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Real Estate Price Measurement and Stability Crises

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# Real Estate Price Measurement and Stability Crises\*

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## Abstract

This paper considers the suitability of four widely used real estate price indices (the S&P Case-Shiller Index; the FHFA index; the NCREIF NPI; and the historical NAREIT series) for valuing and monitoring the credit risk of U.S. mortgages. Our evaluation focuses on four properties of these indexes: unbiased estimation of the drift of real estate price dynamics; unbiased estimation of the volatility of real estate price dynamics; suitability for measuring correlation between interest rates and real estate prices; suitability for measuring growth dynamics, or the effects of real options components of real estate values. We find, despite their widespread use, that these indices generate downwardly biased estimates of the idiosyncratic volatility of prices around the index and, thus systematically undervalue embedded default options in mortgage products. We also identify other specific properties, or required assumptions underlying the construction of these indices, that are likely to be problematic for mortgage pricing. These properties include the fact that none of these indices adequately address the index number problem for real estate assets. These price metrics thus mix price and quantity dynamics in non-transparent ways leading to likely biases in the measurement of the correlation between real estate “prices” and economic fundamentals, such as interest rates, and expected skewness in real estate price distributions arising from the real option components of real estate values. Overall, this analysis suggests there is a need to re-evaluate the use of these indices for mortgage risk management and to develop dynamic hedonic price indices that both address the index number problem and allow for flexible specifications for price and quantity dynamics.

JEL classification: G14.

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# 1 Introduction

One important feature in the run up to the current financial crisis was the rapid growth of the outstanding stock of mortgage debt in the United States. More surprisingly, large regulated financial institutions increased their share of mortgage debt to total assets over this same period, despite the potential benefits of instead diversifying their mortgage risk exposure through securitization and sales to a broad base of investors. As shown in Figure 1, from 1999 to 2006, there was a 634 basis point increase in the mortgage exposure<sup>1</sup> of FDIC insured financial balance sheets. This change represented more than a doubling of the mortgage holdings of these institutions from \$2.18 trillion in 1999 to \$4.5 trillion in 2006. By December of 2006, more than 37% of the holdings of insured financial institutions were comprised of mortgages.<sup>2</sup>

Another feature of the exposure of financial institutions to mortgage risk was the growth of large mortgage positions in off-balance sheet vehicles that were often structured with back-stop credit lines to the institution. These off-balance sheet vehicles were usually structured with significant duration risk due to the short-term maturities of their liabilities and the long-term maturities of their assets – primarily securitized mortgages bonds. Unfortunately, the full magnitude of this additional mortgage risk exposure can only be measured *ex post* when institutions re-consolidated these assets back onto their balance sheets.<sup>3</sup>

Although mortgage holdings more than doubled over the run-up period to the crisis, the stock of risk-weighted assets that were held by these institutions<sup>4</sup> grew significantly less rapidly (See, Acharya and Richardson (2010) and Stanton and Wallace (2010a)). The International Monetary Fund reported that the total assets of the ten largest publicly traded financial institutions doubled between 2002 and 2007, to 15 trillion euros, whereas risk-weighted assets grew to only about 5 trillion euros.<sup>5</sup> The stock of risk-weighted assets grew

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<sup>1</sup>These are both securitized and whole loans

<sup>2</sup>Another important feature of the summary statistics on depository institutions (SDI) over this period is the dramatic reduction in the number of reporting institutions, due to voluntary mergers and acquisitions in the earlier period, and forced mergers and bank closures at the end of the period. In 1992, there were 13,853 institutions represented in the SDI survey, however, by the second quarter of 2010 there were only 7830 institutions.

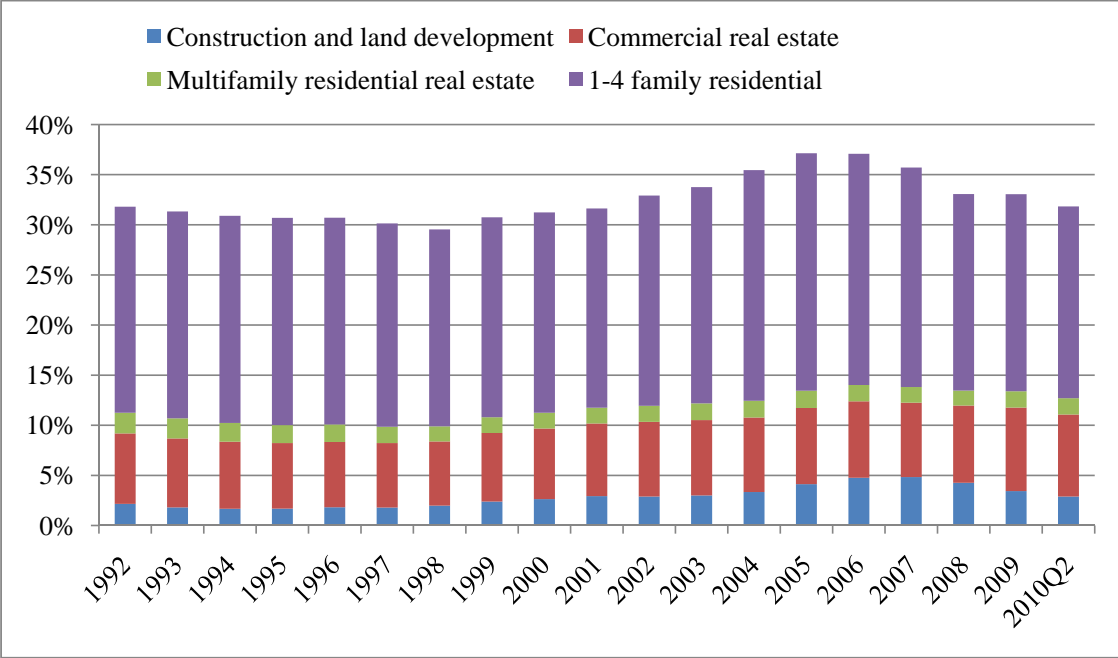
<sup>3</sup>As an example, Citigroup re-consolidated \$49 billion of assets from seven SIVs in December, 2007 (See, <http://www.bloomberg.com/apps/news?pid=newsarchives&sid=aT0Ix2iDnZRk>). In June, 2007 Citigroup re-consolidated an additional \$10 billion of mortgage CDOs on their balance sheet. The source for this information was hand collected from the proxy statements of ten large CDOs: Stockbridge CDO Ltd.; Singa Funding; Raffles Place II; Funding HSPI Diversified CDO Fund I; Palmer 2007-1; Armitage ABS CDO; HSPI Diversified CDO Fund II; Pinnacle Peak CDO I; Bonifacius; Jupiter High Grade CDO VII that was hand collected from the Irish stock exchange.

<sup>4</sup>These are the assets that determine the capital requirements of financial institutions.

<sup>5</sup>See, International Monetary Fund Global Financial Stability Report, April, 2008, p. 31, <http://www.imf.org/external/pubs/ft/gfsr/2008/01/pdf/chap1.pdf>.

Figure 1: Real Estate Mortgage Holdings as a Percentage of Total Assets for FDIC Insured Financial Institutions in the U.S.

This figure presents the real estate mortgage holdings of FDIC insured financial institutions. The holdings for residential, commercial, multi-family, and real estate construction loans are reported as their respective percentage of the total assets of these institutions. The data were obtained from the FDIC - Statistics on Depository Institutions Report, <http://www2.fdic.gov/sdi/index.asp>.

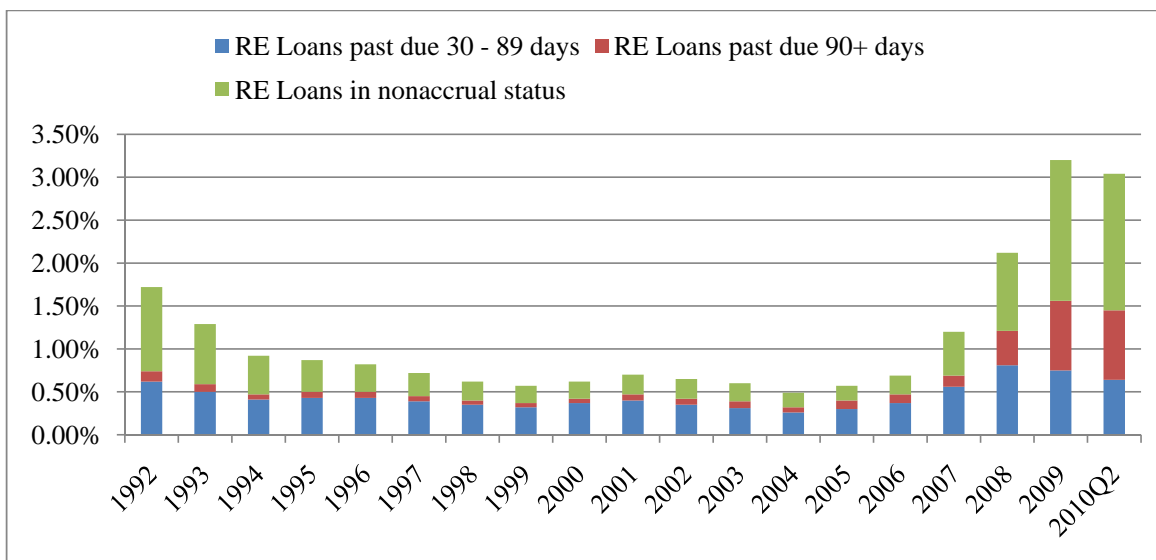


more slowly for several reasons. First, off-balance sheet assets often recorded no, or lower, risk weights. Second, most of the mortgages that were held by financial institutions were held in the form of AAA-rated mortgage backed securities. Since AAA-MBS had 20% risk weights, requiring capital holdings of 1.6% times the face amount of the bonds, banks could avoid the 50% risk weights required for whole mortgages. Third, although commercial mortgages were primarily held by banks as whole loans, usually with BBB or better ratings, most CMBS were rated AAA (See, Stanton and Wallace (2010a)). Overall, the transformation of mortgages into AAA-rated mortgage bonds substantially increased the leverage of FDIC insured financial institutions (See, He, Khang, and Krishnamurthy (2010)).

