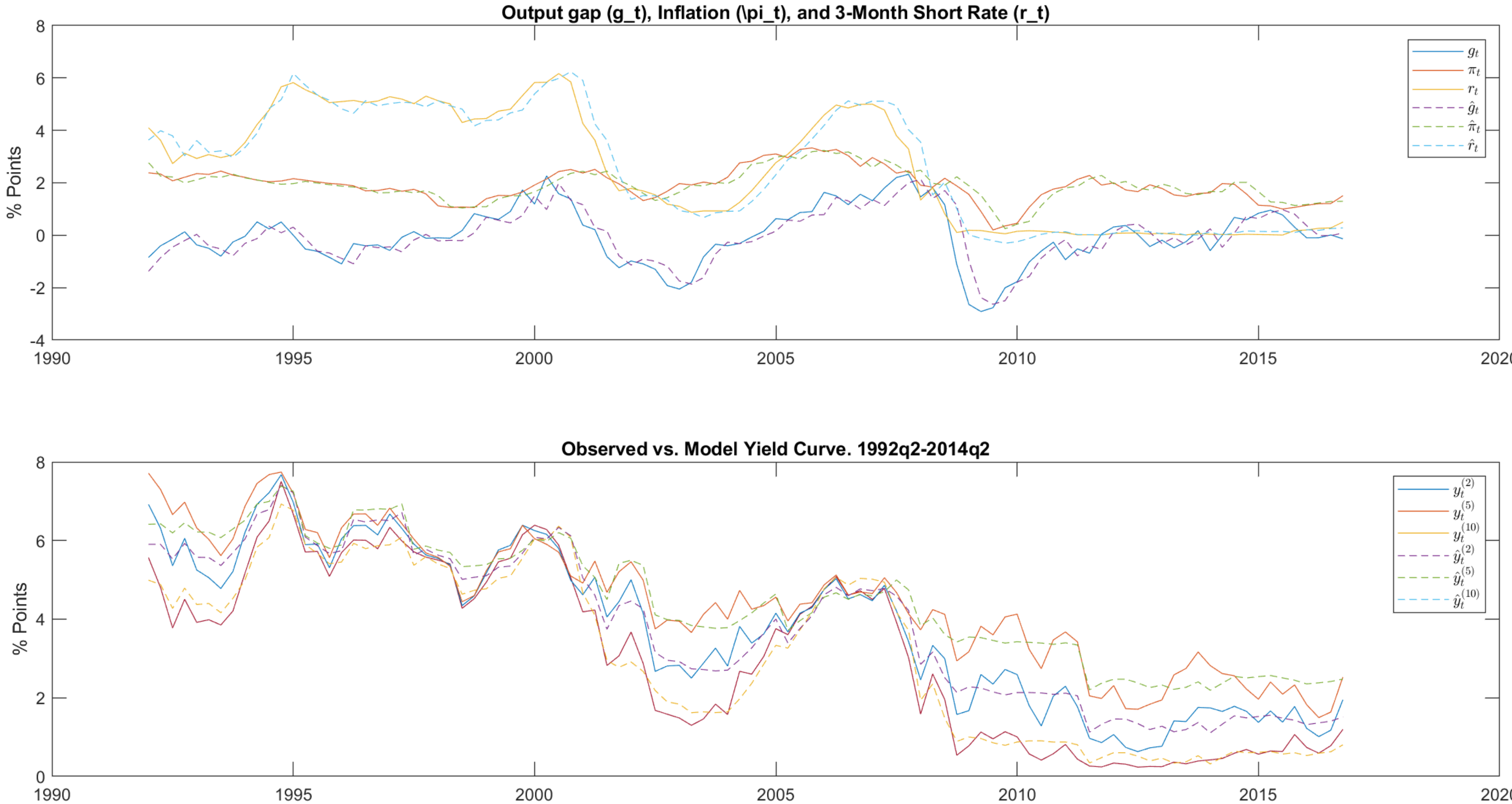

Figure 2.4: Depiction of the model fit to the data. We exclude real state cap rate data from 2006q1-2008q4 in the estimation. The top panel plots the macro state variables (output gap, g_t; inflation, π_t; short rate, r_t) alongside the one-step-ahead model forecasts (variables with "carets"). The bottom panel plots the various treasury strip prices (2-, 5-, and 10-year strip yields) against the fitted model values.

