Pricing the US Residential Asset through the Rent Flow: A Cross-Sectional Study*

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Abstract

A calibrated Lucas (1978) style dynamic exchange economy to value the U.S. rental residential properties through the rent cash flows can match the cross-section of the average price rent ratios from 1978 to 2007 with reasonable parameter values. However, from the view point of this calibration the period from 2002 to the end of 2007 appears severely overpriced. The model significantly understates the time series volatility of the price rent ratios. Moreover, the model understates the average rate of price appreciation and overstates the volatility of price appreciation. Recalculating the economies with conservatively calibrated transaction costs for the housing asset using the appropriate procedure in He and Modest (1995) mean that the average price rent ratios can assume any value within a large range which typically includes the half and twice the empirical average price rent ratio. Results exhibit robustness to simplifying the rent growth rates as an i.i.d. process or allowing for Kreps and Porteus (1978) utility rather than Constant Relative Risk Aversion (CRRA). About a third of the large cross-sectional variation in overpricing from 2002 to 2007 can be explained by the various dimensions of the regional subprime lending activity, one at a time: no or low documentation loans, origination year (2005 and before, 2006 and 2007), cash-out refinances, ARM loans and borrower FICO scores. In addition, the cross-section of average overpricing can predict the magnitude of the regional house price depreciations from 2007 until the third quarter of 2008 with more than 30% R-squared.

1 Introduction

There is substantial recent interest in understanding the residential property valuations in the US, especially after the recent financial crisis. Although many authors note that house price appreciations have drastically accelerated in the new millennium (see for example Shiller (2008)), it appears that the literature has not yet subjected a consumption based rational asset pricing model to the scrutiny of the actual house prices.

This paper presents a Lucas (1978) style consumption based asset pricing framework to price the housing asset in a single good economy. The housing asset in this paper is treated as a claim to future rent cash flows that can be used to buy the single consumption good. The representative consumer consumes a perishable goods flow calibrated to the aggregate US consumption of services and nondurables and the rent flows are calibrated to the shelter components of the Consumer Price Index (CPI) data available for many US regional classifications. To price the rent flow, we use the same stochastic discount factors often used to price common stock through the dividend flow (see for example Mehra and Prescott (1985), Lynch (2003) or Bansal and Yaron (2006) among many others).

In calibrated dynamic exchange economies where the representative consumer has a Constant Relative Risk Aversion (power) utility function, we find that the model is able to match the cross section of time series average level of the empirical price to monthly rent ratios for the nineteen regional classifications for the period from 1978 to 2007 with reasonable parameter values. Despite the parsimonious specification of the consumer euler equations, the regional heterogeneity in the rent flows allows the model to fit the average levels. From the view point of this calibration the period from 2002 to the end of 2007 appears severely overpriced. The model significantly understates the time series volatility of the price rent ratios. In addition, the model understates the average rate of price appreciation and overstates the volatility of price appreciation. Recalculating the economies with calibrated transaction costs for the housing asset mean that the average price rent ratios can assume any value within a large range which typically includes the half and twice the empirical average price rent ratio. Results exhibit robustness to simplifying the rent growth rates as an i.i.d. process or allowing for Kreps and Porteus (1978) utility rather than CRRA. And about a third of the large cross-sectional variation in overpricing can be explained by the various dimensions of the regional subprime lending activity, one at a time: no or low documentation loans, origination year (2005 and before, 2006 and 2007), cash-out refinances, ARM loans and borrower FICO scores. Moreover, the cross-section of average overpricing can predict the magnitude of the regional house price depreciations from 2007 until the third quarter of 2008 with more than 30% R-squared.

These findings highlight the aspects in which the residential asset price phenomena is anomalous from the view point of the consumption based asset pricing models which had some recent success in pricing equity portfolios starting with the equity dividend cash flows (see for example Hansen, Heaton and Li (2005) and Bansal, Kiku and Yaron (2007)). Moreover, the significant association of the difference between the empirical and theoretical price rent ratios with some particular measures of regional subprime activity and with subsequent price falls, suggest and quantify the important aspects of the US housing market in leading to the recent unsustainable house valuations in the country. The cross sectional approach taken in this paper proves useful especially since the time series dimension of available subprime activity data is quite limited or non-existent.[1]

The base specification we consider consists of an exchange economy with a representative consumer with power utility. There is a housing asset in the economy which produces a flow of the single good calibrated to the Rent of Primary Residence shelter component of the CPI available from the BLS. The real rent flows are calibrated by deflating with the national CPI all-items-less shelter also available from the BLS. The construction of the pricing kernel requires the calibration of aggregate consumption which we take as the consumption of non-durables and services less housing from the National Income and Product Accounts (NIPA) tables of the Bureau of Economic Analysis (BEA). In solving the euler equations implied

[1] See for example the American CoreLogic data provided by the Federal Reserve Bank of New York compiled using the Loan Performance dataset.

by the infinite horizon consumer's dynamic utility optimization problem, the joint process of aggregate consumption and rent growth rates is called for, which we characterize by a reduced form VAR. In implementing the VAR, we allow for the state dependence of the growth rates to be able to incorporate any low frequency dependence of the two variables on the business cycle. Parsimoniously, we use the dividend yield on the value weighted NYSE, AMEX and NASDAQ as the only predictive variable.

While the estimation results of the VAR at a monthly frequency reveal interesting low frequency business cycle dynamics for rent growth (see section 4.1), the results turn out robust to simplifying the growth process as i.i.d. (see section 5.2). Once estimated, the cash flow VAR is discretized using a methodology similar to Lynch and Balduzzi (2000) and given the discretization, the consumer's euler equation represents a linear system that can be solved using the approach described in Lynch (2003) and Mehra and Prescott (1985).

We use the discretized consumption and rent growth processes in a GMM framework to estimate the utility parameters similar to Constantinides and Ghosh (2008). Given the point estimates of the cash-flow processes, the model produces a cross section of the time series average of price rent ratios for the regions. This cross section of average price rent ratios in turn can be compared with the empirical cross section of average price rent ratios to guide the utility parameter values. In particular, we estimate the utility parameters by a formal over-identified GMM system with the moment conditions designed to fit the empirical cross section of the average price rent ratios.

Surprisingly, the GMM J-statistics are insignificant, with a risk aversion point estimate of 2 and an annual rate of time-discount of 0.99, indicating that the model can match the cross-section of the average price rent ratios from 1978 to 2007 with reasonable parameter values (see Table 5, Panel B). While there is a total of twenty regions, only 19 is used for estimating the utility preference parameters, we omit U.S. since it is the covered by the other 19.[2]

[2]Results are insensitive to the inclusion of the U.S. to the GMM estimation. Further, results are largely insensitive to the exclusion of the four larger areas: Northeast Urban, Midwest Urban, South Urban and West Urban.

The empirical range for the average price rent ratios calculated from 1/1975 to 6/2007 is between 194 and 333 (see Table 4). The empirical range for the volatility is between 8 and 38 (see Table 4). The theoretical mean and volatility ranges are from 190 to 330 and from 0.2 to 7 respectively (see Table 6). The model, while matching the ballpark of the averages, significantly understates the volatility of price rent ratios.

Turning to the price appreciation results, for the average rate of monthly price appreciations an empirical range is calculated from -0.03% to 0.40% (see Table 4). For the volatility of price appreciation the empirical range is 0.11% to 0.30% (see Table 4). On the other hand, the model understates the average rate of price appreciation and overstates the volatility by producing respective ranges of from -0.11% to 0.11% and from 0.41% and 0.86% (see Table 6).

Glaeser and Gyourko (2007) and Van Nieuwerburgh and Weill (2009) emphasize the distinction between owners and renters and owned homes and rented homes. Therefore, we are concerned about whether the price rent ratios that we use (available from Campbell et. al. (2008)) can be interpreted as a matched price rent ratio (i.e. price and rent associated with the same residence). To address this issue, where available, we compare the OFHEO growth rates (used in Campbell et. al. (2008) and used in this paper) with the Case-Shiller condominium price index, available from the Standard&Poors website. We find that the two series are very highly correlated with similar means and variances. Since condominiums are often rented as well as sold, we are able to reasonably use the Campbell et. al. (2008) data in our calibration of the model. We provide a detailed discussion of this issue in section 4.2.1..

A number of authors have argued that starting with around year 2000 (see Shiller (2008), Van Nieuwerburgh and Weill (2009), Favilukis et. al (2009)) the price rent ratios have risen fast. In Table 4, using the Campbell et. al. (2008) data, we report the means and standard deviations for the price rent ratio and price appreciations but using the start date as the first half of 2002 rather than the earlier dates indicated in the first column of that table, highlighting this unusual period. These price rent ratios are much larger than the theoretical price rent ratios with the cash flow calibration from the first half of 1978 to the second half of 2007 (the unconditional cash flow calibration).[3] In fact, in unreported results, using the same GMM framework described above we test and reject the hypothesis that our unconditional cash flow calibration can match the average price rent ratio for this latter period.[4]

So, how can we explain the price rent ratios for this period? Of course, to the extent that the model price rent ratio results presented in this paper can be interpreted as fundamentals based valuations, the difference between the empirical and model implied price rent ratios can be thought of as the non-fundamental part of the empirical prices. To understand the difference, we run cross sectional regressions of the regional differences on a constant and various subprime activity measures (one at a time) taken from the website of the Federal Reserve Bank of New York and are provided by the FirstAmerican CoreLogic Inc. using the Loan Performance Data. All twenty regions including the U.S. is used in the regressions. In particular, in the regressions the dependent variable is the difference between logs of empirical (of the period between the first half of 2002 and the second half of 2007) and theoretical price rent ratios (of the period between the first half of 1978 and the second half of 2007) for the 20 regions considered in this paper. The independent variable is the log of one subprime activity measure for the same 20 regions. We focus on the 13 fields which are the percent variables since it is important to use scaled variables (with the total number of subprime loans in that state) rather than unscaled. Results are suggestive of the features of the US housing market which lead to the current non sustainable level of prices. In particular, the percent subprime loans as a fraction of total number of mortgage loans outstanding means higher empirical price rent ratios relative to theoretical, borderline statistically significant with a t-statistic of 1.58 (see Table 13). Higher than 660 (lower than 600) FICO scores are associated with higher (lower) empirical prices again relative to the theoretical. The associated coefficient value of

[3]In fact for all regions, the difference is more than three standard deviations. The exception is Houston for which the difference is negative. Since the standard deviation of the average is less than the standard deviation of the variable, the price rent ratios of 2002 to 2007 appear even more extreme from the view point of the model.