The AAA ratings of bank-held mortgage instruments were based upon the rating agency certification of the credit quality of the instruments. These empirical credit evaluations were largely based on the historical credit performance of the stock of U.S. mortgages, or more commonly on the stock of mortgages underlying bonds previously rated by the agencies. Figure 2 presents the sum of seriously delinquent and nonaccrual mortgage assets held by FDIC insured institutions. As shown delinquencies and foreclosures remained substantially below 1% of the aggregate asset holdings for the fourteen years following the resolution of the Savings and Loan (S&L) crisis in 1989.

Figure 2: Real Estate Mortgage Loans that are Delinquent or Non-Accruing as a Percentage of Total Assets for FDIC Insured Financial Institutions in the U.S.

This figure presents the real estate mortgage holdings of FDIC insured financial institutions that are delinquent or non-accruing. These holdings are reported as their respective percentage of the total assets of these institutions. The data were obtained from FDIC - Statistics on Depository Institutions Report, <http://www2.fdic.gov/sdi/index.asp>.



Historically the *de minimis* levels of credit risk found in the outstanding stock of mortgage products and the “plain vanilla” contractual structure of this stock presented a significant problem for the development of empirical credit risk models for new mortgage products. The rating agency models were uniformly hampered by the low frequency of actual credit events, the lack of comparability between the contractual structures of the existing mortgage stock and new mortgage products, and the low “out-of-sample” forecasting power of reduced-form models based on short performance histories of mortgages. As shown in Figure 2, the actual credit experience of the mortgage stock of FDIC insured financial institutions in the U.S. turned out to have been an order of magnitude worse than the experience of the prior period and is currently just over 3%.

Another common element of most mortgage valuation technology in the U.S. was the reliance on four price series for modeling residential and commercial asset price dynamics. During the run-up to the crisis, there was a surprising lack of capital investment in new real estate price index technology. Instead most market participants relied on easily accessible existing, often free, indices and estimated out-of-sample dynamics for these indices using vector autoregressions. The lack of methodological developments in pricing technology was in stark contrast to the rapid progression of methodological innovations in the rest of the U.S. fixed income markets. For real estate markets, there was little research and no developmental breakthroughs on the higher moments of real estate asset price distributions or on the effects of jumps in these dynamics. There was also an important lack of consensus concerning the level and sign of the correlations between the asset price dynamics between regions and types of property markets and between asset prices and interest rates.

Part of the reason for this lack of investment was that prepayment was considered to be the first order risk for mortgage investments. For this reason, many mortgage valuation models focussed exclusively on the development of proprietary interest rate models to support their mortgage trading platforms. The introduction of house prices into mortgage valuation modeling began with an increased recognition of the importance of house price dynamics on prepayment speeds (See, Kau, Keenan, Muller, and Epperson (1992), Hayre (2001), Deng and Quigley (2002), and Downing, Stanton, and Wallace (2005)).<sup>6</sup> The inclusion of asset price dynamics in commercial mortgage valuation models was first introduced by Titman and Torous (1989), Kau, Keenan, Muller, and Epperson (1990), and Vandell (1992).

The purpose of this paper is to consider the ways in which the commonly used measures of real estate asset price dynamics may introduce significant biases into the mortgage valuation

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<sup>6</sup>Automated underwriting was developed by the GSEs and was introduced in 1996. This credit scoring technology focused on the likelihood that the borrower would continue to make installment payments on mortgages or any other credit instrument. Although the borrower’s debt capacity was a focus of these models, capacity was anchored by income dynamics rather than by house price dynamics.

and risk management models that are used in the U.S. The intent of the paper is not to minimize the numerous alternative causal explanations for the viral spread of credit risk problems from the sub-prime mortgage market to a generalized collapse of the U.S. financial system in 2007. Rather the goal of the paper is to lay out the ways in which current strategies to measure real estate asset prices may be problematic for the development of measures to assess the systemic risk associated with the embedded put options in commercial and residential mortgages. These price indices may also lead to biased assessments of the capital adequacy for structured mortgage products, including assessments of the adequacy of the 5% “skin-in-the-game” requirement for securitized products, found in the Dodd-Frank Financial Reform Act.

The paper is organized into 8 sections. In the next section, we review some outstanding facts concerning the evolution of mortgage risk in the run-up to the financial crisis. Section 3 reviews the basics of mortgage valuation modeling and summarizes what needs to be known about asset prices for these models to provide a reasonable assessment of mortgage values and accurate systemic risk metrics such as duration, convexity, and value-at-risk. In Section 4, we review available real estate price indices in the U.S. Section 5 summarizes the properties of real estate price indices with respect to volatility and the limitations of these volatility estimates for mortgage valuation modeling. Section 6 discusses the current lack of consensus concerning the level and sign of correlations between real estate asset prices and interest rates and the implications for the specification of real estate price indices. In Section 7, we consider the real option component of real estate prices and discuss the biases in mortgage valuation that are introduced by ignoring this component of price dynamics. Section 8 concludes.

## 2 The Evolution of U.S. Mortgage Leverage

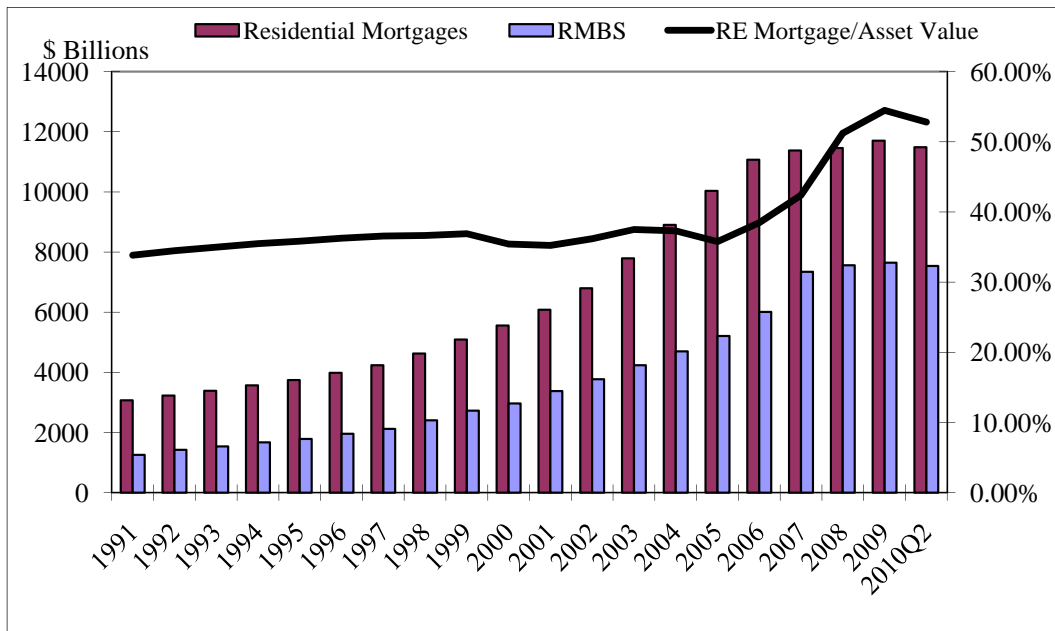
Several recent studies have documented the role of loosening credit standards in subprime mortgage origination (See, Demyanyk and Van Hemert (2009), Mian and Sufi (2009a), and Mian and Sufi (2009b)). In contrast, Glaeser, Gottleib, and Gyourko (2010) use housing transaction data and find that the median loan-to-value ratios in 2005 were no higher than in 1999.<sup>7</sup> They also find that about 10% of home buyers purchased homes with no equity in both periods. Figure 3, presents the aggregate stock of residential mortgages and mortgage backed securities in the U.S. against a plot of the aggregate ratio of mortgage loans outstanding to the total value of residential real estate. As shown, the rapid growth of residential mortgages

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<sup>7</sup>The data source for this conclusion was more than one million transaction records obtained from a large data vendor, DataQuick

from 1999 through 2006 was not accompanied by an increase in leverage ratios, suggesting that over this period increases in loan balances closely tracked increases in residential real estate prices. Instead, aggregate leverage remained approximately constant in the U.S. housing market at a long-run average of 36.6%. From 2006 onward, however, leverage ratios grew about 17% to the current level of 52%. The growth in the aggregate leverage ratios in the U.S. corresponds quite closely to the June 2006 peak in the widely used S&P Cash-Shiller house price index and its subsequent steady decline. Figure 3, thus suggests that the increase in leverage is likely to be a function of the inability of mortgage borrowers to re-balance the capital structure of their residential real estate investments as house prices fell rather than due to the relaxation of credit underwriting standards in the latter stages of the credit boom.<sup>8</sup>

Figure 3: Aggregate Stock of Residential Mortgages and Residential Mortgage Backed Securities Compared to the Aggregate Leverage Ratio for Residential Real Assets in the U.S. The dollar amount (in billions) of the outstanding aggregate U.S. stock of residential mortgages and mortgage backed securities is reported on the left axis from 1991 through 2010Q2 . The aggregate residential leverage ratio is reported on the right axis. The leverage ratio is computed as the ratio of the value of the outstanding stock of residential mortgages to the value of residential real estate in the U.S.. The data were obtained from the Federal Reserve Board Flow of Funds Accounts of the United States, Table L.218, L.219, and B.100-B.103 (See, <http://www.federalreserve.gov/releases/z1>).