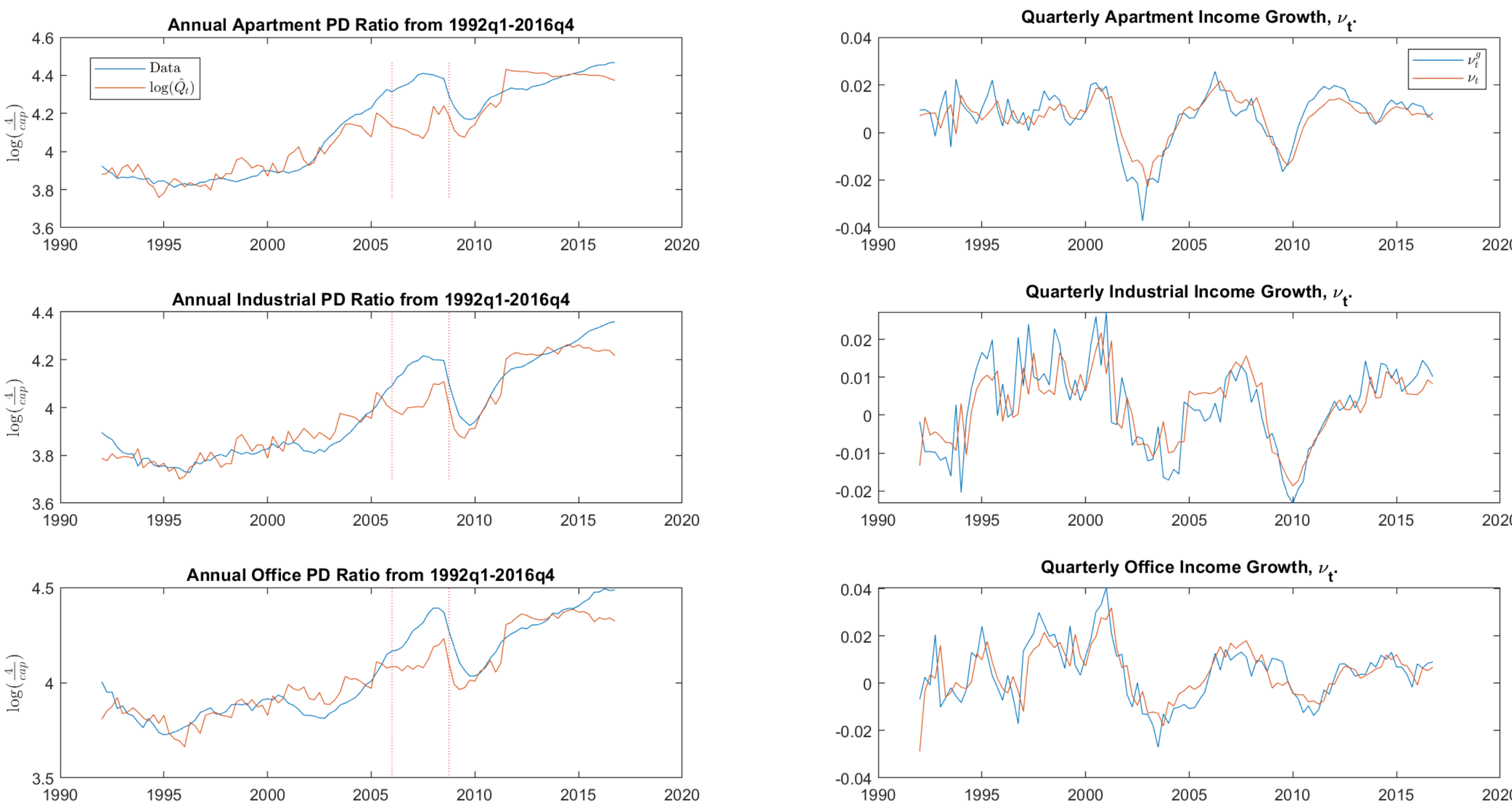

Figure 2.5: Depiction of the model fit to the data. We exclude real state cap rate data from 2006q1-2008q4 in the estimation. The panels on the left plot the model fit to the log of annualized price-to-NOI or "PD" ratio for each of the three RE investment categories. The panels on the right plot NOI growth against expected NOI growth conditional on inflation, the output gap, and lagged NOI growth.

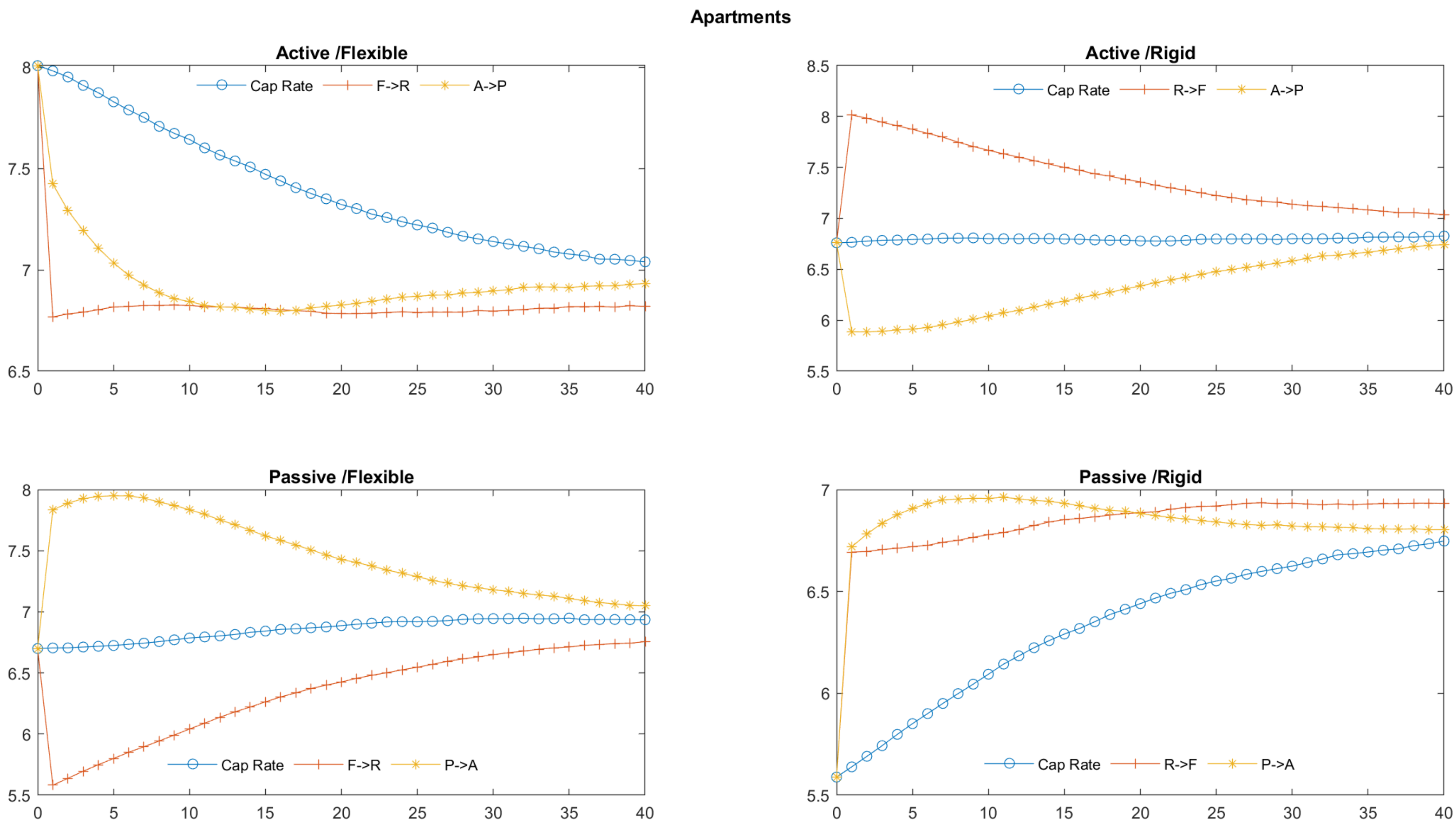

Figure 2.6: Estimated model dynamics of apartment cap rates (earnings-to-price ratios). Each period represents one quarter. Quarter 0 is initialized to the expected value of macro-fundamentals conditional on the regime (the regime is labeled above each plot). The blue circles correspond to the baseline estimate. The red pluses and yellow stars correspond to experiments in which at quarter 1 there is a single regime change (Active $\leftrightarrow$ Passive, or Rigid $\leftrightarrow$ Flexible).