[4]Unreported results also show that even when the cash flows are calibrated to after 2002, the model is rejected.

0.68 means that, close to half of the cross sectional variation of the non-fundamental part of the empirical prices can be explained by the cross sectional variation of the percentage of high FICO loans within the state universe of subprime loans. Higher fractions of subprime loans originated in 2007 or 2006 (before 2005) means higher (lower) relative empirical prices. No or low documentation fraction of subprime loans also means higher empirical prices; and so is the ARM (Adjustable Rate Mortgage) loans. Larger fraction of subprime loans used for purchases (cash-out refinances) mean lower (higher) empirical prices relative to theoretical. And nearly all associated t-statistics are significant. Moreover, unreported results show that results presented above are quantitatively similar when we use alternative starting dates like the 2000, 2001 or 2003 rather than 2002.

The difference between the empirical and model implied price rent ratios can also be considered as an independent variable rather than a dependent variable. To the extent that the historical empirical price rent ratios has been high relative to the model price rent ratios, one would expect subsequent prices to decline. To explore this intuition, we run a cross sectional regression of the absolute value of the percentage nominal house price fall for the regions on a constant and the difference between the empirical (of the period between the first half of 2002 and the second half of 2007) and model implied (of the period between the first half of 1978 and the second half of 2007) price rent ratios. We take the house price measures from the website of the National Association of Realtors (NAR). We consider various starting measurement dates for price declines ranging from 2006 to 2008 though the end date of measurement is always the third quarter of 2008. Results show that without much regard to the start dates considered for the price measurement, the difference between empirical and theoretical price rent ratios explain subsequent price falls. We obtain a coefficient of 0.57 when we start the price changes from 2007, with the implication that close to a third of the cross sectional variation in house price percent changes from 2007 to third quarter of 2008 can be explained by the cross sectional differences between the historical and theoretical price rent ratios (see Table 14).

An important feature of the residential housing markets is the transactions costs associated with the housing unit (see for example Mayer (2003)). The presence of transaction costs might significantly affect the pricing implications of the consumption based pricing models presented in this paper. To assess the effects of transactions costs, for power utility, we follow He and Modest (1995) and use the euler inequalities that replace the euler equations of consumption. To calibrate the proportional cost rate to use in the model, we use data from a popular website which provides state level closing cost dollar figures for a two hundred thousand dollar mortgage by means of surveys.[5] These costs include origination fees and title and closing fees and can be regarded as lower bounds for the proportional costs since there are also non-pecuniary costs associated with buying or selling a house. The calibrated costs range from 1.4% to 2% of the purchase price of a house[6]. Using calibrated utility parameter values from similar no transaction costs economies, we find that the presence of transaction costs can substantially enlarge the feasible set of equilibrium price rent ratios to include the equilibrium price rent ratio of the associated no transaction cost economy. We report a range of lower bounds from 68 to 93 for the average price rent ratios (see Table 15). The upper limits typically include twice the empirical average price rent ratios reported in Table 4 and is unreported.

Importantly, the range of results presented in this section are robust to simplifying rent growth rates as an i.i.d. process or allowing for Kreps and Porteus (1978) utility rather than power. For the Kreps and Porteus (1978) specification, the GMM J-statistic is insignificant with an elasticity of intertemporal substitution (EIS) of 0.9, a risk aversion of 6 and a rate of annual time discount of 0.97 (see Table 7, Panel B).

The paper is organized as follows: section two discusses the related literature, section three describes the economy, section four presents the calibration of the cash flows and the

[5]www.bankrate.com.

[6]Yao and Zhang in their base line calibration use larger transaction cost values, 3% for buying and 6% for selling. Mayer (2003) investigates the price performance of real estate auctions in selling real estate relative to the more traditional method of negotiated sale. Estimates from auctions in Los Angeles during the boom of the mid 1980s show a discount that ranges between 0 and 9 percent, while similar sales in Dallas during the real estate bust of the late 1980s obtained discounts in the 9 to 21 percent range.

calculation of the empirical statistics of the house prices, section five provides the results and finally section six concludes.

2 Related Literature

A few papers consider the rapid price appreciation and the behavior of price rent ratios in the new millenium. Case and Shiller (2003) ask the question of whether there is a bubble in the housing market. They explore the time series relationships between housing prices and fundamentals like personal income, unemployment and mortgage interest rates. They do not focus on rents like we do. Van Nieuwerburgh and Weill (2009) present and solve a spatial dynamic equilibrium model of the housing market where agent's can move in response to wage shocks. They show that if housing supply can not adjust immediately, house prices compensate for cross sectional productivity differences. In the model, calibrated 30 year increase in wage dispersion across the metropolitan areas are able to produce the 30 year increase in house price dispersion in the data. While we do not restrict the agents from moving across regions, we do not explicitly model the movement of the agents. Our analysis only assumes that the equilibrium is such that there are tenants in all regions at all times. Favilukis et.al.(2009) present an incomplete markets two-sector equilibrium model of housing and non-housing production where heterogenous households face idiosyncratic and aggregate risks. The model is able to match the change in the national price rent ratio in the data given the calibrated change in the foreign ownership of U.S. Treasury and domestic debt. In their set-up it proves harder to match the level of the national price rent ratio. Our set-up, while abstracting from the foreign capital influx, is able to match the level.

A number of papers focus on life cycle portfolio choice with housing. Campbell and Cocco (2003) consider a theoretical model of mortgage choice between FRM (Fixed Rate Mortgages) and ARM (Adjustable Rate Mortgages). In an environment with uncertain inflation a nominal FRM has a risky real capital value, whereas an ARM has a stable real capital value but short-term variability in required real payments. Numerical solution of their life-cycle model with borrowing constraints and income risk shows that an ARM is generally the attractive contract but less so for a risk-averse household with a large mortgage, risky income, high default cost, or low moving probability. Cocco (2005) considers a theoretical dynamic portfolio choice model and shows that investment in housing plays a crucial role in explaining the patterns of cross-sectional variation in the composition of wealth and the level of stockholdings observed in portfolio composition data. In his model, due to the investment in housing, younger and poorer investors have limited financial wealth to invest in stocks, which reduces the benefits of equity market participation. House price risk crowds out stockholdings, and this crowding out effect is larger for the low financial net-worth investors.[7] Koijen et. al. (2008) introduces a variable which captures the long-term bond risk premium calculated as the difference between the long-term interest rate and the recent average of short-term interest rates. They find that this variable can be motivated theoretically and further can explain the aggregate time series shares of FRM and ARM mortgages in the US. de Jong, Driessen, van Hemert (2007) formulate a dynamic portfolio choice model where agents are allowed to hedge against background house price risk by being able to trade in housing futures. They show that even though agents would like to hedge, the extent is limited due to the large idiosyncratic house price risk which can not be hedged using futures on a city-level house price index. In a related strand, some papers consider the effects of housing wealth on the consumers. Caroll, Otsuka and Slacalek (2006) estimate that higher housing wealth translates into higher consumption much more so than higher stock market wealth. They report a next-quarter marginal propensity to consume from a $1 change in housing wealth of about 2 cents with a final long run effect of 9 cents. Case et. al. (2005) report corroborating results where they find a statistically significant and rather large effect of housing wealth upon household consumption.

A few papers consider consumption based models with a housing asset. Piazzesi et. al.

[7]Other papers also have considered the effects of risky, illiquid housing on savings and portfolio choice (see for example Davidoff (2005), Flavin and Yamashita (2002), Fratantoni (2001), Goetzmann (1993), Hu (2005), Skinner (1994), Li and Yao(2009) and Yao and Zhang (2005) the references therein).

(2006) considers a consumption-based asset pricing model where housing is explicitly modeled both as an asset and a consumption good. Households with nonseparable preferences across the goods mean that they are concerned about the fluctuations in the relative share of housing in their consumption basket. Since the housing share moves slowly, a concern with composition risk induces low frequency movements in stock prices that are not driven by news about cash flow. The model predicts that the housing share can be used to forecast excess returns on stocks which they verify to be valid empirically. Lustig and van Nieuwerburgh (2005) use an incomplete markets dynamic equilibrium model and emphasize the role of housing as a collateral asset which allows economic agents to risk share. In their model, a decrease in house prices reduces the collateral value of housing, increases household exposure to idiosyncratic risk, and increases the conditional market price of risk. Indeed using aggregate data for the US, they find that a decrease in the ratio of housing wealth to human wealth predicts higher returns on stocks. Neither of these papers focus on the rental income from the properties as our paper and a cross-section of regions is not considered.

There is a strand of literature that empirically tries to identify sources of house price variation. For example, Poterba (1991) proposes that changes in the after-tax user cost of housing is responsible for large shifts in housing demand and that these demand shifts in turn explain a large part of house price movements. The user cost of housing includes factors like marginal income tax rate, nominal interest rate, the property tax rate, the depreciation rate of building capital, the premium required on assets with the risk characteristics of housing, the maintenance costs and expected rate of nominal house price appreciation which are all independent variables in his regressions. Our specification ignores the important tax and depreciation issues in pricing the house asset but able to produce endogenous real house price appreciation. Sinai and Souleles (2005), emphasize the role of owning a house as a hedge against fluctuations in rents. They use a simple model of tenure choice with endogenous house prices and find that rent risk (the volatility of rent growth) leads to higher house prices relative to rents which they are able to support theoretically as well. Van Lamont and Stein (1999) empirically document that in cities where the loan to value ratio is higher, house prices react more to personal income shocks. Similarly, Stein (1995) emphasizes the role of the down payment not only for volatility of house prices but also for the house trading volume.