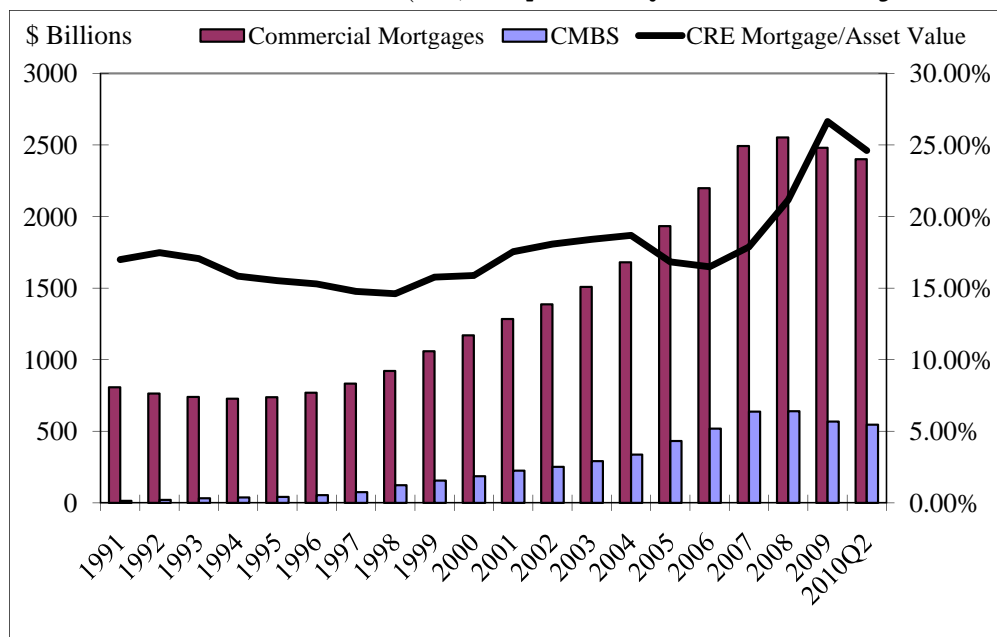
<sup>8</sup>This interpretation is consistent with the effect that homeownership indivisibility has in amplifying the ratchet effect modeled in Khandani, Lo, and Merton (2010).



Figure 4 graphs the aggregate stock of commercial mortgages and commercial mortgage backed securities in the U.S. against a plot of the aggregate ratio of commercial mortgage loans outstanding to the total value of commercial real estate. Driessen and Van Hemert (2009) and Stanton and Wallace (2010a) find scant evidence that the underwriting standards for commercial mortgages deteriorated significantly in the run up to the crisis. Here again, as shown in Figure 4, the increase in the stock of commercial loans in the U.S. slightly outpaced the increase in commercial real asset values between 1999 and 2004 and leverage ratios rose by about 1%. However, aggregate leverage ratios subsequently fell by about 1%, in 2005 and 2006, suggesting that asset values outpaced underwritten loan limits in the aggregate. After 2006, however, leverage ratios rose rapidly as the REIT total returns index moved into negative territory as will be discussed in the next section of the paper. Here again, these graphs suggest that the inability of commercial borrowers to re-balance their capital structures rather than important weakening of commercial mortgage underwriting

Figure 4: Aggregate Stock of Commercial Real Estate Mortgages and Commercial Real Estate Mortgage Backed Securities Compared to the Aggregate Leverage Ratio for Commercial Real Estate Assets in the U.S.

The dollar amount (in billions) of the outstanding aggregate U.S. stock of commercial mortgages and mortgage backed securities from 1991 through 2010Q2. The aggregate residential leverage ratio is reported on the right axis. The leverage ratio is computed as the ratio of the total value of the outstanding stock of commercial mortgages to the total value of commercial real estate. The data were obtained the Federal Reserve Board Flow of Funds Accounts of the United States, Table L.220 and Tables B.100-B.103 Balance Sheet (See, <http://www.federalreserve.gov/releases/z1>).



standards in the aggregate drove the recent increase in aggregate leverage. Similar, to the residential mortgage market, the commercial market appears to be tracking a widely used real estate price measure.

A possible interpretation of these two graphs is that mortgage underwriting standards in the aggregate appear to have closely tracked two of the most important asset price indices: the S&P Case Shiller index for housing and the REIT return index for commercial real estate. Since these indices were also widely used in loan underwriting, in loan risk management through scenario testing, and in pricing commercial and residential loans, it may be that the dynamics of the indices also affected the banks' decisions concerning the allocation of mortgage products within their portfolios and their evaluation of the riskiness of these strategies. Thus, the strengths and weaknesses of the price index could have lead to systematic biases in the mortgage risk management activities of bankers. In the next sections of the paper, we

will consider the suitability of these metrics for the determination of mortgage underwriting criteria and mortgage valuation.

### 3 The Mortgage Valuation Problem

As previously discussed, the primary sources of risk that are accounted for in all mortgage valuation models are interest rates and house/property prices. These exogenous risk-factors are also arguments to other explanatory variables that are essentially transformations of interest rates, asset prices, and time, such as the time elapsed since the mortgage was issued, the unpaid remaining mortgage balance, or the loan-to-value ratio. The commercial and residential mortgages valuation frameworks that are used in the United States include: 1) structural valuation models of the mortgage cash flows in which the optimal exercise policies for the embedded prepayment and default options are explicitly solved for given exogenously fitted dynamics of the exogenous risk-factors; 2) reduced-form models where the timing of mortgage cash flows are estimated empirically with hazard rates fitted to proxies for asset prices, interest rates and other factors, and prices are calculated as expected values from Monte Carlo simulations of probability weighted cash flows;<sup>9</sup> and 3) hybrid models that augment structural models to include embedded hazard estimates for potential frictions on optimal exercise policies due to transactions costs.<sup>10</sup> Despite differences in modeling structure, all three of these valuation frameworks require similar information about interest rate and asset price dynamics including estimates for the long run drift of each, the instantaneous standard deviation of each, and the correlation between them.

**Interest Rate Dynamics** All three classes of mortgage valuation are functions of interest rate dynamics. The Cox, Ingersoll, and Ross (1985) (CIR) model is widely used in the mortgage pricing literature (See, for example Dunn and McConnell (1981a), Dunn and McConnell (1981b), Foster and Order (1984), Schwartz and Torous (1989), Stanton (1995), Kau, Keenan, Muller, and Epperson (1992), and Longstaff (2005)), among many others.). However, term structure modeling is a highly developed field and there are many functional forms that have been adapted for fitting these models.<sup>11</sup> Under (CIR), interest rates are

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<sup>9</sup>There is often a disconnect between the information set used for the empirical hazard rate estimation – limited to a specific draw of recent historical performance data with low event frequency – and the Monte Carlo simulations defined over the full information set of the stochastic fundamentals.

<sup>10</sup>For good reviews of these mortgage modeling and risk management techniques see Hayre (2001), Davidson, Sanders, Wolff, and Ching (2003), and Schoenbucher (2003).

<sup>11</sup>For an excellent review of this literature see Veronesi (2010).

governed by

$$dr_t = (\kappa(\theta_r - r_t) - \eta r_t)dt + \phi_r \sqrt{r_t} dW_{r,t}, \quad (1)$$

where  $\kappa$  is the rate of reversion to the long-term mean of  $\theta_r$ ,  $\eta$  is the price of interest rate risk, and  $\phi_r$  is the proportional volatility in interest rates.  $W_{r,t}$  is a standard Wiener process.

**House Price Dynamics** House prices for individual properties,  $H_t$  are conventionally assumed to evolve according to a geometric Brownian motion (See, Foster and Order (1984), Kau (1995), Kau, Keenan, Muller, and Epperson (1990), Downing, Stanton, and Wallace (2005), and Downing, Jaffee, and Wallace (2009)). For ease of notation we drop the mortgage specific subscript so that the price dynamics of a specific house can be written as:

$$dH_t = \theta_{H,t} H_t dt + \phi_{H,t} H_t dW_{H,t}, \quad (2)$$

where  $\theta_{H,t}$  is the expected appreciation in house prices, and  $\phi_{H,t}$  is the volatility of house prices. Denoting the flow of rents accruing to the homeowner by  $q_{H,t}$ , after risk-adjustment house prices evolve according to:

$$dH_t = (r_t - q_{H,t}) H_t dt + \phi_{H,t} H_t dW_{H,t}. \quad (3)$$

Again, the process  $W_{H,t}$  is a standard Wiener process. The correlation between the interest rate and the house price process is usually assumed to be zero,  $E[dW_r dW_H] = \rho_{H,r} dt = 0$ .

**Commercial Mortgage Modeling** Commercial real estate property prices are also usually assumed to evolve according to a geometric Brownian motion (See, for example Titman and Torous (1989), Childs, Ott, and Riddiough (1996), Dierker, Quan, and Torous (2005), Titman, Tompaidis, and Tsyplakov (2005), and Stanton and Wallace (2010a), among others):

$$dp_t = (\theta_{p,t} - q_{p,t}) p_t dt + \phi_{p,t} p_t dW_{p,t}. \quad (4)$$

The parameter  $\theta_{p,t}$ , the expected annual total return on the property, is not needed for risk-neutral pricing. Under risk-neutrality property prices evolve according to:

$$dp_t = (r_t - q_{p,t}) p_t dt + \phi_{p,t} p_t dW_{p,t}. \quad (5)$$

However, we will need to calibrate  $\theta_{p,t}$  in order to compute default rates. For default rate calculations,  $\theta_{p,t} = r_t + \mu$ , where  $\mu$  is the real estate risk premium. The parameter  $q_{p,t}$  is the net income (on an unleveraged basis) accruing to the property owner, and  $\phi_{p,t}$  is the volatility

of the property return.  $W_{p,t}$  is a standard Wiener process and the correlation between the interest rate and the property price process,  $E[dW_r dW_p] = \rho_{pr} dt = 0$ , is usually assumed.