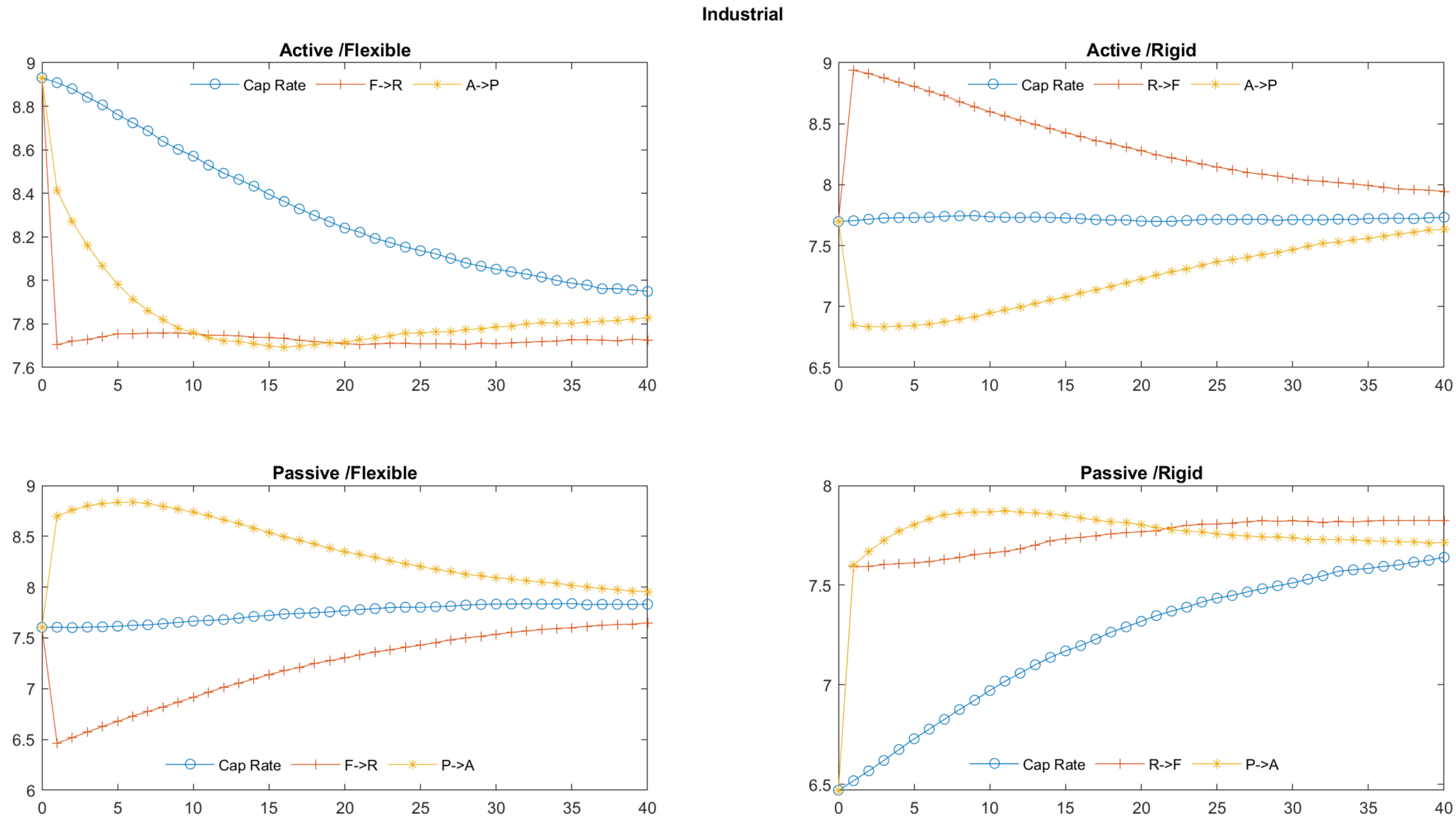

Figure 2.7: Estimated model dynamics of industrial cap rates (earnings-to-price ratios). Each period represents one quarter. Quarter 0 is initialized to the expected value of macro-fundamentals conditional on the regime (the regime is labeled above each plot). The blue circles correspond to the baseline estimate. The red pluses and yellow stars correspond to experiments in which at quarter 1 there is a single regime change (Active $\leftrightarrow$ Passive, or Rigid $\leftrightarrow$ Flexible).