Some papers focus on the design and choice between mortgage contracts. Campbell and Cocco (2003) assume the type of the mortgage contracts is pre-fixed, though Dunn and Spatt (1985) consider mortgage contract design and clauses explicitly through a bilateral game with asymmetric information between the bank and the borrower. [8] Finally, some papers focus on the housing market transaction costs. Campbell et. al. (2009) use data on house transactions resulting in the change of ownership for the entire state of Massachusetts from 1987 to 2008 for a total of close to 1.8 million transactions and estimate the community effects of foreclosure. They find that a foreclosure at a distance of 0.05 miles lowers the price of a house by about 1%.

While the above mentioned papers carefully explore a wide spectrum of issues related to the housing asset and the implications of house prices for consumers and stock market returns in particular, none formulates a theoretical model for actually pricing the housing asset itself through a consumption based model, which is the main contribution of our paper.

3 The Economy

Like Mehra and Prescott (1985) and Lucas (1978), we consider a standard one-good pure exchange economy. There is a single consumer interpreted as a representative for a large number of identical consumers. The consumption good is perishable so at each period, the representative consumer consumes the exogenously specified and calibrated aggregate consumption. There is a financial asset (the housing asset) which provides consumption good flows calibrated to residential rent flows in the US. We assume that residential rent

[8]A number of other papers have looked at optimal mortgage design, see for example Piskorski and Tchistyi (2008), Mayer et. al. (2008) and mortgage contract modification and renegotiation, Hubbard and Mayer (2008).

flows are stationary in the growth rate rather than the level.

3.1 The Representative Agent Preferences

The representative agent maximizes either the Constant Relative Risk Aversion (power) utility or the time inseparable Kreps-Porteus (1978) utility adopted by Epstein and Zin (1989) and Weil (1989).

With power utility, the representative agent maximizes the life time utility with intermediate consumption where her objective function can be written as:

$$E\left[\sum_{t=1}^{\infty}\delta^t \frac{C_t^{1-\gamma}}{1-\gamma}|S_1\right], \tag{1}$$

where γ is the relative-risk-aversion coefficient and δ is the time discount parameter and $E[.|S_t]$ denotes the expectation taken using the conditional distribution given the state of the economy at time t. C_t is the consumption at time t. A well known feature of this utility specification is that it restricts the elasticity of intertemporal substitution to be the reciprocal of the coefficient of relative risk aversion. These preferences have been extensively used in empirical work by Grossman and Shiller (1981), Hansen and Singleton (1982), and many others.

Epstein-Zin-Weil specification defines life time utility, Z_t, only recursively. In particular

$$Z_t = \left[(1-\delta)C_t^{\frac{1-\gamma}{\theta}} + \delta\left(E_t\left[Z_{t+1}\right]\right)^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{2}$$

where γ is the coefficient of relative risk aversion, δ is the time discount parameter, $\theta = \frac{1-\gamma}{1-\psi}$ and ψ is the elasticity of intertemporal substitution (EIS). The Epstein-Zin-Weil utility allows the parameters γ and ψ to be independently set; therefore breaking the link between relative risk aversion and elasticity of intertemporal substitution. The Epstein-Zin-Weil utility nests the power utility case when $1/\psi = \gamma$.

3.2 Solving for Price Rent Ratios

The Euler equation for the power representative agent's consumption problem is

$$E_t\left[\delta\frac{P_{i,t+1}+D_{i,t+1}}{P_{i,t}}(C_{t+1}/C_t)^{-\gamma}\right]=1, \tag{3}$$

where C_t is the aggregate consumption at time t, $P_{i,t}$ is the ex-dividend price of any asset i at time t and $D_{i,t}$ is the dividend of the asset i at time t. We introduce a housing asset, with price P_t at time t and rent flow R_{t+1} at time t+1. Then, the euler equation can be rewritten as:

$$E_t\left[\delta\left(P_{t+1}+R_{t+1}\right)\left(C_{t+1}/C_t\right)^{-\gamma}\right]=P_t. \tag{4}$$

We can conveniently restate the above equation like:

$$E_t\left[\delta(\frac{P_{t+1}}{R_{t+1}}+1)\frac{R_{t+1}}{R_t}(C_{t+1}/C_t)^{-\gamma}\right]=\frac{P_t}{R_t}. \tag{5}$$

Given a discretization for the state variable S, we follow Mehra and Prescott (1985) and Lynch (2003) and obtain equilibrium housing price to monthly rent ratios for each state by solving a linear system of equations.

Turning to the Epstein-Zin-Weil utility, Epstein and Zin (1991) use a dynamic programming argument to show that the maximization of the objective function in equation 2 implies an Euler equation of the form:

$$E_t\left[\left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right\}^{\theta}\left\{\frac{1}{1+R_{m,t+1}}\right\}^{1-\theta}(\frac{P_{i,t+1}+D_{i,t+1}}{P_{i,t}})\right]=1, \tag{6}$$

where $R_{m,t+1}$ is the return on the asset which delivers aggregate consumption as it's dividends (return on total wealth).

To obtain state by state equilibrium price to monthly rent ratios for the Epstein-Zin-Weil utility, we first solve for the return on total wealth. To achieve this, we set the dividends on this asset to aggregate consumption and the γ equal to $1/\psi$ and therefore speacializing the Epstein-Zin-Weil euler equation to the power utility case. We solve for the usual linear system of equations to obtain the equilibrium price-consumption ratios. Then, we perturb γ from $1/\psi$ to the desired γ value, using the price-consumption ratio of the previous step as the starting value to the system of non-linear equations that arise when $\gamma \neq 1/\psi$. In perturbing the γ, we place five thousand equally spaced grid points, in logarithmic scale, between $1/\psi$ and the desired γ value to ensure that the initial steps are small. The ending price-consumption ratios in conjunction with the consumption process yield, $R_{m,t+1}$. We then substitute the returns $R_{m,t+1}$ into the euler equation given in equation 6. This euler equation given the $R_{m,t+1}$ defines a linear system of equations in the price to monthly rent ratios.

3.3 Transaction Costs

In the presence of transaction costs for the assets in the economy, the euler equations of consumption are replaced by the euler inequalities. With power utility, He and Modest (1995) shows that if the transactions costs are paid in proportion to the amount traded and if the asset i has proportional cost, ρ_i, then the returns earned on the assets in equilibrium must satisfy:

$$\frac{1-\rho_i}{1+\rho_i} \leq E_t\left[\delta \frac{U'(C_{t+1})}{U'(C_t)} \frac{P_{i,t+1}+D_{i,t+1}}{P_{i,t}}\right] \leq \frac{1+\rho_i}{1-\rho_i}, \tag{7}$$

where $U(C) = C^{1-\gamma}/(1-\gamma)$. And for Epstein-Zin-Weil utility a similar line of argument can show that the weaker equilibrium restrictions can be written as:

$$\frac{1-\rho_i}{1+\rho_i} \leq E_t\left[\left\{\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\right\}^{\theta}\left\{\frac{1}{1+R_{m,t+1}}\right\}^{1-\theta}\left(\frac{P_{i,t+1}+D_{i,t+1}}{P_{i,t}}\right)\right] \leq \frac{1+\rho_i}{1-\rho_i} \tag{8}$$

An important component of the residential market transactions costs is the closing costs associated with the mortgage on the property. These costs are varied and may include origination fees and title and closing fees. Closing costs may be taken as a lower bound for transaction costs associated with the housing asset.

A linearly equally spaced grid with one hundred nodes between the upper limit and the lower limit is used and the resulting equal number of euler equations are solved with the same techniques as in section 3.2 but replacing the unity value on the right hand side with the grid node values. The lower (upper) bound for the price rent ratio is obtained when the euler equation is evaluated at the upper (lower) limit of the euler inequality.

4 Calibration

4.1 Aggregate Consumption and Rent Flows

The conditional joint distribution of aggregate consumption growth and the housing asset rent flow is allowed to be state dependent. The evolution of the joint distribution is described by a reduced form vector autoregression. In particular,

$$r_{t+1} - r_t \equiv \Delta r_{t+1} = a_r + b_r d_t + \nu_{t+1} \tag{9}$$

$$c_{t+1} - c_t \equiv \Delta c_{t+1} = a_c + b_c d_t + \epsilon_{t+1} \tag{10}$$

$$d_{t+1} = a_d + b_d d_t + \eta_{t+1}, \tag{11}$$

where r_t and c_t are real logarithmic rent and consumption for month t, and d_t is the end of the month t dividend yield. a_r, a_c and a_d are the regression intercepts and b_r, b_c and b_d are the regression coefficients. $\nu_{t+1}, \epsilon_{t+1}$, and η_{t+1} are stationary through time with zero unconditional mean and covariance matrix Σ.

Each of the rent, consumption and dividend yield series have different beginning and end dates. Rather than truncate each series to the longest common dates across the three, we run the three regressions with the longest data available for each pair. Error variances come from these regressions where error covariances come from the covariance of the contemporaneous errors. In theory, conditional correlations need not lie between -1 and 1 for a given sample, but empirical correlations never violate this range. The regressions are always run using exact-identified GMM and the errors come from the Newey-West procedure. We allow for 3 or 12 months of lags in computing the standard errors.

To calibrate the real per capita consumption growth we use the Table 2.3.5U from the Bureau of Economic Analysis (BEA). We add the dollar amounts for nondurables and services and subtract the dollar amount for housing. We normalize by population and deflate against US City Average CPI, all items. The logarithmic difference of this variable is $c_{t+1} - c_t$ in the paper.

We construct the 12 month dividend yield (d) series from the value weighed return series on NYSE, AMEX and NASDAQ with and without dividends following the procedure described in Fama and French (1988). The value weighted series are taken from the CRSP. Dividend yield is always normalized to have zero mean and unit variance. Estimation results of equations 10 and 11 are given in Table 1. Consumption data is available from 1/1959 to Dec/2006 and dividend yield data is available from 1/1927 to 1/2007. b_c is estimated at -0.03%, which can be considered borderline significant with a -1.56 t-statistic. Since dividend yield is a counter-cyclical variable, a negative coefficient intuitively means pro-cyclical consumption growth. The coefficient point estimate is relatively small compared to the unconditional standard deviation of consumption growth, 0.510%. This result is consistent with the long horizon risk literature demonstrating a small component in aggregate consumption growth predictable at low business cycle frequencies (see for example Bansal, Kiku and Yaron (2007), Kiku (2006), Bansal and Yaron (2004), Hansen, Heaton and Li (2005) and references therein). The autoregressive parameter for the dividend yield is estimated at 0.98 indicating the high persistence of this variable at a monthly frequency.