**Calibrating Interest Rate and Asset Price Dynamics** Empirical term structure modeling of interest rates is a well established focus of a voluminous academic literature (See, Veronesi (2010) for an excellent survey.) and is central to the risk modeling activities that are carried out daily in large financial institutions. Fitting long-run equilibrium term structure models, such as the CIR model, requires long time series of interest rate auction data.<sup>12</sup> An alternative class of term structure models, the market models, accurately fit to the current term structure and require current auction price information for Treasury instruments of varying maturities as well as information from options markets, such as the caplet market, to calibrate the instantaneous standard deviation,  $\phi_r$ .<sup>13</sup>

Empirical estimation of house and commercial property price dynamics is much less established both in the academic literature (See, Meese and Wallace (1992), Meese and Wallace (1997), Meese and Wallace (2003), Matthey and Wallace (1998), Matthey and Wallace (2001), Torous, Valkanov, and Plazzi (2004), and Plazzi, Torous, and Valkanov (2010).) and in risk management practice.<sup>14</sup> A key impediment to the robust development of models of real estate asset price dynamics is the lack of comprehensive historical price and characteristics data for the assets, the lack of trading volume in the real estate derivatives markets, and many outstanding theoretical and practical questions concerning how to solve the “real estate index number problem” – how to measure and monitor the prices and attribute compositions of comparable real estate assets over time. Two particular weakness in the state-of-the-art of the empirical modeling of these asset price dynamics is a lack of robust estimates for the instantaneous standard deviations of these dynamics and robust estimates for the correlation between asset dynamics in different geographic regions and between real estate asset and interest rate dynamics. Having robust estimates of volatility and correlation, of course, are of first order importance to obtaining accurate measurement of mortgage default risk and to the development of risk management tools that include covariance or other measures of systemic risk (See, Brunnermeier (2009) and Brunnermeier (2010)).

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<sup>12</sup>See, Pearson and Sun (1989)

<sup>13</sup>See, for example Hull and White (2009) and Heath, Jarrow, and Morton (1992)

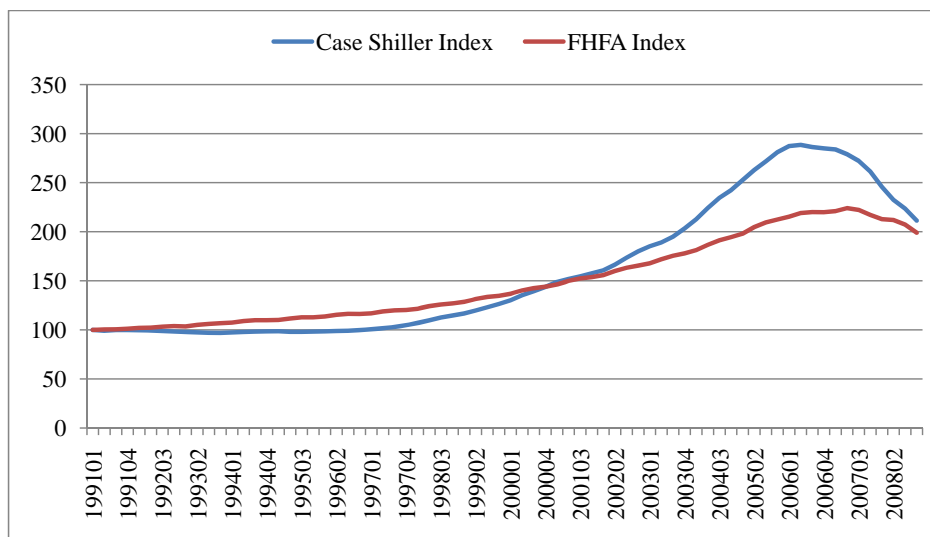
<sup>14</sup>Assumptions about the properties of these price dynamics do, however, play an important role in the standard Cash/Shiller weighted repeat sales estimator (See, Case and Shiller (1988) and Case and Shiller (1989)) who assume prices follow a random walk with constant drift.

## 4 Indices of Real Estate Price Dynamics

### 4.1 Residential Indices

In the United States, there are two dominant single-family residential house price indices used for estimating housing returns and for mortgage valuation: the repeat-sales indices of S&P Case-Shiller and of the Federal Housing Finance Agency (FHFA).<sup>15</sup> The S&P Case-Shiller family of indices includes twenty monthly metropolitan regional indices, two composite indices, and a quarterly national index that tracks an aggregate of the nine U.S. Census divisions. The FHFA family of indices provides quarterly estimates of housing prices for three hundred and eighty one metropolitan areas in the U.S. plus monthly aggregate U.S. and Census Division indices. Despite their dominance in the U.S., no other country uses repeat-sales house price indices. Instead, other countries rely on either hedonic indices, in which prices are estimated as functions of the characteristics of houses, or indices constructed from the mean, or median, value of observed transactions prices.<sup>16</sup>

Figure 5: U.S. Comparison of the S&P/Case-Shiller 10 city index indices and the Federal Housing Finance Administration (FHFA) Housing Price Index for purchase transactions in the U.S.



<sup>15</sup>The FHFA house price indexes (HPI) are based on the Case-Shiller repeat-sales index methodology (see Case and Shiller (1988, 1989), and Calhoun (1996)). This in turn is based on a methodology developed by Bailey, Muth, and Nourse (1963)). Prior to July 2008, the HPI was maintained by the Office of Federal Housing Enterprise Oversight (OFHEO).

<sup>16</sup>Beauvois, David, Dubujet, Friggit, Gouriéroux, Laferrère, Massonet, and Vrancken (2006) report that France, Hong Kong, Norway, Great Britain, Sweden, and Switzerland use hedonic indices, while Germany, Austria, Belgium, Canada, Spain, and Holland use mean or median, indices.

As shown in Figure 5, despite the common econometric methodology that underlies the two indices, the S&P Case-Shiller indices and the HPI often do not agree. The FHFA has recently started publishing reconciliation tables to, at least partially, explain observed differences that have ranged from 3% to 4% in growth rates (See OFHEO (2008)). One explanation for the observed differences in these indices is that the underlying data sources differ. The FHFA index is estimated using data from the origination portfolios of the GSEs, Freddie Mac and Fannie Mae, and these portfolios are restricted to properties that collateralize conventional conforming mortgages with balances currently below \$417,000 (\$729,750 for high cost areas) and with FICO scores greater than 620. The S&P Case-Shiller index is estimated from data obtained from county assessors and recorder offices. These data include all recorded loans including many alternative and subprime loan products. There are also geographic location differences in the S&P Case-Shiller and the FHFA indices.

An important limitation with repeat sales house price indices and all transaction-based indices is sample-selection bias. Since housing is heterogeneous and trading is infrequent, observed average transaction prices may be uninformative measures of actual supply and demand conditions. As shown in Goetzmann and Peng (2006) and Noyv-Marx (2008), in the presence of seller reserves, when trading volume increases (decreases), returns of purely transaction-based indexes will be lower (higher) than actual appreciation rates of the market value of houses. These discrepancies will be greater when changes in trading volume are more important. The expected bias in uncorrected transaction-based house price indexes leads to underestimates of the volatility of the housing returns.

One proposed empirical solution for the sample selection biases of transaction-based indexes is to apply the Heckman (1979) two step estimators (See Hwang and Quigley (2003); Gatzlaff and Haurin (1997); and Gatzlaff and Haurin (1998)). With this method, the sample generating process is estimated in the first stage, and the selection corrected transaction-based index is estimated in the second stage. A second empirical strategy, developed by Goetzmann and Peng (2006), introduces information on trading volume to mitigate the bias in the estimation of the transaction-based index. A limitation with these strategies is that the standard Heckman correction model assumes that the unobserved prices for properties that do not transact are independent and can be integrated out of the likelihood for the second stage estimating pricing equation. ? address the sample selection problem using a Bayesian filtering procedure that is a dynamic version of a Heckman correction model and allows unobserved prices to be serially correlated. All of these studies, show that the standard uncorrected repeat sales indices over-estimate price appreciation in run-ups.

Another problem with repeat sales price indices is their inability to control for secular and/or business-cycle shifts. A large part of classical index number theory is concerned with

appropriate weights for the consumption basket, or the *housing investment* portfolio. Repeat sales indices, however, update the consumption basket each period in non-transparent ways through the addition of new transaction pairs composed of ever-varying (but unmeasured) characteristic sets. Because repeat sales indices do not control for a well-defined characteristic basket, it is not possible to identify secular shifts in preferences over housing characteristics (such as the effect of everyone installing granite counters). In particular, repeat sales indices do not account for price movements that are associated with new housing construction (because all new units are single sales) even though in some geographic areas and periods these new home sales can be up to 20% or more of total housing transactions. Remodeling is also not systematically accounted for, even though remodeling investment is between 2% and 3% of GDP in the U.S. (see Downing and Wallace (2007)). In addition, the volume and characteristics of houses that transact may vary over the business cycle as the marginal buyer changes due to factors such as shifts in the credit supply channel (see Mian and Sufi (2009a)). These effects introduce additional potentially important sources of sample selection bias.