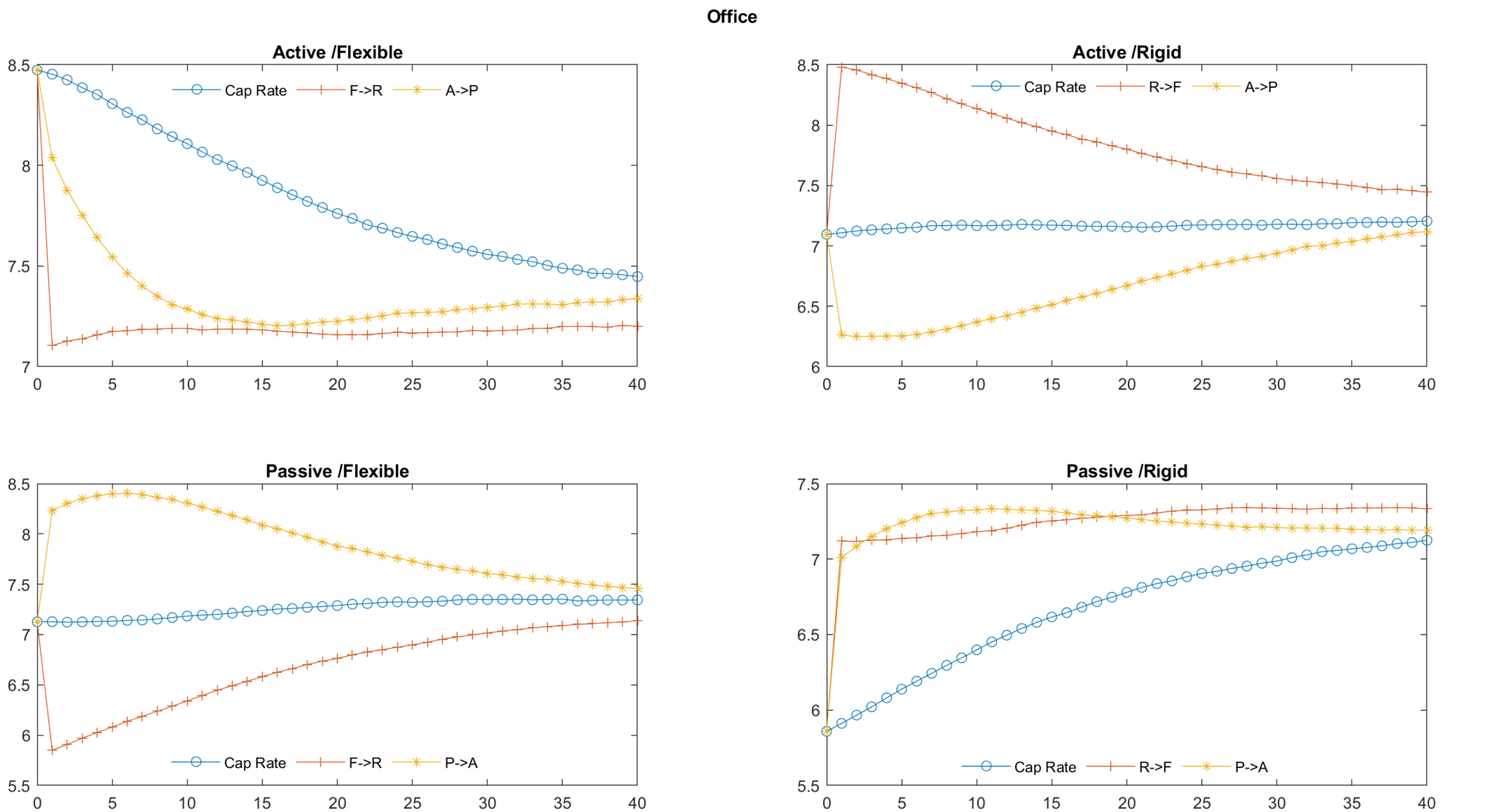

Figure 2.8: Estimated model dynamics of office cap rates (earnings-to-price ratios). Each period represents one quarter. Quarter 0 is initialized to the expected value of macro-fundamentals conditional on the regime (the regime is labeled above each plot). The blue circles correspond to the baseline estimate. The red pluses and yellow stars correspond to experiments in which at quarter 1 there is a single regime change (Active ↔ Passive, or Rigid ↔ Flexible).

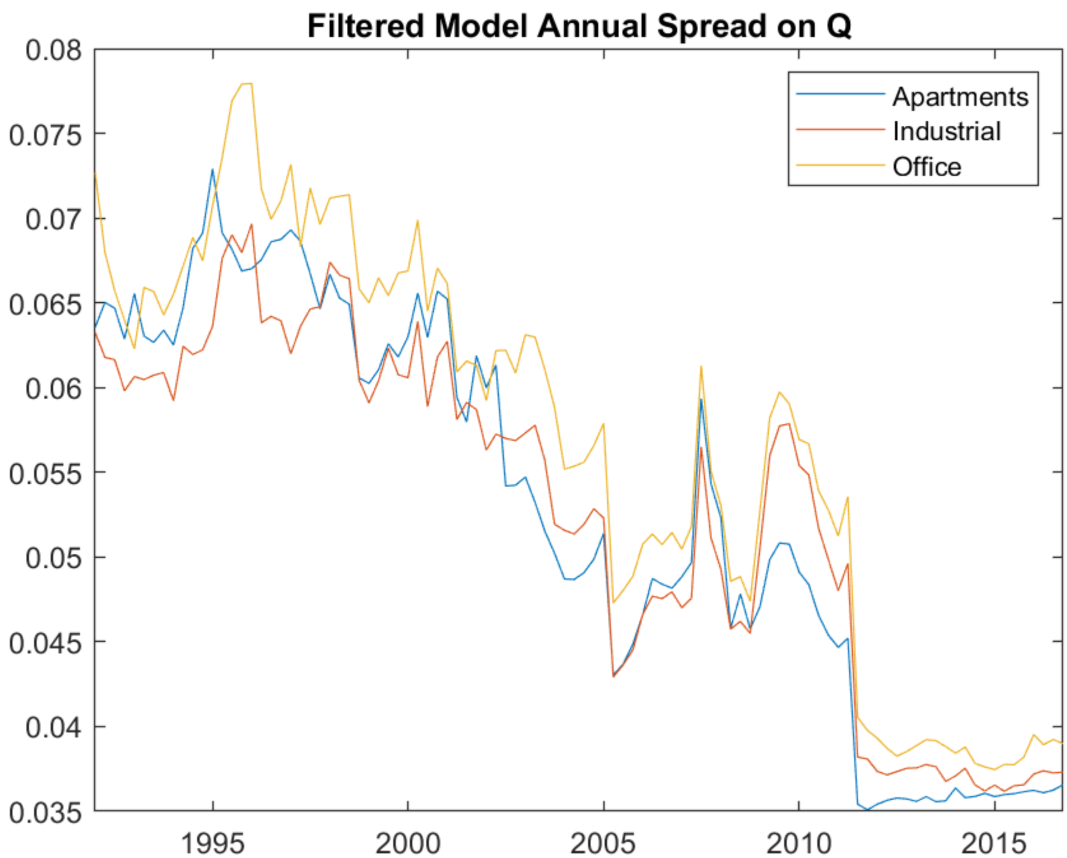

Figure 2.9: Model implied time-series of real estate risk-premia calculated by subtracting model cap rates under the $\mathbb{P}$-measure from cap rates calculated under the $\mathbb{Q}$-measure.