To calibrate the real rent flows, we start with the CPI (All Urban Consumers) Rent of Primary Residence not seasonally adjusted shelter component levels available from the

Bureau of Labor Statistics (BLS). The BLS calculates this component of CPI by directly asking sampled renter households their monthly rent.[9] While the BLS provides the CPI information for 45 regional classifications, the data is available for 34 regional classifications at a monthly frequency. Although sparse data often is available for earlier dates than we use in our study, we truncate earlier observations with no contiguity at a monthly frequency. We deflate the rents using the U.S. City Average, (not seasonally adjusted) all-items-less-shelter CPI level. Then we work with the difference of logarithms of the rental flows, $(r_{t+1} - r_t)$ in the paper. Of the 34 regional classifications, we omit size based classifications and end up with the 20 urban areas given in the first column Table 2.[10] Table 2 also reports the estimation results of equation 9. Like the consumption growth regression, the dividend yield is available from 1/1927 to 1/2007 and is always normalized to have zero mean and unit variance, all rent data ends in 1/2007. The start dates are varied but most all regions start from 2/1947, 2/1978 or 2/1987.

The regression R-squareds are typically rather small ranging from 4.99% to 0.06%. Almost all intercepts are estimated as positive indicating real growth in terms of all non-shelter CPI items. Turning to the regression coefficients all but one point estimate is negative which indicates intuitively procyclical rent growth. Moreover, almost all negative coefficients are statistically significant.

The VAR specification for the rent and consumption growth and dividend yield is very parsimonious especially since the only predictive variable for both of the growth rates is the lagged dividend yield. However, it also implies a particular pattern of predictability for $(r_{t+T} - r_t)$ and $(c_{t+T} - c_t)$ using d_t as the predictive variable. A natural concern associated with using the VAR is the possibility of misspecification which, if present, would be expected to affect the pricing results. To help assess whether this is an issue, we derive the moments associated with such a predictive regression for an arbitrary horizon of T months. In partic-

[9]Unreported results available from the authors show that our qualitative results are largely insensitive to using the Owner's Equivalent Rent shelter component rather than the Rent of Primary Residence.

[10]BLS provides CPI values for size A,B/C and D urban areas with populations respectively at 1.5 million, between 50 and 1.5 million and less than 50 thousand.

ular we note that, the rent growth equation 9, the consumption growth equation 10 and the dividend yield equation 11 imply;

$$y_{t+T} - y_t = a_y^T + b_y^T d_t + \epsilon_T \tag{12}$$

where ϵ_T is stationary though autocorrelated at a monthly frequency and

$$b_y^T = b_y \left[(1 - b_d^T)/(1 - b_d) \right] \tag{13}$$

$$a_y^T = T a_y + (b_y a_d/(1 - b_d))(T - (1 - b_d^T)/(1 - b_d)) \tag{14}$$

where y can be c or r. Starting with the moments for $T = 1$ which were used to obtain the parameter estimates in Table 1 and 2, we add moments for one or more other Ts all greater than 1. We add $T = 12$ to obtain one GMM system, $T = 12$ and 24 to obtain another, and both $T = 12$, $T = 24$ and $T = 36$ to obtain a third.

The Appendix A illustrates the steps of the implementation of the GMM estimation and Table 3 reports coefficient estimates and t-statistics. Focusing on row 1 of Table 3, we see that b_c stays the same at -0.03% when the additional long horizon frequency combinations are included in the GMM estimation (compare with Table 1). The rows below report for the rent growth equations for the regions. Comparing Tables 2 and 3, regardless of the chosen additional frequencies, almost always the coefficient estimates are similar in magnitude yet t-statistics only strengthen. The resulting GMM systems with additional frequencies are overidentifed but the GMM J statistic is always insignificant. Moreover, the results are similar for Newey-West standard errors obtained using 3 or 12 lags. It appears that the VAR specification is doing a good job of capturing rent and consumption growth predictability at both low and high frequencies, therefore in the rest of the paper, the calibration in Table 2 is used.

The VAR system presented in equations 9, 10 and 11 is discretized using the Tauchen and Hussey (1991) quadrature approximation.[11] Once the AR(1) describing the dividend yield is constructed, the dividend yield shocks implied by the discretization can be used to calculate the consumption and rent shocks similar to Lynch (2001). 19 grid points are used for the dividend yield state and 3 grid points are used for the consumption and rent shocks.[12] Unreported results available from the authors show that the quadrature values almost always replicate the data values, which suggests that the discretization is capturing the important features of the data.[13]

4.2 Utility Specification Parameters

The GMM framework can also be used for estimating the utility parameters: the relative risk aversion coefficient, γ and the time discount parameter, δ for the power specification and the elasticity of intertemporal substitution, ψ, in addition, for the Epstein-Zin-Weil specification. For any set of utility parameters, given the process characterized by the point estimates of equations 9, 10 and 11, the price rent ratios resulting from the procedures in section 3.2 can be compared to the actual price rent ratios (for the calculation of actual price rent ratios see the section, Empirical price rent Ratios, below) for the regions. One can then choose the utility parameters to obtain the best match between the model and empirical price rent ratios. In particular, consider a GMM error vector defined as:

$$g_T = 1/T \times \begin{bmatrix} \sum_{t=1}^{T}(P_t/R_t(\delta, \gamma, d_t; a_c, b_c, a_r^1, b_r^1, a_d, b_d) - \overline{(P^1/R^1)}) \\ \vdots \\ \sum_{t=1}^{T}(P_t/R_t(\delta, \gamma, d_t; a_c, b_c, a_r^m, b_r^m, a_d, b_d) - \overline{(P^m/R^m)}) \end{bmatrix} \tag{15}$$

In the above equation, a_c, b_c, a_d and b_d are the regression point estimates for the consumption growth and dividend yield equations described in section 4.1 and provided in Table 1.

[11]The authors would like to thank George Tauchen for making the Gauss code available through ftp.

[12]Balduzzi and Lynch (1999) find that the resulting approximation with three return points is able to capture important dimensions of the value weighted NYSE, AMEX and NASDAQ market predictability in the data.

[13]The only exception is the autoregressive coefficient of the dividend yield whose persistence is slightly understated by the quadrature approximation.

a_r^i and b_r^i are the regression point estimates of the rent growth equation for region i described in the same section and provided in Table 2. $\overline{(P^i/R^i)}$ is the empirical time series average of the price rent ratio for region i from t to T. $P_t/R_t(\delta, \gamma, d_t; a_c, b_c, a_r^i, b_r^i, a_d, b_d)$ is the model implied price rent ratio for region i at time t as a function of the preference parameters, δ, γ and the dividend yield at time t and parameterized over the cash flow parameters that follow the semicolumn. Integers from 1 to m index the regions considered in the estimation. It is straightforward to construct the error vector for the Epstein-Zin-Weil specification by allowing $P_t/R_t(.;.)$ to be a function of ψ (the elasticity of intertemporal substitution) as well. In application, the framework is useful since it is able provide overidentication as the number of parameters (2 or 3) is much less than the number of regions considered.

For each region, the model is able to produce price rent ratios for the 19 dividend yield nodes that represent the support of the unconditional distribution with zero mean and unit variance. To map from the empirical dividend yield, we normalize the dividend yield observations from 1/1978 (the start date of the longest common period for the regional rent-price ratio data) to 1/2007 (the end date of the dividend yield data) to have zero mean and unit variance. To obtain biannual numbers from the monthly dividend yield observations, we take the average of the six associated monthly values.[14] We use the model price rent ratio value for the closest dividend yield node to the empirical value calculated in this way. For the above error vector to have the same number of observations for each region we use 1/1978 as the start date.

Notice that the set-up is general enough so that the cash flow calibrations can come from a longer sample period than the the period over which the empirical price rent ratio averages are calculated.

Following Constantinides and Ghosh (2008), the GMM system is optimized over a discrete set of parameter values. The risk aversion coefficient is allowed to be 1.2, 1.5 and values from 2 to 10 in the increments of 1; and the time discount parameter can be 0.95, 0.97 and 0.99 at

[14]Results are virtually the same if we use the start or the end of period dividend yield values.

the annual frequency. The annual time rates of discounts are converted into the monthly by taking the 1/12th powers. And for the Epstein-Zin-Weil utility, elasticity of intertemporal substitution can range from 0.3 to 1.5 in the increments of 0.3. The set of grid nodes allowed for the utility parameters include that used by Constantinides and Ghosh (2008).[15]

In implementing the GMM, for the first stage weighing matrix we use an economically motivated diagonal weighing matrix with the diagonal elements being the number of housing units in each region.[16] [17] We chose the set of discrete preference parameter values that minimize the objective function and for this set of parameter values we construct the spectral density matrix, S, of the errors using either 3 or 12 newey-west lags at the biannual frequency. Then, for the second stage, we repeat the optimization, though, with the updated weighing matrix as the inverse of S. Calculation of the standard errors of the preference parameters estimates requires the jacobian of the error vector. And the partial derivatives needed for the jacobian of the error vector is calculated using a step size equal to 0.001% of the parameter estimate. Given the updated error vector and the inverse of the spectral density it is easy to conduct the GMM J-test for specification.

4.2.1 Empirical Price Rent Ratios

This section explains how we calculate the empirical price rent ratios used in the utility parameter calibration discussed in the last section. The section also describes the calculation of the empirical house price appreciation rates which we later use to compare with the model implications.

The empirical house price to rent ratios and house price appreciations are calculated using rent-price ratio data and house price data provided in Campbell et. al. (2008). The start dates of the rent-price ratios vary with the region but range from the first half of 1975 to

[15]Unreported results show that a reasonably finer set of grid values for the utility parameters yield quantitatively similar results.

[16]For each region, BLS provides the associated states of the region. We sum the number of housing units of the associated states, where the individual state housing unit numbers are obtained from the data provided by the Federal Reserve Bank of New York website compiled from the American CoreLogic data.