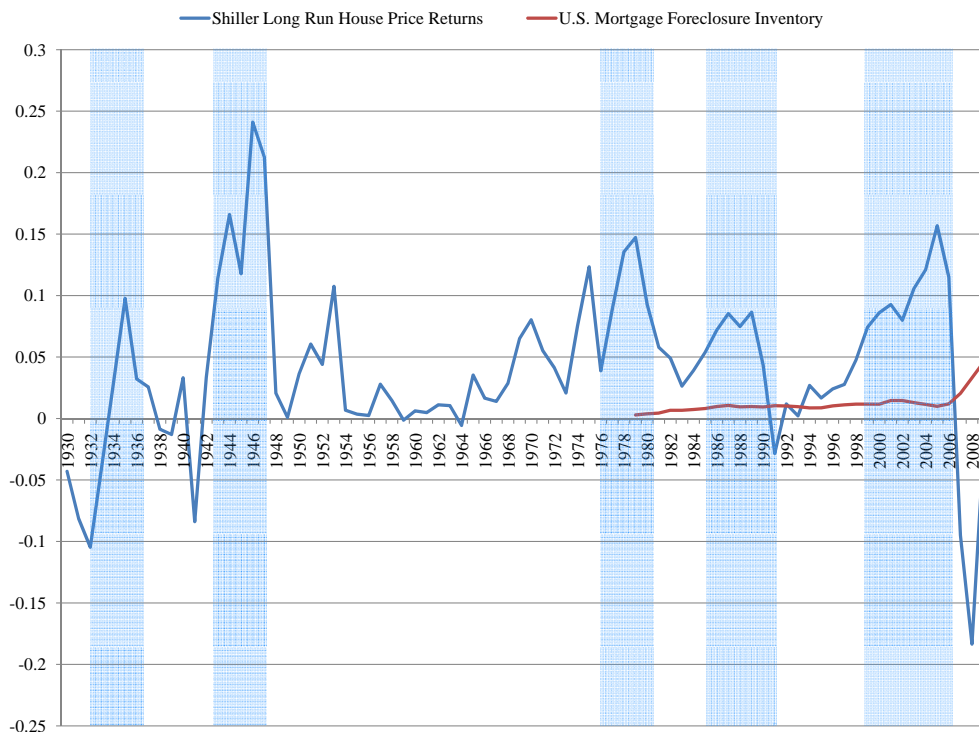
A less well researched concern with repeat sales indices is the underlying assumption in this estimator that house prices have a *constant* expected return over time, i.e. it is assumed that  $\theta_{H,t}$  is a constant. This assumption is problematic because the econometrician does not observe the constant growth rate, so each quarterly estimate of the index generates a new draw on the long-run mean. As a result, the entire index is retroactively updated on a monthly or quarterly basis. The effect of these historical revisions is to compress volatility which is also likely to be time-varying due to the effects of secular and business cycle shifts on prices. The revisions, which have been empirically found to be largely systematically downward (see Clapham, Englund, Quigley, and Redfearn (2006) and Stanton and Wallace (2010b)), also introduce a downward bias on the estimates of the house price volatility around the index. Since accurate measurement of house-specific volatility is critical in many economic settings, including asset pricing, portfolio allocation, the choice between investment and consumption, and derivative valuation, downward-biased volatility estimates is an especially troubling limitation of weighted repeat sales index methods.

In Figure 6, we graph the outstanding foreclosure inventory in the U.S. and long run S&P Case-Shiller residential house price index. As identified by Corradin, Fillat, and Vergara-Alert (2010) and shown in Figure 6, there appear to have been five prolonged episodes of significant house price appreciation (defined as at least two years of positive growth and at least one year of growth in excess of 5% annually) since 1930. The first episode occurred after the Great Depression; the second episode occurred after World War II from 1944 through 1947; the third episode occurred in the 1970's inflationary boom; the fourth episode is associated with the S&L driven credit expansion from 1984 through 1989; and, as previously



discussed, the fifth, and current, episode is associated with an important expansion in the availability of mortgage credit. The figure shows that each of these infrequent acceleration periods have always been followed by a period of rapid decelerations in returns.

Figure 6: U.S. Long Run Case Shiller Index Returns to U.S. Housing and the Mortgage Bankers Association (MBA) Outstanding Foreclosure Inventory in the U.S.



The long returns cycles suggest that long historical data series would be required to obtain robust estimates of the long-run drift of residential price dynamics and that this drift is likely to be time varying.<sup>17</sup> Unfortunately, the Mortgage Bankers Foreclosure Inventory series only goes back to 1979, so it is difficult to identify important patterns between the two series, other than the obvious spike in the foreclosure inventory when residential real estate returns plummeted at the end of 2007.

The dynamics presented in Figure 6, and corroborated elsewhere (See, Case and Shiller (1989) and Meese and Wallace (1997)), also indicate that house prices in the U.S. are mean-reverting and thus predictable. This suggests that the time varying drift term in Equation (6), should be further specialized to account for the predictability of the drift,  $\theta_{H,t}$ . One

<sup>17</sup>This observation is consistent with Merton (1980), who established that good estimates of the drift of stochastic processes requires very long time series of auction price data.

possible specialization, would be to assume that  $\theta_{H,t}$  follows an Ornstein-Uhlenbeck process:

$$d\theta_{H,t} = \kappa(\bar{\theta} - \theta_{H,t})dt + \phi_{\theta}dW_{\theta,t}, \quad (6)$$

where  $\kappa$  is the speed of mean reversion,  $\bar{\theta}$  is the long run mean. Dynamics of this type have recently been considered by Corradin, Fillat, and Vergara-Alert (2010), in a generalization of the classic Grossman and Laroque (1990) model of the optimal portfolio choice with durable goods (housing) and transaction prices. Their theoretical results, corroborated with empirical findings, indicate that the optimal trading policies of homeowners are time varying and decrease, alternatively increase, when housing prices are expected to rise, alternatively expected to fall (See, page 30, Corradin, Fillat, and Vergara-Alert (2010)). As previously discussed, these dynamics would not be consistent with the usual weighted repeat sales estimator.

## 4.2 Commercial Real Estate Indices

There are two dominant indices available to measure commercial real estate returns: the National Council of Real Estate Investment Fiduciaries (NCREIF) National Property Index (NPI) total returns series<sup>18</sup> and the National Association of Real Estate Investment Trust (NAREIT) returns series.<sup>19</sup> The NCREIF NPI is a measure of the total returns for investment grade properties that are held in the investment portfolios of U.S. pension funds. The NAREIT series tracks the total returns of all the publicly traded U.S. real estate investment trusts (REITs). Neither of these series address the index number problem since there are no controls for the underlying quality and composition of the real estate stock and the unit prices of this stock.

**NCREIF NPI** The NCREIF National Property total returns series is the most widely used benchmark of property-level commercial real estate investment performance in the U.S. The NCREIF total returns series is compiled from both the capital and the income performance of NCREIF monitored properties. Similar to the problems with the measurement of residential price dynamics, the NCREIF measures are also affected by infrequent trading and heterogeneity of the assets (Geltner and Goetzmann (1998) and Tu, Yu, and Sun (2004)), potential bias in transaction based indices induced by selection problems and liquidity variability (See, Fisher, Gatzlaff, Geltner, and Haurin (2003), Fisher, Geltner, and Webb (1994), and Gatzlaff and Geltner (1998)) and problems with seasonality and appraisal smoothing in

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<sup>18</sup><http://www.ncreif.org/property-index-returns.aspx>

<sup>19</sup><http://www.reit.com/IndustryDataPerformance/FTSENAREITUSRealEstateIndexHistoricalValuesReturns.aspx>

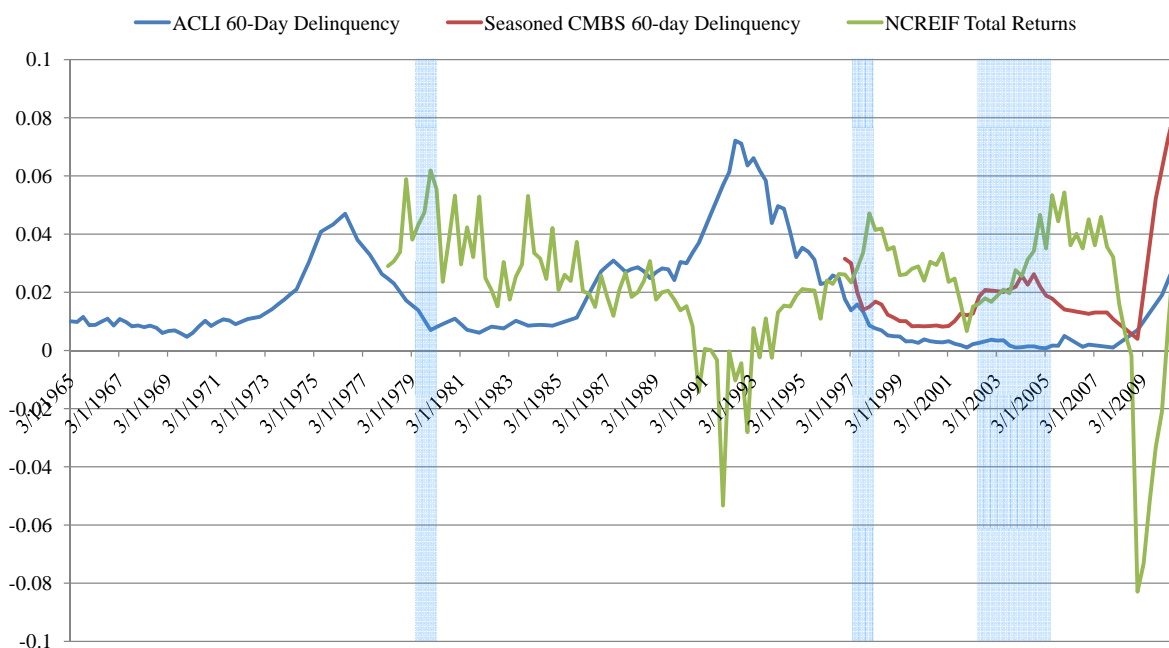
appraisal based indices (Clayton, Geltner, and Hamilton (2001)). The primary shortcoming with the NCREIF returns index is that it includes appraisals of property values in addition to transaction prices. The properties in the NCREIF database that do not transact are typically not re-appraised every quarter, and more properties are re-appraised in the fourth calendar quarter than in any other quarter. As noted by Geltner and Goetzmann (1998), the shortcomings of the NCREIF NPI induce smoothing, lags, and artificial seasonality in the returns series.