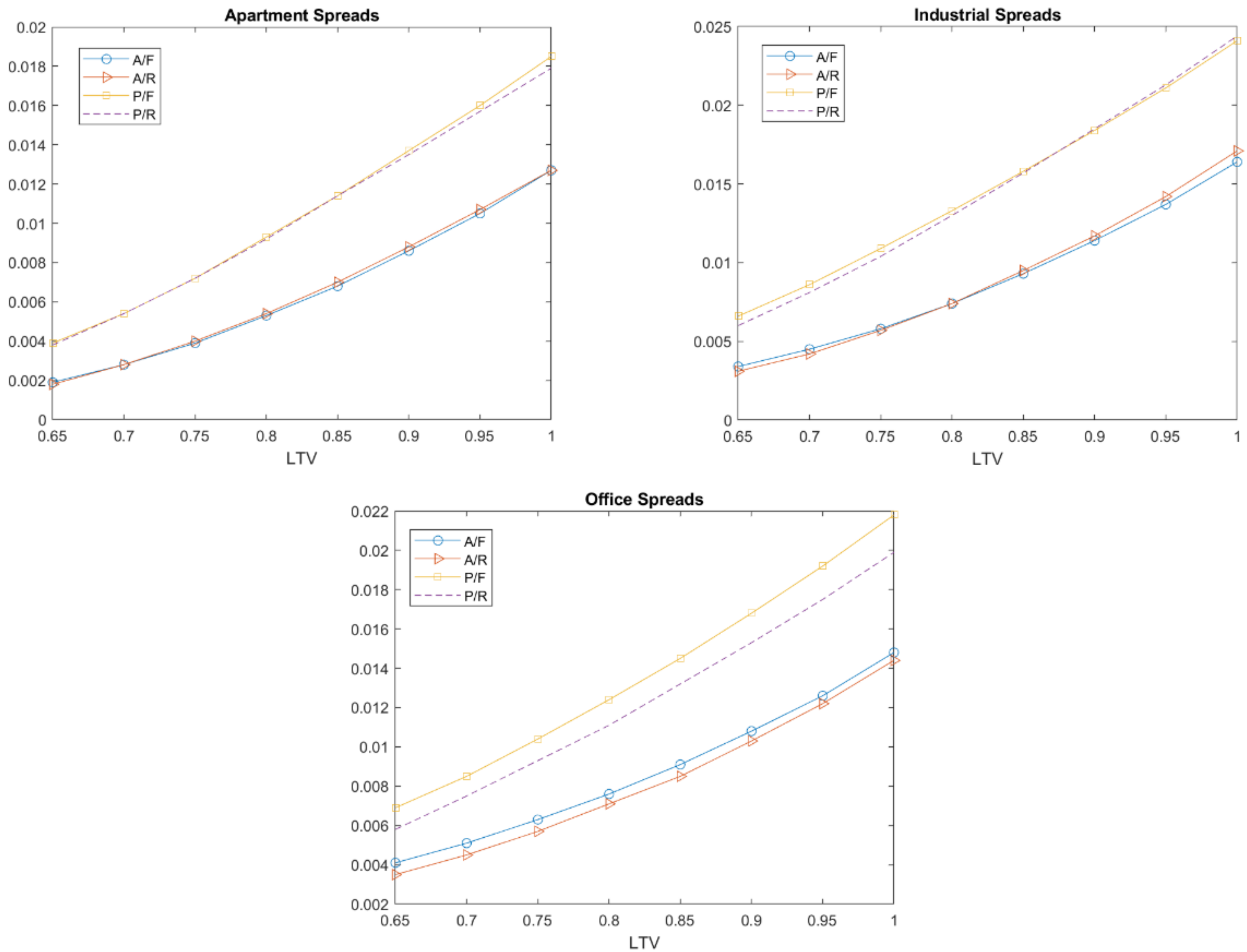

Figure 2.10: Model-imputed default spreads on interest-only mortgages secured to a diversified portfolio of real estate assets. The x-axis denotes loan-to-value (LTV) and the y-axis measures spreads over 10-year treasury strips. Each line corresponds to one of four combinations of the two regimes state variables in the model. To calculate the mortgage values, the prevailing macro-fundamentals are assumed to be at their expected value conditional on the regime.

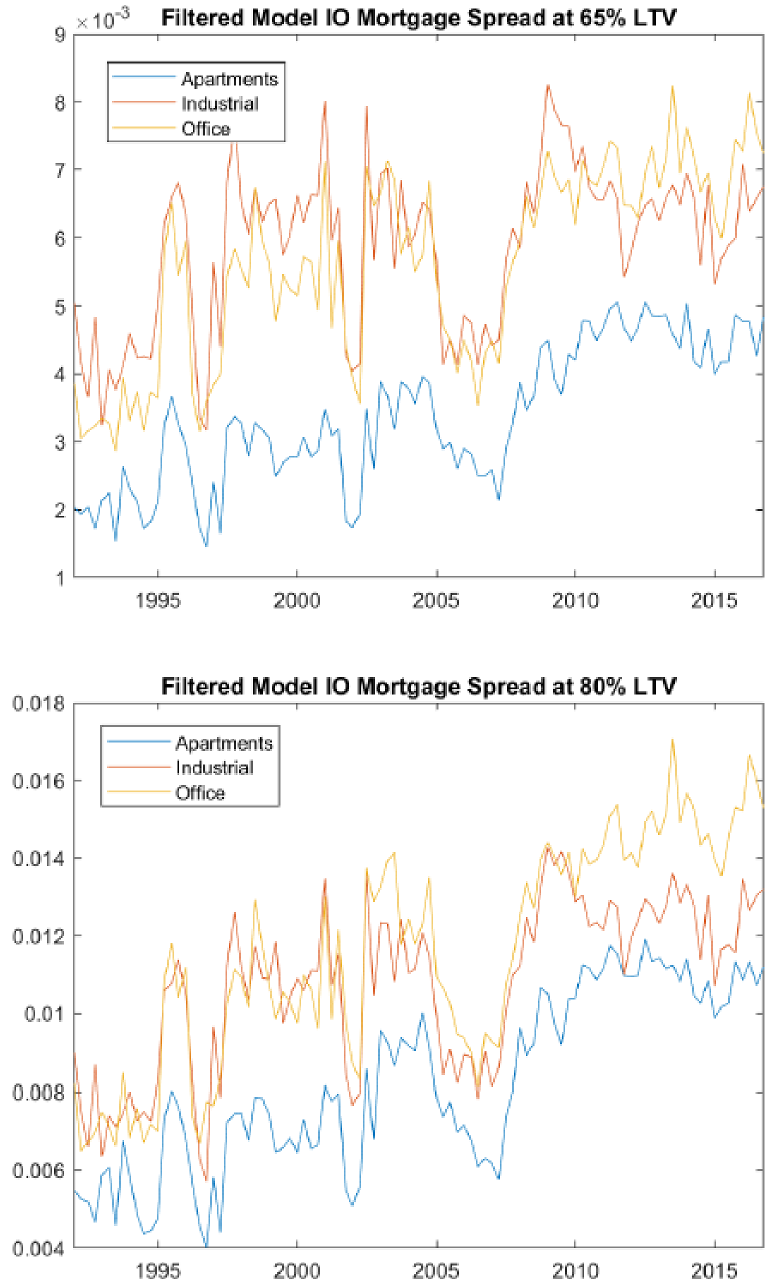

Figure 2.11: Time series of model-imputed default spreads on newly issued interest-only mortgages secured to a diversified portfolio of real estate assets. The y-axis measures spreads over 10-year treasury strips. The top (bottom) figure corresponds to a mortgage with 65% (80%) loan-to-value (LTV) at origination.