[17]Results are virtually the same if the identity matrix rather than the diagonal matrix is used in the first stage.

first half of 1978. Using the repeat-transactions house price index published by the Office of Federal Housing Enterprise Oversight (OFHEO), Campbell et. al. (2008) measure changes in the price of owner-occupied housing. The OFHEO index is computed from data on price changes of owner-occupied homes that transact more than once, and as a result the index approximately measures constant-quality price changes (see Calhoun (1996) for a description of the repeat-transactions methodology used by OFHEO). Like our paper, for the rent cash flows they use rent of primary residence of the CPI shelter component from the Bureau of Labor Statistics (BLS) and deflate house prices and rental growth using CPI all items less shelter available from the BLS. All the rent and house price data they use is available at a biannual frequency. Given the growth rates of rental and house prices, one can calculate price rent ratios for all other dates if the ratio is known for one date and micro data from the 2000 Decennial Census of Housing (DCH) is used to benchmark the level of the rent price ratio in 2000, employing a procedure described by Davis, Lehnert, and Martin (2008).

We start with their biannual rent to price ratios observed biannually and calculate time series estimates of the averages and standard deviations of price to monthly rent ratios observed at a monthly frequency.[18] [19]

Turning to the empirical house price appreciations, we start with their real biannual house price appreciations and calculate estimates of the times series averages and standard deviations of monthly price appreciations observed at the same frequency.[20]

The averages and the standard deviations are reported in Table 4. The average price to monthly rent ratios range between 194 for Houston and 333 for Los Angeles. The time series standard deviations range from 7.58 for Dallas to 38.19 for Los Angeles. For all areas but Houston, there has been positive real price appreciation on average. Average

[18]We would like to thank Campbell et. al (2008) for making their data publicly available.

[19]First we invert their ratios and multiply by 6 to obtain price to monthly rent ratios observed biannually. We simply take the average of this series and report as the mean estimate of the price to monthly rent ratio. To calculate the standard deviation of the price to monthly rent ratio at a monthly frequency we take the standard deviation of the inverted and scaled series and divide by the square root of 6.

[20]We raise each observation to power 1/6 to obtain monthly gross appreciations observed biannually and report the average of the resulting series as the mean estimate of the monthly price appreciation. To obtain the standard deviations, we take the standard deviation of the resulting series and divide by the square root of 6.

price appreciations range from -0.03% for Houston to 0.40% for San Francisco (monthly). Standard deviation of price appreciations range from 0.11% for Atlanta to 0.30% for Los Angeles. For the price rent ratios the standard deviation is roughly an order of magnitude smaller than the mean, while for the price appreciations the two are roughly the same order of magnitude.

There is a concern about whether the price rent ratios we use to calibrate our utility specification parameters, can be interpreted as a matched price rent ratio (i.e. price and rent associated with the same residence). Campbell et. al. (2008) start with a matched price rent ratio at year 2000 from the micro data available from the Decennial Survey of Housing and use the growth rates of the two variables to calculate the ratios biannually before and after 2000. They use the rent of primary residence CPI shelter component from the BLS (deflated by CPI all items less shelter) to calculate the rent growth rates. This data is compiled by surveys of renters. For prices, they use the repeat-transactions house price index published by the Office of Federal Housing Enterprise Oversight (OFHEO) to calculate the growth rates, which by definition are owned homes. Glaeser and Gyourko (2007) and Van Nieuwerburgh and Weill (2009) emphasize the distinction between owners and renters and owned homes and rented homes. For the rent-price ratios to truely reflect matched residences before and after 2000, the OFHEO growth rates has to reasonably mimic the growth prices of rented homes. To address this issue we compare the OFHEO growth rates with the Case-Shiller condominium price index, available from the Standard&Poors website. The Case-Shiller condominium price index is available monthly from for Los Angeles, San Francisco, Chicago, Boston and New York from 1/1995 to 8/2009. From 1/1995 to 12/2007, using the biannual times series of OFHEO prices available from Campbell et. al. (2008), we obtain high correlations between the percent changes in the prices of the five pairs. We also obtain a close match in means and variances.[21]

[21]The correlations are 0.82, 0.92, 0.58, 0.79 and 0.86 which are quite high (we average the monthly prices in Case-Shiller data to obtain bi-annual prices before calculating the percent changes). The means are 5.34%, 5.03%, 2.83%, 4.42%, and 4.65% respectively in Case-Shiller and 5.02% 4.56% 2.96% 3.93% and 4.18% in OFHEO respectively for the five regions. The standard deviations are 5.23%, 5.38%, 1.62%, 3.53% and 3.22% in Case-Shiller and 4.38% 3.62%

In short, the Case-Shiller condominium price change data and the OFHEO price changes appear reasonably correlated and have similar means and variances, allowing us to appropriately interpret the Campbell et. al. (2008) price rent ratios as matched.

5 Results

5.1 GMM Utility Parameter Estimates and J-Test for Specification

We estimate the utility parameters for the power and Epstein-Zin-Weil specifications using the GMM framework described in section 4.2.

For power utility, Panel B of Table 5 reports a risk aversion of 2 and a per annum discount rate of 0.99 when all regions are jointly estimated. The risk aversion is very precisely estimated with a standard error of 1% though the time discount rate is estimated much more imprecisely with a standard error of 3.91. The GMM J-test statistic is insignificant with a p-value of 0.29.

Taking the utility parameter values from Panel B of Table 5, Table 6 reports the model implied means and standard deviations of theoretical price rent ratios and price appreciations. Moments of the price appreciation can be calculated from the state by state values of the price rent ratio and the rent growth process. Moments are always calculated using the unconditional distribution of the state variable, d_t.

Table 6 reports a range of average price rent ratios from 190 for St. Louis and 330 for Los Angeles. Note that these values are in the same ballpark as the empirical averages reported in Table 4, indicating that the power utility specification does a fair job in matching the average level of the price rent ratios across the regions. This close match explains the insignificant GMM J-statistic. Again, Table 6 reports a range of theoretical standard deviations for the price rent ratios. The range is from 0.20 for Pittsburgh to 6.80 for Los Angeles. Comparing these standard deviations to the empirical standard deviations of the price rent ratios in

1.42% 2.76% and 2.54% in OFHEO, again respectively for the five regions.

Table 4, we see that the power utility specification substantially understates this moment. Turning to the house price appreciations, a range of values are implied from -0.11% for St. Louis to 0.11% for Los Angeles. A substantially more compact range is implied for the standard deviation of price appreciations from 0.41% for southern states to 0.86% for Boston. Comparing the average power utility price appreciations in Table 6 to data in Table 4, we see that the model substantially understates (over) the average (standard deviation) of price appreciations.

Rather than jointly estimating the utility parameters for all regions, it is of interest to apply the GMM procedure described in 3.2 for allowing the utility parameters to be region specific. Panel A of Table 5 sets the weighing matrix to 1, and reports the utility parameter estimates for the underidentified systems with the degenerate error vector now being only the relevant row of the error vector described in section 4.2. While there is some heterogeneity in the parameter estimates across the regions, risk aversion hovers around 1.2 to 3 and discount rate 0.97 to 0.99.

Turning to the utility parameter estimation results with Epstein-Zin-Weil specification, Panel B of Table 7 reports a risk aversion of 6 and a per annum discount rate of 0.97 and an intertemporal elasticity of substitution of 0.9 when all regions are estimated jointly. The risk aversion parameter is estimated rather precisely with a standard error of 12% though intertemporal elasticity of substitution and the time discount rate is imprecisely estimated with large standard errors. While the GMM J-test statistic is insignificant with a p-value of 0.14, this value is interestingly smaller than the power case, 0.29.

Table 8, takes the parameter estimates from the Panel B of Table 7 and reports the model implied means and standard deviations of theoretical price rent ratios and price-appreciations for the Epstein-Zin-Weil utility specification. A quick look at the results seem to suggest that, while fitting the ballpark of the average price rent ratios quite well, the model suffers from the same features as the power specification. For price rent ratios, the model temporal standard deviation is too low, and for price appreciations, the model temporal average is too low and the standard deviation is too high.

Panel A of Table 7, like in Table 5 for the power case, sets the weighing matrix to 1 and allows the utility parameters to be region specific. There is a larger range for the risk aversion now, ranging from 1.2 to 10 and intertemporal elasticity of substitution ranges from 0.3 to 1.5, though rate of time discount is 0.97 in all regions but one.

5.2 GMM Utility Parameter Estimates and J-Test for Specification, I.I.D. Rent Growth

Results of the multi-frequency GMM estimation described in section 4.1 and presented in Table 3 show that there is evidence for a low frequency predictable component in rent growth. However, it is interesting to also explore a simpler i.i.d. process for rent growth to check robustness. For this purpose, we calibrate the the VAR system given in equations 9, 10 and 11 constraining b_r to be zero for each region. This procedure keeps the unconditional moments of all three variables and the predictive regressions for the consumption growth and the dividend yield the same but adjusts the covariance matrix of the residuals to match the unconditional covariance matrix. Like the predictable rent growth cases considered thus far, the VAR process calibrated in this way can then be used in the procedure described in section 3.2 to obtain implications for the temporal moments of price rent ratio and price appreciations.

Tables 9 and 10 (11 and 12) report results for the power (Epstein-Zin-Weil) utility case similar to Tables 5 and 6 (7 and 8) but with i.i.d. rent growth. Focusing on the power specification, Panel B of Table 9 reports a risk aversion coefficient of 1.2 (rather than 2 for the predictable case in Panel B of Table 5) with a standard error of less than 0.5% and rate of time discount of 0.97 estimated much more precisely then the corresponding predictable rent growth case with a standard error of 0.23 (compare with 3.91 in Table 5). The GMM J-test is insignificant with a p-value very similar to the predictable case at 0.29. Table 10 takes the panel B jointly estimated set of utility parameters and calculates the means and the standard deviations of price rent ratios and price appreciations. The average price rent ratios in Table 10 are uniformly lower than those in Table 6. Since consumption growth is procyclical, this observation might appear as counterintuitive at first since one would expect the pro-cyclical rent growth would be assessed as an additional source of risk and lower equilibrium prices in the presence of predictability. In fact, if utility parameters are kept the same, the model produces lower price rent ratios when rent growth is predictable in a procyclical way.[22] In application, on the other hand, going from predictable to i.i.d. rent growth, risk aversion goes from 2 to 1.2 (pushing up price rent ratios), rate of time discount goes from 0.99 to 0.97 (pushing down price rent ratios). Overall, the rate of time discount dominates the decrease in risk aversion to yield lower price rent ratios.