Figure 7 graphically compares the pre and post crisis commercial delinquency performance with prior historical performance. We plot the aggregate NCREIF NPI against the American Council of Life Insurers (ACLI) 60-day delinquency index.<sup>20</sup> A plot for the seasoned CMBS 60-Day Delinquency rate is also included in the graph because, by 2005, the life insurance companies held more than 50% of the outstanding stock of CMBS in the U.S. (See, Stanton and Wallace (2010a)). As shown, although the long-run average quarterly delinquency rate was about 1.77%. During the recessionary trough of Q2:1975 the delinquency rates rose to 4.7% and by Q1:1993 they had risen to 6.61% of the ACLI portfolios. Currently, the delinquency rate of seasoned CMBS is about 8%. The 1975 recessionary period was characterized by high oil prices (exceeding \$1 a gallon), high unemployment, and high inflation. A sub-peak of increased delinquency occurred in Q2:1987, when rates rose to 3.09% immediately following the 1986 Tax Reform Act and its severe curbs on tax motivated “non-economic” real estate investment. From 1987 onward, the oversupply problems caused by aggressive lending on the part of both S&L’s and commercial banks led to a sustained period of elevated delinquency rates that peaked in Q1:1993. This prolonged episode of elevated delinquency lasted until Q1:1998 when delinquency rates fell prior to the run-up in these rates during the current recession. Unfortunately, the NCREIF indexes do not go back as far as the recessionary trough that occurred in Q1:1975, but anecdotal evidence suggests this recession also led to significant declines in real estate returns due to the recessionary pressures on employment and rigidities in real estate lending markets. The current very elevated rates of delinquency in the CMBS market reflect the severity of the recession and a significant erosion in the asset prices for most property types, but particularly multifamily and hotel properties.

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<sup>20</sup>The ACLI delinquency data reflects the fraction of the commercial real estate portfolios of insurance companies that are 60 days in-arrears by quarter.

Figure 7: National NCREIF Quarterly Total Return Index and American Council of Life Insurers Quarterly 60-Day Delinquency Rates



The NCREIF NPI returns graphed in Figure 7 indicate that the periods of accelerations in returns in commercial real estate are shorter in duration than those of residential real estate episodes, with the exception of the crisis episode. As shown, there appear to be only three significant acceleration episodes in commercial real estate returns: in the high inflation period of the late 70's and early 80's; in high-tech boom of the late 90's; and the current episode. Unfortunately, the data do not include the commercial real estate returns from the Great Depression or those of the early 1970's. Overall, the acceleration episodes for commercial real estate are relatively infrequent and the peak to peak credit performance cycle appears to be about 16 years in length. These time series dynamics, again clearly indicate that long data series would be required to obtain robust estimates of the long-run drift of the commercial real estate returns.

**REIT returns** The second important returns index that is widely used for commercial mortgage valuation is the NAREIT index. One important advantage of the NAREIT returns series over the NCREIF NPI series is that REIT returns are based on equity trading prices, thus avoiding the appraisal biases associated with the largely appraisal-based NCREIF NPI. Of course, it is well known that the net asset value of the underlying real estate portfolio can differ from the market value of the equity of REITS. Unfortunately, the valuation of NAVs is not a reliable science, so usually the NAREIT returns series are used in an uncorrected

form. A second potential problem with using REIT returns as a proxy for the returns to commercial real estate in the U.S. is that REITs hold diversified portfolios of real estate assets, although most REITs are specialized in terms of their property type and geographic focus. The diversification of REIT portfolios should reduce the variance of the index returns, however, most REITs also make extensive use of leverage which pension funds tend not to do. Leverage would be expected to affect both the level and volatility of REIT returns. The combined affects of these forces on the REIT indices of real estate return dynamics is an empirical question.

Figure 8: National NCREIF Total Return Index Series and the NAREIT Total Returns Series

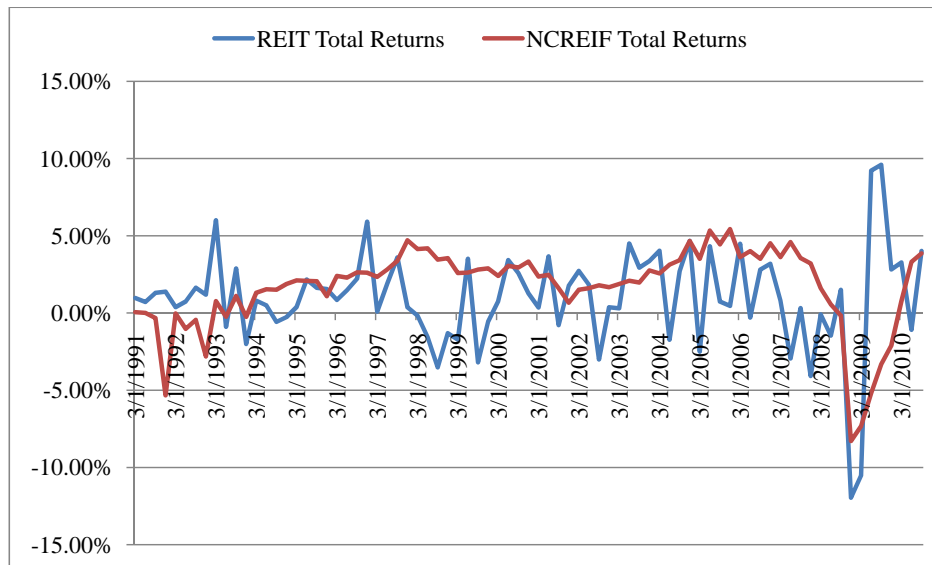


Figure 8 presents a graphical comparison of the NCREIF NPI returns series and the NAREIT returns series. As shown in Figure 8, the effects of appraisal smoothing appear to noticeably dampen the volatility of the NCREIF index compared to the NAREIT index returns. The effects of leverage in the REIT portfolios is another factor that limits the comparability of the two indices. The higher leverage of the NAREIT property portfolios would affect both the level and the volatility of the REIT returns compared to the NCREIF indices that monitor the returns of unlevered pension fund portfolios. Another interesting feature of the two series is, that other than the latest downturn, they do not track peaks and troughs in commercial real estate returns similarly. The important differences in these indices make it difficult to reliably make inference about the dynamics of the stock of commercial real estate in the U.S., even in the sense of having a stable and robust estimate for the drift in these dynamics.

## 5 Real Estate Price Volatility

Since default valuation is a function of volatility, accurate estimates of the instantaneous standard deviation of the house price and commercial real estate price dynamics,  $\phi_{H,t}$  and  $\phi_{p,t}$ , are required to value the default option exposure in the aggregate U.S. mortgage stock, in the outstanding mortgage portfolios of regulated financial institutions, or in the portfolio of a given financial institution. Accurate measurement of volatility is critical in many economic settings, including asset pricing, portfolio allocation, and the choice between investment and consumption. Surprisingly, there is only a small literature on the empirical estimation of the volatility of commercial real estate (See, Stanton and Wallace (2010a), Titman and Torous (1989) and Titman, Tompaidis, and Tsyplakov (2005)). Despite the known biases in repeat sales estimators, repeat sales indices are commonly used to calibrate residential real estate volatility. Known obstacles to obtaining robust estimators for the second moments of these distributions includes the lack of continuous trading in the assets, many fewer transaction prices are available than for other asset classes; and the heterogeneity of these assets which makes it difficult to aggregate the data that are available.

**Residential Real Estate Volatility** As previously discussed, most mortgage valuation in the U.S. uses estimates of  $\phi_H$ , the non-time varying estimate of house price volatility, obtained from the Case and Shiller (1989), or FHFA, weighted repeat sales estimation strategy. Under the basic mathematics of this estimator, it is assumed that the transaction price of a house is a function of the price and quantity of housing services provided,

$$\ln V_{it} = \ln \tilde{v}_{it} + \ln \tilde{q}_{it}, \quad (7)$$

where,  $V_{it}$  is the observed sales price of the house,  $\tilde{v}_{it}$  is the unobservable price per unit of housing services, and  $\tilde{q}_{it}$  is the unobservable quantity of housing services.

Using observable characteristics of the house as a proxy for the unobservable quantity of housing services the value of the house can be written as,

$$\ln V_{it} = X_{it}\beta_t + d_{it}\delta_t + \epsilon_{it}, \quad (8)$$

where  $X_{it}$  is a vector of characteristics (bedrooms, square footage, etc) and  $d_{it}$  is a dummy variable with value 1 if property sold at  $t$ .