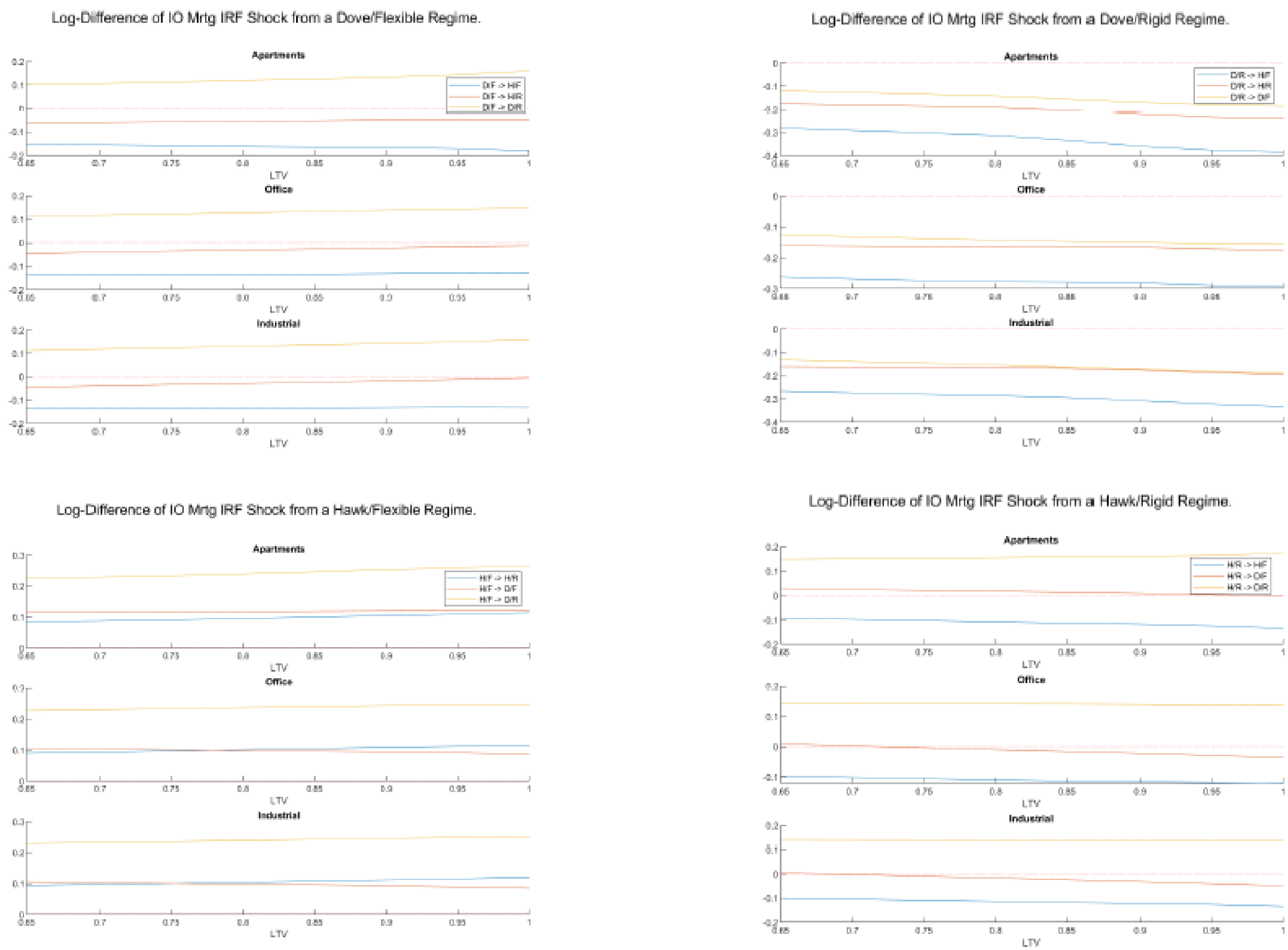

Figure 2.12: Estimated model impact of a regime-change on an interest-only mortgages secured to a diversified portfolio of real estate assets. The x-axis denotes loan-to-value (LTV) and the y-axis measures the change in value of a newly issued mortgage if the interest rate regime is changed. Mortgages values are first calculated based on the expected value of macro-fundamentals conditional on a regime, and the regime is subsequently "forced" to change and the mortgage value is recalculated.

Table 2.1: Summary statistics for the panel variables before and after the 1999q3 monetary policy regime break identified in Bianchi (2013). Asterisks correspond to cases in which the post-1999q3 mean or standard deviation of a variable is significantly different from the corresponding statistic pre-1999q3. The μ_i's denote income growth rates while the c_i's denote cap rates (i.e., earnings yields). The subscripts A, I, and O respectively denote"apartments", "industrial", and "office". The short rate, ten-year strip rate, inflation, and output gap are denoted as r, r_{10}, π, and g.

	pre-1999q3				post-1999q3			
	Mean	SD	min	max	Mean	SD	min	max
μ_A	0.023	0.029	-0.049	0.081	0.011*	0.023	-0.046	0.061
μ_I	0.009	0.033	-0.055	0.06	0.005	0.024	-0.05	0.081
μ_O	-0.003	0.07	-0.158	0.174	0.001	0.035**	-0.097	0.072
c_A	0.084	0.003	0.075	0.088	0.057***	0.012***	0.044	0.081
c_I	0.09	0.004	0.081	0.096	0.068***	0.013***	0.049	0.088
c_O	0.085	0.005	0.072	0.094	0.063***	0.014***	0.043	0.087
r	0.045	0.009	0.027	0.058	0.02***	0.02***	0	0.062
r_{10}	0.063	0.009	0.044	0.077	0.04***	0.012	0.017	0.064
π	0.019	0.004	0.011	0.024	0.02	0.007**	0.002	0.033
g	-0.001	0.005	-0.013	0.008	0.001	0.013***	-0.03	0.023

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2: Correlations of the panel variables before and after the 1999q3 monetary policy regime break identified in Bianchi (2013). The second panel identifies correlation coefficients that are significantly different from those in the first. The μ_i's denote income growth rates while the c_i's denote cap rates (i.e., earnings yields). The subscripts A, I, and O respectively denote"apartments", "industrial", and "office". The short rate, ten-year strip rate, and inflation are denoted as r, r_{10} and π.