The i.i.d. rent growth case suffers from the similar features as the predictable case: for price rent ratios, the model temporal standard deviation is too low, and for price appreciations, the model temporal average is too low and the standard deviation is too high. Notably though, the cross sectional variation, especially in the standard deviations of both the price rent ratio and price appreciations is significantly lower compared to the predictable case.

Turning to the Epstein-Zin-Weil specification results with i.i.d. rent growth, Panel B of Table 11 reports a risk aversion coefficient of 7, a time discount rate of 0.97 and an elasticity of intertemporal substitution of 0.9. Much like the predictable case results presented in Panel B of Table 7, the risk aversion parameter is estimated precisely while the other two parameters are estimated imprecisely. GMM J-test statistic is insignificant with a p-value unchanged at 0.14 reported up to two decimal points. Comparing the average price rent ratios in Tables 8 and 12, unlike the power case, the averages are uniformly higher for the i.i.d. case, reflecting the fact that agent prices the house asset more when the long horizon risk posed by the procyclical rent growth disappears. This is despite the fact that the calibrated risk aversion actually increases from 6 to 7. This finding is consistent with the long

[22]In unreported results, we conveniently fix risk aversion coefficient at 5 and the rate of monthly time discount 0.999; focussing on Northeast urban the average price rent ratio goes from 119.56 to 120.37 as rental growth goes from predictable to i.i.d..

horizon risk literature explaining equity portfolio returns from cash flows and showing that there is a strong interaction between low frequency dynamics of consumption and portfolio dividend cash flows and the Epstein-Zin-Weil utility specification which disentangles the elasticity of intertemporal substitution from the risk aversion coefficient (see Bansal, Kiku and Yaron (2007), Kiku (2006), Bansal and Yaron (2004), Hansen, Heaton and Li (2005) and references therein). Focusing on the other three model implications we consider, much like the predictable case for price rent ratios, the model temporal standard deviation is too low, and for price appreciations, the model temporal average is too low and the standard deviation is too high.

5.3 Explaining the Difference Between Empirical and Model Price Rent Ratios from the First Half of 2002 to the Second Half of 2007

To the extent that the price rent ratio results of power and Epstein-Zin-Weil models presented in this paper can be interpreted as fundamentals based valuations, the difference between the empirical and model implied price rent ratios can be thought of as the non-fundamental part of the empirical prices. And it is of interest to understand which regional factors can help explain the difference. For this purpose, we run cross sectional regressions of the regional differences on a constant and subprime activity measures taken from the website of the Federal Reserve Bank of New York and are provided by the FirstAmerican CoreLogic Inc. using the Loan Performance Data. In particular in the regressions the dependent variable is the difference between logs of empirical and theoretical price rent ratios for the 20 regions considered in this paper. The independent variable is the log of one subprime activity measure for the same 20 regions. The New York Fed website provides state by state values of 55 fields for owner occupied "active" (see New York Fed website for details) subprime housing units.[23] We focus on the 13 fields which are percent variables since it

[23] It is hard to provide a precise definition for subprime borrowers and New York Fed simply notes "Compared with prime mortgages, subprime mortgages are typically made to borrowers with blemished credit history or who provide only limited documentation of their income or assets".

is important to use scaled variables (with total number of subprime loans in that state) rather than unscaled.[24] The empirical price rent ratios are from the average of the price rent ratios from the first half of 2002 to second half of 2007.[25] The theoretical price rent ratios are the unconditional average price rent ratios implied by the four specifications considered: Power and Epstein-Zin-Weil utilities with i.i.d. and predictable rental processes provided in the first columns of Tables 6, 8, 10 and 12. Table 13 reports the results. The table reports coefficients and the t-statistics for the cross sectional regressions where both the independent and the dependent variables are normalized to zero mean and unit variance before the regressions are run. The regressions are estimated using exact identified GMM with no Newey-West correction. The theoretical unconditional averages are taken using the unconditional distribution of the discretization of the dividend yield on the NYSE, AMEX and NASDAQ. The subprime activity measures constitute the row headings of the table.[26]

Focusing on the first column of Table 13 reporting results for the power case where the theoretical price rent ratios are obtained assuming calibrated rent growth predictability, percent subprime loans as a fraction of total number of mortgage loans outstanding means higher empirical price rent ratios relative to theoretical, borderline statistically significant with a t-statistic of 1.58. Higher than 660 (lower than 600) FICO scores are associated with higher (lower) empirical prices again relative to the theoretical, statistically significant with a t-statistic of 4.95 (-4.63). The associated coefficient value of 0.68 means that, close to half of the cross sectional variation of the non-fundamental part of the empirical prices can be explained the cross sectional variation of percentage of high FICO loans within the state universe of subprime loans. Higher fractions of subprime loans originated in 2007 or 2006 (before 2005) means higher (lower) relative empirical prices. No or low documentation fraction of subprime loans also means higher empirical prices; and so is the ARM (Adjustable

[24]The exception is the first row which simply is the percentage subprime loans in the universe of all outstanding loans.

[25]Since, the loan Performance data is available at a state level rather than the 20 regions provided by the BLS, to compute the measure for any BLS region, we calculate the weighted average of the subprime measures using the total number of housing units in the associated states.

[26]For variable definitions see Appendix B.

Rate Mortgage) loans. Larger fraction of subprime loans used for purchases (cash-out refinances) mean lower (higher) empirical prices relative to theoretical. And all associated t-statistics are significant. Cash-out refinances and FICO greater than 660 have the most explanatory power for the gap between empirical and rent based theoretical prices (these two variables have the largest coefficients across the 13 variables). The explanatory powers are slightly higher when the i.i.d. rent growth is assumed in the calculating the theoretical price rent ratios rather than predictable. Nevertheless, using the power utility or Epstein-Zin-Weil utility based theoretical price rent ratios does not make an appreciable difference in the coefficients or the t-statistics. Moreover, unreported results show that results presented above are quantitatively similar when we use alternative starting dates like the 2000, 2001 or 2003 rather than 2002.

5.4 Explaining House Price Declines up to the Third Quarter of 2008

In contrast to the last section, the difference between the empirical and model implied price rent ratios can also be considered as an independent variable rather than a dependent variable. To the extent that the historical empirical price rent ratios has been high relative to the model price rent ratios, one would expect subsequent prices to fall. To explore this intuition, we run cross sectional regressions of the absolute value of the percentage nominal house price fall for the regions on a constant and the difference between the empirical and model implied price rent ratios. Coefficients and the t-statistics are provided in Table 14. Both the dependent and independent variables are log and normalized to have zero mean and unit variance. The start date of house price measurement is provided in the first column and the end date of measurement is always the third quarter of 2008. The regressions are estimated using exact identified GMM with no Newey-West correction. The empirical price rent ratios are from the average of the price rent ratios from the first half of 2002 to second half of 2007. The theoretical price rent ratios are the unconditional average price rent ratios implied by the four specifications considered: Power and Epstein-Zin-Weil Utilities with i.i.d.

and predictable rental processes. As usual, the theoretical unconditional averages are taken using the unconditional distribution of the discretization of the dividend yield on the NYSE, AMEX and NASDAQ. The house price measures are taken from the website of the National Association of Realtors (NAR).[27] Results reported in Table 14 show that irrespective of the start dates considered for the price measurement, the difference between empirical and theoretical price rent ratios explain subsequent price falls. Focusing on the power utility case with predictable rent growth, a coefficient of 0.57 means that close to a third of the cross-sectional house price changes from 2007 to third quarter of 2008 can be explained by the cross sectional differences between historical and theoretical price rent ratios. Like the subprime activity measure regressions considered in the previous section, the explanatory power's is slightly higher when the i.i.d. rent growth is assumed in the calculating the theoretical price rent ratios rather than predictable. Further, using the power utility or Epstein-Zin-Weil utility based theoretical price rent ratios does not make a significant difference in the coefficients or the t-statistics.

5.5 Transaction Costs

An important feature of the residential housing markets is the transactions costs associated with the housing unit (see for example Corradin et. al. (2009), Han (2006), Mayer (2003), van Ommeren (2008) and Schill et. al. (2004)). The presence of transaction costs might significantly affect the pricing implications of the consumption based pricing models presented in this paper. To assess the effects of transactions costs, for power utility, we follow He and Modest (1995) and use the euler inequalities that replace the euler equations of consumption. And for Epstein-Zin-Weil utility the modification is a straightforward extension of the argument provided in that paper. The solution procedure for the transaction cost problem is described in section 3.3.

[27]The NAR house price measures are provided state by state. To calculate the price fall for any BLS region we use the following procedure. All geographic areas of NAR are associated with a state indication, and for each of the state indications of the regions we take the median of the NAR area values.

To calibrate for the proportional cost rate to use in the model, we use data from a popular website which provides state by state closing cost dollar figures for a two hundred thousand dollar mortgage by means of surveys.[28] These costs include origination fees (application, commitment, document preparation, funding, origination or lender, processing, tax service, underwriting and wire transfer), and Title and Closing fees (appraisal, attorney, closing or settlement, credit report, flood certification, pest, other inspection, postage/courier, survey, title insurance and title work). For each of the regional classifications used in the paper the total closing cost as a percentage of the mortgage amount is calculated.[29] The data is collected by our data source for the year 2008. The closing costs can be treated as a lower bound on the one way entry or exit cost into a residential dwelling as there are also moving costs and other non-pecuniary costs associated with changing the neighborhood and the school district. Table 15 reports the percent cost rates for the same regional classifications used throughout the paper. These costs range from 1.41% for St. Louis to 1.99% for Houston.