If the house sells at time  $t$  and  $T$  then the log change in the house price is measured by:

$$\ln V_{it} - \ln V_{iT} = X_{it}\beta_t - X_{iT}\beta_T + d_{it}\delta_t - d_{iT}\delta_T + \epsilon_{it} - \epsilon_{iT}, \quad (9)$$

If, in addition, we assume that the characteristics of the house remain unchanged over time (i.e.  $X_{it} = X_{iT}$ ) and the implicit prices of each characteristic are also unchanged over time (i.e.  $B_t = B_T$ ), then we obtain the repeat sales estimating equation:

$$\ln(V_{it}/V_{iT}) = D_{itT}\delta + \xi_{itT}, \quad (10)$$

where  $D_{itT}$  is a matrix of dummy variables taking a value of -1 at time  $t$ , +1 at time  $T$  and zero elsewhere. The residual,  $\xi_{itT}$ , is equal to  $\epsilon_{it} - \epsilon_{iT}$ .

Consistent with our prior discussion about house price dynamics, as in Equation (6), the Case-Shiller estimator assumes that the average rate of change, or drift in the house price is represented by a constant market price index,  $\theta_H$ . The dispersion, or volatility, of price around the market index is modeled as a log normal diffusion, with a constant instantaneous standard deviation,  $\sigma_p$  and a white noise term associated with cross-sectional idiosyncratic differences in the valuation of unique properties. The volatility of the Gaussian diffusion is assumed to be a function of the time between the paired sales and the property-specific white noise is assumed to be uncorrelated over time and across properties. The S&P Case-Shiller index is obtained from a three stage estimation procedure. Estimates of the volatility parameters are a by-product of the second estimation stage and these are reported on the FHFA web site as a public service.

Table 1 presents volatility estimates from the S&P Case-Shiller web site. As shown, residential real estate annualized returns are 9.31% and their volatility is 2.77% annually. This suggests that residential real estate investments earn higher returns with less risk than stocks or corporate bonds. The only comparable level of returns is for REITs, however, they are substantially more volatile than the other three investment classes. Stanton and Wallace (2010b) compare volatility estimates using a weighted repeat sales estimator and a dynamic version of a hedonic estimator using a forty year long transaction database from the San Francisco metropolitan area. As reported in Table 1, the annualized estimate of  $\sigma_H$  for Alameda County is 12.490% and is 20.877% for San Francisco County and both are precisely estimated. These estimates suggest that houses prices have idiosyncratic volatility around the market index that is comparable to the overall stock market and to REITs (based on the values reported in Table 1). By contrast, the weighted repeat sales estimates for volatility were are 4.57% and 1.23% for Alameda County and San Francisco Counties respectively.

The important differences in these volatility estimates suggest that the volatility of individual house prices around the market index may be quite substantial.<sup>21</sup> As previously

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<sup>21</sup>? also find very large one-period ahead forecasting standard errors using Case-Shiller and FHFA WRS estimates as well as important differences between volatility estimates for their hedonic-based estimator and the WRS estimators.

Table 1: S&P Case-Shiller Web Site Asset Volatility Estimates

This table presents Standard and Poor’s estimated asset class returns and volatility for four asset classes: Housing, Bonds, Stocks and REITS. ([www.indices.standardandpoors.com](http://www.indices.standardandpoors.com))

Annualized		
Asset	Returns	Volatility
Housing	9.31%	2.77%
Bonds	5.97%	3.47%
Stocks	5.91%	14.72%
REITS	11.22%	15.22%

Table 2: Estimates for the Idiosyncratic Component of House Price Volatility

This table presents two estimates for house price volatility: 1) An estimate from the second stage of a weighted repeat sales specification of the squared residuals on the time between sales for Alameda and San Francisco Counties; and 2) An estimates from a dynamic hedonic model of house prices.

	Annualized $\sigma_p$	
	Point Estimate	Standard Error
Estimated Weighted Repeat Sales Alameda	4.575%	0.002%
Estimated Weighted Repeat Sales San Francisco	1.231%	0.116%
Estimated Simple Model Alameda	12.490%	0.041%
Estimated Simple Model San Francisco	20.877%	0.178%



discussed, a number of the assumptions underlying the WRS estimator would be expected to introduce downward bias in estimates of house price volatility. The known bias of the WRS estimator and the empirical evidence suggest that the magnitudes of the bias could be large. Low volatility estimates, of course, could lead to systematic underestimation of the default risk in mortgage products. The acknowledged failure of mortgage valuation and credit scoring technology in the U.S. and the known reliance of this technology on volatility estimates from WRS methods, all suggest that alternative estimators for obtaining unbiased estimates of house price volatility should be considered.

**Commercial Real Estate Volatility** There are three main methods that have been used to estimate commercial real estate volatility, two based on historical data, and one using implied volatility. The historical method to obtain commercial real estate volatility applies the NCREIF or NAREIT indices to calculate the volatility of the historical total returns series.<sup>22</sup> The top panel of Table 3 reports the volatility of various NCREIF total returns series from 1995 to 2005. Theoretically, volatility plays a crucial role in the exercise of default options, however, the shortcomings of the NCREIF and the NAREIT indices and the trading infrequency of real estate assets, present challenges for obtaining property specific measures of total return volatility.

As shown in the top panel of Table 3, the long run average by property-type ranges between 8.93% for multi-family and 5.75% for office properties over the period. These volatilities would be expected to reflect all of the appraisal smoothing problems noted above. In addition, they are computed from an index reflecting the average experience of investment grade real estate assets and thus tell us little about the expected idiosyncratic volatility of a specific asset as would be required in a structural model of commercial mortgage default.

From the National Association of Real Estate Investment Trust (NAREIT) website, it is possible to identify the appropriate property-type grouping for each REIT. The total returns series were then downloaded from CRSP for each REIT and were used to compute firm-specific annualized standard deviation of total returns. Since REITs are leveraged. We use Compustat to obtain each firm's face amount of long-term debt and their total market capitalization to compute the average annual leverage ratio for each firm. We then scaled the leveraged return volatility by one minus the leverage ratio to obtain an estimate of the unlevered volatility.

The bottom panel of Table 3, reports the summary statistics for the computed de-levered REIT volatilities organized by property-type. The mean volatility ranges from a high of 16.8% for industrial REITs to a low of 10.7% for multi-family REITs. As shown, there is

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<sup>22</sup>See, for example, Titman, Tompaidis, and Tsyplakov (2004).

considerable volatility across REITs within property-type groups with standard deviations ranging between 3.1% and 11.3% and this heterogeneity partly reflects differences in firm size and trading volumes. As expected the REIT average volatility estimates exceed those computed using the NCREIF indices and for most property-types are nearly twice as large. The REIT volatility estimates are likely to be a downwardly biased estimate of the true idiosyncratic property-specific volatility because REIT portfolios are diversified.

Stanton and Wallace (2010a) find, not too surprisingly, that the volatility levels reported in Table 3 generate nearly valueless embedded default options in structural commercial real estate valuation models. Instead, they develop an alternative method for estimating idiosyncratic property-level asset return volatilities that involves backing out the volatilities implied by the contractual structure of a sample of CMBS loans. Under this approach, they solve for the asset return volatility that is consistent with the observed coupon spread (coupon less risk-free rate) on a mortgage that is priced at par, holding fixed all of the other features of the mortgage contract.

Their strategy uses a structural model of mortgage prices, much like the well-known procedure for using the Black-Scholes model to back out implied volatilities for stock returns from data on option prices. They implement a structural model following equation 1 and equation 4, subject to appropriate boundary conditions, and solve the resulting two factor partial differential equation for the value of  $\phi_p$  that equates the observed and model prices for each mortgage. This mortgage valuation equation, follows the now-standard structural modelling approaches of Kau, Keenan, Muller, and Epperson (1990) and Titman and Torous (1989). Their mortgage specific implied volatilities, computed for a large sample of commercial mortgages, have several advantages over the historical measures described above. In particular, they are based on market prices and, because they are computed at the loan-level, they control for the specific underwriting characteristics of each loan such as the loan-to-value (LTV) ratio, the coupon, and the amortization and maturity structure. Thus, their method controls for the fact that all of the contractual features of each loan are jointly endogenous.

The estimated pre-crisis implied commercial real estate volatilities that were estimated by Stanton and Wallace (2010a) were: 26.6% for office; 22.8% for multi-family; 24.4% for retail; and 27.0% for industrial with standard deviations of 7.8; 7.9; 8.1; and 7.8 respectively. As is clear, the property-level volatilities implied by their structural model are well above those computed from historical property index returns (the NPI) and those computed by de-levering REIT returns. These implied volatility estimates generate expected default rates for simulated CMBS pools that are about 21% over a ten year holding period under the real probability measure. These default levels are consistent with the long run realized default

Table 3: Total Return Volatility Estimates Using NCREIF Total Return Indexes and De-Levered Firm-level REITs Total Returns over the Period 1995 through 2005

The upper panel of the table reports the annualized total returns volatility computed from the NCREIF quarterly total returns indexes by property type from 1978 through 2006. The lower panel reports the annualized de-levered total returns volatility from 1996 through 2006 for samples of REITs for the reported property types. The data for the upper panel was obtained from NCREIF and from the lower panel from CRSP and Compustat.

	No. of Obs.	Mean %	Std. Dev. %	Minimum %	Maximum %
NCREIF Index Volatilities					
Office Index		5.75			
Multi-Family Index		8.93			
Retail Index		5.80			
Overall Index		5.79			
De-Levered Firm-level REIT Volatilities					
Office REITs	20	15.5	6.6	8.5	39.2
Multi-Family REITs	18	10.7	3.1	5.4	16.4
Regional Mall REITs	9	13.2	10.2	5.4	38.8
Retail REITs	19	15.5	9.4	4.7	48.1
Industrial REITs	5	16.8	11.3	9.0	36.6

rates of about 18% found in the commercial real estate portfolios of insurance companies (See, Esaki (2002) and Esaki (2003)).