pre-1999q3

	μ_I	μ_O	c_A	c_I	c_O	r	r_{10}	π	g
μ_A	0.144	-0.195	0.401	0.508	0.595	0.231	0.103	0.197	-0.052
μ_I		0.02	0.133	0.35	0.235	0.481	-0.134	-0.319	-0.24
μ_O			-0.334	-0.322	-0.324	-0.184	0.059	0.073	0.281
c_A				0.886	0.899	0.444	-0.034	-0.017	-0.657
c_I					0.912	0.604	-0.006	-0.044	-0.696
c_O						0.496	0.067	0.118	-0.608
r							0.02	-0.442	-0.396
r_{10}								0.669	0.089
π									-0.098

post-1999q3

	μ_I	μ_O	c_A	c_I	c_O	r	r_{10}	π	g
μ_A	0.499	0.458**	-0.211**	-0.286***	-0.306***	0.214	0.009	0.229	0.428*
μ_I		0.375	-0.052	-0.217**	-0.222*	0.388	0.219	0.363**	0.462**
μ_O			-0.064	-0.194	-0.216	0.214	0.145	0.155	0.263
c_A				0.931	0.907	0.404	0.617**	-0.127	-0.164**
c_I					0.986***	0.285	0.603**	-0.137	-0.358*
c_O						0.259	0.57*	-0.057	-0.362
r							0.801***	0.576***	0.643***
r_{10}								0.299*	0.294
π									0.606***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Model parameters. The macro fundamentals are modeled as in Bikbov and Chernov (2013). There are two monetary policy regime variables: s_t^m corresponding to a passive versus active policy, and s_t^d corresponding to whether the monetary authorities are "Flexible" or "Rigid" about adhering to their smoothed policy targets. We consider three real estate asset categories: Apartments (A), Industrial (I), and Office (O). Asset cash flow expected growth rates are modeled as $\nu_{j,t} = a_j + \gamma_{j,\pi}\pi_t + \gamma_{j,g}g_t + \rho_j\nu_{j,t-1} + u_{j,t}$.

Parameter symbol	# parameters	Notes
macro fundamentals	34	
m_g	1	drift of g
μ_i	2	smoothing $(i = g, \pi)$
ϕ	1	output gap response to real cost of capital
σ_i	2	shock volatility $(i = g, \pi)$
δ	1	inflation reaction to output gap
Prob$(s^m\|s^m)$	2	prob. of staying in regime (s^m=Passive or Active)
Prob$(s^d\|s^d)$	2	prob. of staying regime (s^d=Flexible or Rigid)
$m_r(s^m)$	2	regime-dependent rate drift
$\rho(s^m)$	2	regime-dependent rate smoothing
$\hat{\alpha}(s^m)$	2	regime-dependent rate response to inflation
$\hat{\beta}(s^m)$	2	regime-dependent rate response to output gap
$\sigma_r(s^d)$	2	regime-dependent rate deviation from smoothed target
σ_y	1	pricing (measurement) error in bond yields
$\Pi_{0,i}$	3	static risk premia $(i \in \{g, \pi, r\}$
$\Pi_{x,ii'}$	9	drift risk-adjustment $(ii' \in \{g, \pi, r\})$

asset fundamentals	25	
a_j	3	asset income drift $(j = A, I, O)$
$\gamma_{j,\pi}$	3	asset income inflation sensitivity $(j = A, I, O)$
$\gamma_{j,g}$	3	asset income output gap sensitivity $(j = A, I, O)$
ρ_g	3	asset income autocorrelation $(j = A, I, O)$
$\sigma_{j,W}$	3	real estate income idiosyncratic volatility $(j = A, I, O)$
$\sigma_{j,Z}$	3	real estate common income shock exposure $(j = A, I, O)$
$\sigma_{j,Q}$	3	pricing (measurement) error in asset $(j = A, I, O)$
$\sigma_{j,\nu}$	3	measurement err. in expected NOI growth $(j = A, I, O)$
λ_Z	1	real estate risk Sharpe ratio (net of macro fundamentals)

Table 2.4: Parameter estimates: Macro dynamics. Bootstrapped 95 percent Confidence interval in are parentheses. The TSM model estimates only include zero coupon bond price. The CAP model estimates incorporate information from real estate income and prices. An active (passive) MP regime is denoted by "A" ("P"). A flexible (rigid) MP regime is denoted by "F" ("R").

Macro Fundamentals

	$m_g \times 10^3$	μ_g	μ_π	$\phi \times 10^2$	$\delta \times 10^2$
CAP	0.32	0.54	0.53	0.05	0.61
	(-4.95,4.35)	(0.53,0.60)	(0.51,0.57)	(0.04,0.22)	(0.26,3.48)
TSM	0.39	0.53	0.49	0.02	0.45
	(-87.34,36.27)	(0.53,0.61)	(0.47,0.50)	(0.02,1.63)	(0.22,1.29)

Monetary Policy

	$m_r(A)$	$m_r(P)$	$\rho(A)$	$\rho(P)$	$\hat{\alpha}(A)$	$\hat{\alpha}(P)$	$\hat{\beta}(A)$	$\hat{\beta}(P)$
CAP	-0.42	-0.13	0.98	0.96	0.43	0.10	0.66	0.08
	(-1.18,-0.20)	(-0.68,0.10)	(0.95,0.99)	(0.91,0.97)	(0.24,0.89)	(0.06,0.31)	(0.35,1.33)	(0.05,0.27)
TSM	-0.45	-0.58	0.98	0.98	0.29	0.26	0.06	-0.00
	(-1.74,0.30)	(-1.70,0.31)	(0.97,0.98)	(0.97,0.98)	(0.28,0.47)	(0.20,0.37)	(0.05,0.10)	(-0.02,0.02)

Volatilities

	σ_g	σ_π	$\sigma_r(F)$	$\sigma_r(R)$	σ_y
CAP	0.589	0.252	0.910	0.329	0.402
	(0.501,0.834)	(0.208,0.354)	(0.835,1.659)	(0.316,0.939)	(0.376,0.884)
TSM	0.56	0.25	1.16	0.35	0.26
	(0.30,0.97)	(0.19,0.34)	(0.55,2.31)	(0.19,1.13)	(0.20,1.75)

Table 2.7: Parameter estimates: Asset-market dynamics. The first three panels report estimated income dynamics parameters. The last panel reports the Sharpe ratio of real estate risk net of macro fundamentals. Bootstrapped 95 percent Confidence interval in are parentheses. The TSM model estimates only include zero coupon bond price. The CAP model estimates incorporate information from real estate income and prices. An active (passive) MP regime is denoted by "A" ("P"). A flexible (rigid) MP regime is denoted by "F" ("R").