Table 15 also reports the price rent ratio (monthly) results for the transaction cost cases. The presence of transaction costs theoretically enlarges the feasible set of equilibrium price rent ratios to include the equilibrium price rent ratio of the associated no transaction cost economy. Since the calibrated bounds turn out rather large we use the quarter of the cost rates given in Table 15. The utility parameters come from Panel B of Tables 5 and 7 for the power and Epstein-Zin-Weil utilities, respectively. Surprisingly, for each of the regions considered, there is a cost rate less than the maximum allowed so that the upper bound is twice as large as the average price rent ratios reported in Table 6 or 8. Therefore we report only the lower bounds in column 2 (3); these lower bounds range from 68 (67) for Dallas to 93 (91) for Chicago for power (Epstein-Zin-Weil) utility. The lower bounds are uniformly slightly higher for the power utility.

[28] www.bankrate.com.

[29] For the geographical areas that have more than one state associated, we use the median percent closing costs of the associated states. Pricing results are similar when we use the average rather than the median.

6 Conclusion

The paper explored the implications of a Lucas (1978) style model for pricing the housing asset where the house is treated as a claim to future rent flows. Rent flows are calibrated to the regional level of Rent of Primary Residence shelter component of the CPI from the BLS. The representative consumer is assumed to consume a consumption flow calibrated to the US aggregate nondurables and services. The representative consumer has a Constant Relative Risk Aversion utility. Rent and consumption growth rates are allowed to be state dependent to allow for potential low frequency dependence on the business cycle. We estimate the cash flows using a reduced form VAR and the utility parameters are estimated by over-identified GMM systems with the moment conditions designed to fit the cross section of average price rent ratios. The GMM J-statistics are insignificant. The implication is that the model can fit the cross section of empirical average price rent ratios. Even so, the model significantly understates the volatility of price rent ratio and the average rate of price appreciation and overstates the volatility of price appreciation. The presence of transaction costs are shown to significantly affect the pricing implications of the consumption based pricing models presented in this paper. To assess the effects of transactions costs, for power utility, we follow He and Modest (1995) and use the euler inequalities that replace the euler equations of consumption. The presence of transaction costs theoretically enlarges the feasible set of equilibrium price rent ratios so that, much too high price rent ratios than the empirical are still theoretically feasible. The difference between empirical and theoretical price rent ratios are related to the subsequent price changes and the various measures of regional level recent subprime loan activity. Results are robust to simplifying rent growth rates as an i.i.d. process or allowing for Kreps and Porteus (1978) utility rather than power. We think these are important results that enhance our understanding of the valuation of the housing asset especially in the aftermath of the recent financial crisis. For future work, we plan on incorporating the maintenance expenses of rental residential properties into the analysis. Since the maintenance expenses effect the net cash flows, they will likely affect pricing of the properties.

Appendix A: Implementation of the GMM Estimation

For simplicity, the appendix describes only the case where there is a single *additional* frequency, T, in addition to the one month frequency and for the rental growth set of equations (equations 9 and 11 in the text).

The four parameters are a_r, b_r, a_d and b_d. There are six normal regression moment conditions:

$$\begin{aligned} E(d_{t+1} - a_d - b_d d_t) &= 0 && (16) \\ E((d_{t+1} - a_d - b_d d_t)d_t) &= 0 && (17) \\ E(r_{t+1} - a_r - b_r d_t) &= 0 && (18) \\ E((r_{t+1} - a_r - b_r d_t)d_t) &= 0 && (19) \\ E(r_{t,t+T} - a_r^T - b_r^T d_t) &= 0 && (20) \\ E((r_{t,t+T} - a_r^T - b_r^T d_t)d_t) &= 0, && (21) \end{aligned}$$

where

$$b_r^T = b_r \left[(1 - b_d^T)/(1 - b_d)\right] \qquad (22)$$

$$a_r^T = Ta_r + (b_r a_d/(1 - b_d))(T - (1 - b_d^T)/(1 - b_d)). \qquad (23)$$

The sample error vector, g_T, of the moment conditions is:

$$g_T = 1/T \times \begin{bmatrix} \sum_{t=1}^T (d_{t+1} - a_d - b_d d_t) \\ \sum_{t=1}^T ((d_{t+1} - a_d - b_d d_t)d_t) \\ \sum_{t=1}^T (r_{t+1} - a_r - b_r d_t) \\ \sum_{t=1}^T ((r_{t+1} - a_r - b_r d_t)d_t) \\ \sum_{t=1}^T (r_{t,t+n} - a_r^T - b_r^T d_t) \\ \sum_{t=1}^T ((r_{t,t+n} - a_r^T - b_r^T d_t)d_t) \end{bmatrix}. \qquad (24)$$

D, (the jacobian of g_T), is defined as;

$$D = \begin{bmatrix} \frac{\partial g_T^1}{\partial a_d} & \frac{\partial g_T^1}{\partial b_d} & \frac{\partial g_T^1}{\partial a_r} & \frac{\partial g_T^1}{\partial b_r} \\ \frac{\partial g_T^2}{\partial a_d} & \frac{\partial g_T^2}{\partial b_d} & \frac{\partial g_T^2}{\partial a_r} & \frac{\partial g_T^2}{\partial b_r} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial g_T^6}{\partial a_d} & \frac{\partial g_T^6}{\partial b_d} & \frac{\partial g_T^6}{\partial a_r} & \frac{\partial g_T^6}{\partial b_r} \end{bmatrix}, \tag{25}$$

where g_T^i is the ith element of g_T for $i = 1, 2, 3, ..., 6$.

We can explicitly write D as;

$$D = \begin{bmatrix} -1 & -\bar{d}_t & 0 & 0 \\ -\bar{d}_t & -\bar{d_t^2} & 0 & 0 \\ 0 & 0 & -1 & -\bar{d}_t \\ 0 & 0 & -\bar{d}_t & -\bar{d_t^2} \\ \frac{-\partial a_r^T}{\partial a_d} - \frac{\partial b_r^T}{\partial a_d}\bar{d}_t & \frac{-\partial a_r^T}{\partial b_d} - \frac{\partial b_r^T}{\partial b_d}\bar{d}_t & \frac{-\partial a_r^T}{\partial a_r} - \frac{\partial b_r^T}{\partial a_r}\bar{d}_t & \frac{-\partial a_r^T}{\partial b_r} - \frac{\partial b_r^T}{\partial b_r}\bar{d}_t \\ \frac{-\partial a_r^T}{\partial a_d}\bar{d}_t - \frac{\partial b_r^T}{\partial a_d}\bar{d_t^2} & \frac{-\partial a_r^T}{\partial b_d}\bar{d}_t - \frac{\partial b_r^T}{\partial b_d}\bar{d_t^2} & \frac{-\partial a_r^T}{\partial a_r}\bar{d}_t - \frac{\partial b_r^T}{\partial a_r}\bar{d_t^2} & \frac{-\partial a_r^T}{\partial b_r}\bar{d}_t - \frac{\partial b_r^T}{\partial b_r}\bar{d_t^2} \end{bmatrix}, \tag{26}$$

where $\bar{d}_t$ is the sample mean of d_t and $\bar{d_t^2}$ is the sample mean of d_t^2.

D, can be explicitly calculated since the below derivatives can also be written explicitly like belows:

$$
\begin{aligned}
\frac{\partial a_r^T}{\partial a_d} &= (b_r/(1-b_d))(T-(1-b_d^T)/(1-b_d)) && (27)\\
\frac{\partial a_r^T}{\partial b_d} &= b_r a_d T(1-b_d)^2 - b_r a_d\left[(Tb_d^{T-1})(1-b_d)^2 + 2(1-b_d)(1-b_d^T)\right]/(1-b_d)^4 && (28)\\
\frac{\partial a_r^T}{\partial a_r} &= T && (29)\\
\frac{\partial a_r^T}{\partial b_r} &= a_d/(1-b_d)\left[T-(1-b_d^T)/(1-b_d)\right] && (30)
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial b_r^T}{\partial a_d} &= 0 && (31)\\
\frac{\partial b_r^T}{\partial b_d} &= b_r\left[(Tb_d^{T-1})(1-b_d) + (1-b_T^d)\right]/(1-b_d)^2 && (32)\\
\frac{\partial b_r^T}{\partial a_r} &= 0 && (33)\\
\frac{\partial b_r^T}{\partial b_r} &= (1-b_d^T)/(1-b_d). && (34)
\end{aligned}
$$

Since the number of moment conditions is greater than the number of parameters, the system is overidentified. GMM prescribes,

$$min_{a_d,b_d,a_r,b_r} g_T' S^{-1} g_T, \tag{35}$$

where S can be set to the identity matrix initially.

We start with the exactly identified set of a_r, b_r, a_d, b_d without the extra frequency, T (these are the OLS estimates). We then consider the system including the extra frequency T, with S=I where I is the identity matrix. As suggested by Ferson and Foerster (1994), the procedure then iterates between the parameters and S until the input parameters are close to the output parameters (each parameter satisfies the condition that absolute value of the ratio of the difference between the exit value to the one before the exit value to the exit value is less than 10−3). After initialized as the identity matrix, S is always calculated as described in Newey-West (1987) with lags equaling to the longest horizon included in the system. Asymptotic variance-covariance matrix of the estimates can be calculated by $(D'S^{-1}D)^{-1}/n$, where n is the number of observations.

Appendix B: Definitions of Subprime Activity Measures used in Table 13

The subprime activity measures used in Table 13 are taken from the website of the Federal Reserve Bank of New York and are provided by the FirstAmerican CoreLogic Inc. using the Loan Performance Data. Below we reproduce the variable definitions provided by the Federal Reserve Bank website. All variables are scaled with the total number of subprime loans in that state. The exception is the first row which simply is the percentage subprime loans in the universe of all outstanding loans.

subprime loans: Compared with prime mortgages, subprime mortgages are typically made to borrowers with blemished credit history or who provide only limited documentation of their income or assets.

FICO ≥ 660 / FICO ≤ 600 : FICO is a credit bureau risk score. The higher the FICO score, the lower the likelihood of delinquency or default for a given loan. Also, everything else being equal, the lower the FICO score, the higher will be the cost of borrowing/interest rate.