## 6 Correlation

From the equilibrium conditions of the classical asset pricing literature, real estate asset prices are the present value of future rents and this relationship implies negative correlation between interest rates and asset prices. Empirically, however, the shape of the term structure of interest rates may also include information about expected future growth rates, and to the extent that these growth rates simultaneously affect rents, it is empirically possible to realize zero valued, or even slightly positive correlations, between interest rates and rents. Furthermore, sign switches in these correlations tend to move over the business cycle with peaks associated with positive correlations and troughs associated with negative correlations. As a result, there remains an ambiguity about both the magnitude and sign of  $E[dW_r dW_p]$ .

Similarly, in the housing investment literature, equilibrium in the market for existing owner-occupied housing requires that homeowners, in their role as investors, earn the same one-period return on housing investments as on other alternative investments (See, Poterba (1984), Kearn (1979)). When the investor's choice is between owning and renting houses, the no-arbitrage condition implies that the short-term rent must equal the costs of owning. The rent-to-price ratio would then be determined by the user cost of capital, in a manner similar to how earnings/price ratios on stocks are determined by a factor that includes the interest cost, dividends, and expected appreciation. In the static version of this model, Poterba (1984) derives the no-arbitrage rent-to-price ratio as:

$$\frac{R_t}{H_t} = [(1 - t_y)(i + t_p) + d + \alpha + m - g^e], \quad (11)$$

where  $R_t$  is the per period marginal rental value of the housing services generated by the owner occupied homes,  $H_t$  is the house price at time  $t$ ,  $i$  is the nominal interest rate,  $t_y, t_p$  are the marginal income and property tax respectively,  $d$  is depreciation,  $\alpha$  is the risk premium required on assets with the risk characteristics of housing,  $m$  is the maintenance costs, and  $g^e$  is the investor's expected rate of nominal house price appreciation.

As is clear from the no-arbitrage condition, house prices would be anticipated to be negatively correlated with interest rates which is the finding in most empirical tests of this condition (See, Poterba (1984), Meese and Wallace (1992), Meese and Wallace (2003), and Himmelberg, Mayer, and Sinai (2005), among others). In a recent paper, Glaeser, Gottlieb, and Gyourko (2010) use simulations to solve a dynamic version of the model, assuming a

CIR interest rate process. Using data that includes the crisis years, they find semi-elasticities that are significantly lower than the semi-elasticities of -20 found by Himmelberg, Mayer, and Sinai (2005). Glaeser, Gottleib, and Gyourko (2010) argue that their finding of significantly lower but negative semi-elasticities are likely to reflect: 1) a wedge between private discount rates and market rates arising from borrower credit constraints; 2) the effects of supply responses in highly unconstrained local housing markets that largely offset interest rate effects; and 3) the fact that housing investors may be far less rational than is assumed in these markets, as suggested by Shiller (2005).

Another recent paper in the housing risk management literature (See, Corradin (2008)), considers the joint determination of rents and mortgage rates, since most owner occupied housing is purchased with mortgages with embedded default options. An important finding in this work, is that because defaulting homeowners move into the rental market, the rent risk premium directly affects the homeowners likelihood of default and, symmetrically, the lender charges a default risk premium *ex ante* that accounts for the homeowners optimal default strategy and the dead weight loss it incurs. This result suggests that the banks' responses to lending conditions may not only influence the housing market, but bankers decisions could also be influenced by the housing market, or by metrics for the dynamics of rents and prices. This endogeneity complicates empirical testing for the correlation between interest rates and house prices.

## 7 Real Option Components of Asset Prices

Aggregate residential investment is a significant share of gross domestic product (GDP). In the pre-crisis periods these investments accounted for nearly six percent of quarterly GDP in 2004 and the first two quarters of 2005, or approximately 35 percent of quarterly gross private domestic investment.<sup>23</sup> Given the significance of these expenditures, it is not surprising that a good deal of research has focussed on the determinants of housing investment. Previous approaches to modeling housing investment decisions include studies of aggregate housing investment in the classical  $q$ -theory framework, such as Kearl (1979), Poterba (1984) and Rosen and Topel (1988), and studies of investment under uncertainty by professional developers of new housing, such as Capozza and Sick (1991), Williams (1993), Capozza and Li (1994), and Downing and Wallace (2007)).

Most of the “real estate” real options literature has focused on aggregate demand uncertainty, assuming an irreversible linear production technology. Williams (1993) and Grenadier (2002) derive the symmetric Nash equilibrium development strategy for homogeneous pro-

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<sup>23</sup>These figures are drawn from the Bureau of Economic Analysis, Table 1.1.5, Gross Domestic Product.

ducers and find that the optimal investment trigger is a decreasing and convex function of the number of producers. Thus, fear of preemption leads to immediate investment and a diminished option value to delay. The optimal option exercise trigger, though increasing in the volatility of the demand shocks, is again attenuated by free entry. The trigger level is also a decreasing function of the drift in stochastic demand, so that all else being equal, producers invest sooner when growth in demand is higher. Finally, the optimal investment trigger is increasing in interest rates so the value of the option would increase at higher exogenous riskless interest rates. These models suggest that in competitive markets with perfectly elastic demand and linear production technology, uncertainty would delay investment, but the dominant effect of preemption would drive investment back to the Marshallian zero profit condition. These countervailing effects suggest that, in aggregate, uncertainty may have no effect on investment delays.

Novy-Marx (2005) considers an economy with aggregate demand shocks in a market characterized by an increasing cost-to-scale production technology and heterogeneity in the opportunity costs of adjustment. He finds that prices are negatively skewed because aggregate industry capacity responds asymmetrically to aggregate demand shocks, since real estate investors can add capacity quickly in response to rising demand but cannot adjust capacity as quickly to falling demand due to irreversibility. The degree of asymmetry in the equilibrium path of prices depends on the cost-to-scale of adding new capacity and the elasticity of prices with respect to supply. Under the assumed production technology, real option premia are found to be considerably higher than the rents to monopoly (or oligopoly) as in Williams (1993) or Grenadier (2002). The option value of waiting increases in volatility and the level of the interest rate and falls in the level of demand growth. In aggregate, firms have an incentive to delay investment due both to asymmetry in the price response and to significant positive option premia. Overall, the expected timing of real estate investments would be infrequent and lumpy.

Uncertainty in real options models affects irreversible investment in two ways: 1) through the effect of the firm's current investment on the expected path of its marginal profitability of capital and 2) through the effects of competitors' investments on the path of this marginal product. The first channel will always lead to a positive relationship between uncertainty and investment delays when demand curves are downward sloping and/or the production technology is characterized by decreasing returns to scale. The second channel leads to the same positive correlation since negative shocks will lead prices to fall and positive shocks will lead prices to be limited due to free entry. For these reasons, firm and aggregate level price elasticities of demand are important determinants of the relationship between uncertainty and investment in real world applications. Although there is not a consensus concerning the

empirical magnitude of the U.S. aggregate price elasticity of demand for housing, the bulk of evidence to date indicates that the demand-curve for housing is downward sloping. Still less is known about the underlying production technology for housing or other real estate assets, rendering the relationship between uncertainty and real estate investment an open empirical question.

Real option considerations are potentially important for the construction of real estate price indices. Theoretically price dynamics should be observed with jumps and the price distributions should be characterized by significant skewness arising from the real option exercise policies. These results suggest further specialization for Equations (6) and (4). One possible refinement would be to represent the equilibrium price process for real estate assets as an “attenuated” geometric Brownian, following Novy-Marx (2005). This attenuated process can be written as:

$$\ln P_t = \log P_0 + \ln Z_t - d \ln Y_t \quad (12)$$

where  $P_0$  is the initial market value of the asset,  $Z_t$  is a multiplicative demand shock,  $d$  is the depreciation rate, and  $Y_t$  is a supply term that is a function of the maximum of  $Z_t$  up to time  $t$ . Furthermore, the “attenuated” geometric Brownian is consistent with the intuition of Glaeser, Gottleib, and Gyourko (2010) concerning the importance of heterogeneity in the supply and demand elasticities of regional real estate markets in responses to shocks in fundamentals such as interest rates. Another alternative refinement would be to represent the multiplicative demand shocks as Poisson jumps in the diffusion that arise from investments that change the asset such as capital investments in energy efficiency technology. Neither of these components appear in the price index technology that is commonly used to value mortgages.

## 8 Conclusions

This paper has considered the suitability of four widely used real estate price indices (the S&P Case-Shiller Index; the FHFA index; the NCREIF NPI; and the historical NAREIT series) for valuing and monitoring the credit risk of U.S. mortgages. Our evaluation focuses on four properties of these indexes: unbiased estimation of the drift of real estate price dynamics; unbiased estimation of the volatility of real estate price dynamics; their suitability for measuring correlation between interest rates and real estate prices; their suitability for measuring growth dynamics, or the effects of real options components of real estate values. We find, despite their widespread use, that these indices generate downwardly biased estimates of the idiosyncratic volatility of prices around the index and, thus systematically

undervalue embedded default options in mortgage products. We also identify other specific properties, or required assumptions underlying the construction of these indices, that are likely to be problematic for mortgage pricing. These properties include the fact that none of these indices adequately address the index number problem for real estate assets. These price metrics thus mix price and quantity dynamics in non-transparent ways leading to likely biases in the measurement of the correlation between real estate “prices” and economic fundamentals, such as interest rates, and expected skewness in real estate price distributions arising from the real option components of real estate values. Overall, this analysis suggests there is a need to re-evaluate the use of these indices for mortgage risk management and to develop dynamic hedonic price indices that both address the index number problem and allow for flexible specifications for price and quantity dynamics.



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