Apartment

$\gamma_{A,g}$	$\gamma_{A,\pi}$	ρ_A	$\gamma_{A,c} \times 10^3$
1.21	0.31	0.56	1.21
(0.91,2.18)	(-0.26,0.81)	(0.39,0.86)	(-2.17,5.08)

$\sigma_{A,W} \times 10^2$	$\sigma_{A,Z} \times 10^2$	$\sigma_{A,Q} \times 10^2$	$\sigma_{A,\nu} \times 10^2$
0.42	0.30	6.15	0.41
(0.34,0.57)	(0.20,0.64)	(0.10,12.30)	(0.37,0.60)

Industrial

$\gamma_{I,g}$	$\gamma_{I,\pi}$	ρ_I	$\gamma_{I,c} \times 10^3$
0.60	0.73	0.64	-2.24
(0.36,1.65)	(0.13,1.30)	(0.39,0.83)	(-5.40,1.43)

$\sigma_{I,W} \times 10^2$	$\sigma_{I,Z} \times 10^2$	$\sigma_{I,Q} \times 10^2$	$\sigma_{I,\nu} \times 10^2$
0.47	0.35	5.26	0.49
(0.41,0.66)	(0.30,0.72)	(0.10,9.86)	(0.42,0.67)

Office

$\gamma_{O,g}$	$\gamma_{O,\pi}$	ρ_O	$\gamma_{O,c} \times 10^3$
0.77	0.71	0.71	-1.32
(0.52,1.80)	(0.11,1.26)	(0.52,0.88)	(-4.38,2.11)

$\sigma_{O,W} \times 10^2$	$\sigma_{O,Z} \times 10^2$	$\sigma_{O,Q} \times 10^w$	$\sigma_{O,\nu} \times 10^2$
0.51	0.26	7.34	0.57
(0.42,0.73)	(0.22,0.71)	(0.13,13.89)	(0.47,0.76)

λ_Z
0.42
(-0.34,0.76)

Table 2.5: Parameter estimates: Macro risk premia. Bootstrapped 95 percent Confidence interval in are parentheses. The TSM model estimates only include zero coupon bond price. The CAP model estimates incorporate information from real estate income and prices. An active (passive) MP regime is denoted by "A" ("P"). A flexible (rigid) MP regime is denoted by "F" ("R").

$\mathbf{\Pi_0}$	g	π	r
CAP	-0.34	1.48	-1.67
	(-0.94,0.71)	(1.29,3.56)	(-2.23,-0.76)
TSM	0.59	-3.2	-2.01
	(0.35,0.99)	(-3.57,-2.74)	(-3.21,-1.32)

$\mathbf{\Pi_x}$		g	π	r
g	CAP	1.38	-0.16	0.43
		(0.89,2.46)	(-0.64,0.22)	(0.29,0.85)
	TSM	2.26	-1.29	-2.18
		(1.67,2.94)	(-1.82,-0.22)	(-2.75,-1.15)
π	CAP	-14.02	2.64	-3.10
		(-14.53,-12.73)	(1.85,4.20)	(-3.98,-2.38)
	TSM	0.91	2.94	0.73
		(0.45,2.01)	(2.27,3.68)	(-0.06,1.38)
r	CAP	0.52	0.46	-0.07
		(-0.29,1.19)	(-0.19,0.72)	(-0.27,0.10)
	TSM	-0.01	0.48	0.04
		(-0.79,0.98)	(-1.33,0.83)	(-0.60,0.56)

Table 2.6: Parameter estimates: Macro regime persistence (quarterly probability of remaining in current regime). Bootstrapped 95 percent Confidence interval in are parentheses. The TSM model estimates only include zero coupon bond price. The CAP model estimates incorporate information from real estate income and prices. An active (passive) MP regime is denoted by "A" ("P"). A flexible (rigid) MP regime is denoted by "F" ("R").

	CAP	TSM
Active monetary policy regime variable s_t^m		
$s_t^m = A$	97.45	97.39
	(55.96,98.69)	(95.51,99.86)
$s_t^m = P$	98.43	92.70
	(56.72,98.91)	(83.59,99.86)
Flexible monetary policy regime variable s_t^d		
$s_t^d = F$	98.23	93.41
	(55.76,98.88)	(87.57,98.84)
$s_t^d = R$	96.94	90.40
	(86.10,98.54)	(48.85,99.83)

Table 2.8: Model implied real estate risk-premia calculated by subtracting model cap rates under the $\mathbb{P}$-measure from cap rates calculated under the $\mathbb{Q}$-measure. The risk premium depends on both the regime and the value of the macroeconomic fundamentals. We simulate the macroeconomic fundamentals in each regime and calculate the corresponding real estate risk premium. The table reports the mean and 95%-intervals for the risk premium in each regime. An active (passive) MP regime is denoted by "A" ("P"). A flexible (rigid) MP regime is denoted by "F" ("R").

Regime	A/F	A/R	P/F	P/R
Apartments	0.065	0.054	0.052	0.041
	(0.044,0.095)	(0.039,0.075)	(0.034,0.075)	(0.031,0.052)
Industrial	0.06	0.05	0.054	0.041
	(0.045,0.081)	(0.040,0.062)	(0.035,0.076)	(0.032,0.052)
Office	0.065	0.054	0.057	0.044
	(0.046,0.093)	(0.041,0.071)	(0.035,0.085)	(0.032,0.057)

APPENDIX A

CHAPTER 1 APPENDIX

This is the appendix for the first chapter. The appendices go at the end after all of the chapters, not after the chapter it corresponds to.

A.1 Description of ULURP

The ULURP sets forth a legislative process that any rezoning in NYC needs to follow. This section serves as a brief description of the data-points that will be collected.

First a application is submitted either by an individual, company, interest group, or the mayor's office. The application is then certified by the city planning commission a sub-committee of the City Council (CC) usually within 6 months (though no official time-limit is imposed). Once certified, the process continues. Dates of both submission of application and certification are collected.

Once the application is certified, the community board (CB) holds a town meeting where affected residents are allowed to discuss, vote, and send forth a recommendation to the BP and CPC. The date, vote tally, and recommendation (recommend, recommend with revisions, or do not recommend) is collected.

If the project affects a single borough, with the information from the CB, the BP makes a recommendation to the CPC. The date, and recommendation are collected. The BP has 30 days from receiving the CB recommendation. If the project affects multiple boroughs, a borough board (BB) is formed and votes on a recommendation.

Upon receiving the BP's recommendation, the CPC holds a vote on the proposal. They either vote to approve, approve with changes, or reject a proposal. Zoning map changes are required to go in-front of the City Council (CC). The date and outcome are collected.

The CC then reviews the proposal within 50 days of the CPC vote. The vote tally and recommendation are collected. If the vote passes, the mayor has 5 days to veto. In the case of a veto, the CC can overrule the veto with a 2/3rds majority and has 10 days to do so.

To add an additional source of nuance to the proposal, it is an unwritten tradition in the CC where the CC typically votes with the local member; giving the local member veto power.

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