LTV: LTV stands for the combined Loan to Value and is the ratio of the loan amount to the value of the property at origination. Some properties have multiple liens at origination because a second or piggyback loan was also executed. Our data capture only the information reported by the first lender. If the same lender originated and securitized the second lien, it is included in our LTV measure. Home equity lines of credit, HELOCS, are not captured in our LTV ratios.

no or low documentation: Percent Loans with Low or No Documentation refers to the percentage of owner-occupied loans for which the borrower provided little or no verification of income and assets in order to receive the mortgage.

purchases: Purchases refers to loans originating due to the purchase of a property. Loans may also originate due to Cash-Out Refinancing and other unspecified reasons.

cash out refinances: Cash-Out Refinances means that the borrower acquired a nonprime loan as a result of refinancing an existing loan, and in the process of refinancing, the borrower took out cash not needed to meet the underwriting requirements.

loans used for other purpose: Percent Loans Used for Other Purchases is the percent of loans which were not originated for cash-out refinancing or purchase.

ARM loans: ARMs stands for adjustable rate mortgages and means that the loans have a variable rate of interest that will be reset periodically, in contrast to loans with interest rates fixed to maturity.

References

Bansal, R., Yaron, A., 2004. Risks for the long- run: A potential resolution of asset pricing puzzles. Journal of Finance 59, 481-509.

Bansal, R., Kiku, D.,Yaron, A., 2007. Risks for the long-run: estimation and inference. Unpublished working paper.

Calhoun, C., 1996. OFHEO house price indexes: HPI technical description, Office of Federal Housing Enterprise Oversight.

Case, E., K., Quigley, M., J., and Shiller, R., 2005. Comparing wealth effects: the stock market versus the housing market. Advances in Macroeconomics 5, 1-34.

Case, E., K., Shiller, R., 2003. Is there a bubble in the housing market? Brookings Papers on Economic Activity, 2 299-362.

Campbell, J., 1999, Asset prices, consumption and the business cycle, in John B. Taylor, and Michael Woodford, eds.: Handbook of Macroeconomics, Elsevier Science, North-Holland, Amsterdam.

Campbell, J., Giglio, S., Pathak, P. 2009. Forced sales and house prices. Unpublished working paper.

Campbell, J., Cocco, J., 2003. Household risk management and optimal mortgage choice. Quarterly Journal of Economics 118, 1449 - 1494

Campbell, S., Morris, D., Gallin, J., Martin, R., 2008. What moves housing markets: a variance decomposition of the rent-price ratio. Journal of Urban Economics 66, 90-102

Carroll, C., D., Otsuka, M., Slacalek, J., 2006. How large is the housing wealth effect? Unpublished working paper.

Constantinides, G., Ghosh, A., 2008. Asset pricing tests with long run risks in consumption growth. Unpublished working paper.

Cocco, J., 2005. Portfolio choice in the presence of housing. The Review of Financial Studies 18, 535567.

Corradin, S., Filla, J., Vergara-Alert, C.,2009. Optimal Portfolio Choice with Predictability in House Prices and Transaction Costs, Unpublished working paper

Davidoff, T., 2005. Labor income, housing prices, and homeownership. Journal of Urban Economics 59, 209-235.

Davis, A. M., Lehnert,. A. and Martin, R.F., 2008. The rent-price ratio for the aggregate stock of owner-occupied housing. Review of Income and Wealth, 54, 279-284.

Dunn, K., Spatt, C., 1985. An analysis of mortgage contracting: prepayment penalties and the due-on-sale clause. Journal of Finance, 40, 293-308.

Epstein, L., Zin, S.,1989. Substitution, risk aversion and the temporal behavior of consumption and asset returns: Econometrica 57, 937-969.

Epstein, L., Zin, S.,1991. Substitution, risk aversion and the temporal behavior of consumption and asset returns: An empirical investigation. Journal of Political Economy 99, 263-286.

Favilukis, J., Ludvigson, C., S., and Van Nieuwerburgh, S., 2009. The macroeconomic effects of housing wealth, housing finance, and limited risk-sharing in general equilibrium. Unpublished working paper.

Ferson, W., Foerster, S., 1994. Finite sample properties of the generalized method of moments in tests of conditional asset pricing models. Journal of Financial Economics 36, 29-55.

Flavin, M.,Yamashita, T., 2002. Owner-occupied housing and the composition of the household portfolio. American Economic Review 92, 345362.

Fratantoni, M., 2001. Homeownership, committed expenditure risk, and the stockholding puzzle. Oxford Economic Papers 53 241259.

Glaeser, E., Gyourko, J., 2007. Arbitrage in housing markets. Unpublished working paper.

Goetzmann, W., 1993. The single family home in the investment portfolio. Journal of Real Estate Finance and Economics 6, 201222.

Grossman,S., Shiller,R., 1981. The determinants of the variability of stock market prices. American Economic Review 71, 222-227.

Hall, R. E., 1988, Intertemporal substitution in consumption. Journal of Political Economy 96, 339-357.

Han, L., 2006. Hedging House Price Risk in the Presence of Lumpy Transaction Costs. Unpublished working paper.

Hansen, L., Singleton, K., 1982. Generalized instrumental variables estimation of nonlinear rational expectations models. Econometrica 50, 1269-1289.

Hansen, L., Heaton, J., N, Li, 2005. Consumption strikes back? Measuring long-run risk. Unpublished working paper.

He, H., Modest, M., D., 1995. Market frictions and consumption-based asset pricing. The Journal of Political Economy 103, 94-117.

Hu, X., 2005. Portfolio choices for home owners. The Journal of Urban Economics 58, 114-136.

Hubbard, G., Mayer, C., 2008. house prices, interest rates, and the mortgage market meltdown, Working paper, Columbia Business School.

de Jong, F., Driessen, J., van Hemert, O., 2007. Hedging house price risk: portfolio choice with housing futures. Unpublished working paper.

Kiku, D., 2006. Is the value premium a puzzle?. Unpublished working paper.

Koijen, R., Van Hemert, O., and Van Nieuwerburgh, S. 2008. Mortgage timing. Forthcoming in the Journal of Financial Economics.

Lamont, O., Stein, J., 1999. Leverage and house-price dynamics in U.S. cities, Rand Journal of Economics 30, 498-514.

Li, W., Yao, R., 2009. The life-cycle effects of house price changes. Forthcoming in the Journal of Money, Credit and Banking.

Lynch, A., 2001. Portfolio Choice and Equity Characteristics: Characterizing the Hedging Demands Induced by Return Predictability, Journal of Financial Economics 62, 67- 130.

Lynch, A., 2003. Portfolio Choice with Many Risky Assets, Market Clearing and Cash Flow Predictability. Unpublished working paper, NYU.

Lucas, R., 1978. Asset prices in an exchange economy, Econometrica 46, 1429-1445.

Lustig, H. N., Van Nieuwerburgh, S., G., 2005. Housing collateral, consumption insurance and risk premia: an empirical perspective, Journal of Finance, Vol 60, 1167-1219.

Mayer, C., 2003. Assessing the Performance of Real Estate Auctions. Federal Reserve Bank of Boston.

Mayer, C., Piskorski, T., and Tchistyi, A., 2008. The inefficiency of refinancing: why prepayment penalties are good for risky borrowers. Working Paper, Columbia Business School.

Mehra, R., Prescott, 1985. The equity premium, Journal of Monetary Economics 15, 145-161.

Newey, W., West, K., 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix , Econometrica 55, 703-708.

Van Nieuwerburgh, S., Weill, P., 2009. Why has house price dispersion gone up? Forthcoming in the Review of Economic Studies.

Van Ommeren, Jos., 2008. Transaction Costs in Housing Markets. Unpublished working paper.

Piazzesi,M., Schneider, M., Tuzel, S., 2007. Housing, consumption and asset pricing. Journal of Financial Economics 83, 531-569.

Piskorski, T., Tchistyi, A., 2008. Stochastic house appreciation and optimal mortgage lending. Working Paper, Columbia Business School.

Poterba, J., 1991. House price dynamics: the role of tax policy and demography. Brookings Papers on Economic Activity 2, 143-203.

Shiller, R., 2008. The subprime solution, Princeton University Press, Princeton, NJ.

Schill, M., Voicu, I., and Miller, J., 2004. The condominium v. cooperative puzzle: an empirical analysis of housing in new york City. NYU, Law & Economics Research Paper No. 04-003.

Sinai, T., Souleles, N., 2005. Owner-occupied housing as a hedge against rent risk, Quarterly Journal of Economics 120, 763-789.

Skinner, J., 1994. Housing and saving in the United States in Yukio Noguchi and James M. Poterba, eds., Housing Markets in the United States and Japan (Chicago, IL: University of Chicago Press), 191-213

Stein, J., 1995, Prices and trading volumes in the housing market: a model with down payment effects. The Quarterly Journal of Economics 110, 379-406.

Tauchen, G., Hussey, R., 1991. Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models. Econometrica 59, 317-96.

Vissing-Jorgensen, A., 2002. Limited asset market participation and elasticity of intertemporal substitution. Journal of Political Economy 110-4, 825-853.

Yao, R., Zhang, H., 2005. Optimal consumption and portfolio choices with risky housing and borrowing constraints. The Review of Financial Studies 18, 197239.

Table 1. Regression intercepts, coefficients, t-statistics, variable and residual variances: Consumption and Dividend Yield. The table provides estimation results for the VAR specification given in equations 10 and 11. The system is estimated by exactly identified GMM using monthly observations. Standard errors come from the Newey and West (1987) procedure with 3 or 12 lags. Regression intercepts, coefficients, variable and error variances, covariances and correlations are reported. The dividend yield (d/p) is normalized to have zero mean and unit variance. The dividend yield is the 12-month dividend yield on the value weighted NYSE,AMEX, and NASDAQ constructed using the procedure described in Fama and French (1988) using return series on the NYSE, AMEX and NASDAQ with and without dividends from the CRSP. Consumption is log, real, per capita data from the table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing. Real consumption is obtained by deflating against US City Average CPI, all items from the Census Bureau and is multiplied by one hundred before the regressions are run. Error covariances come from matching date residual covariances while error variances come from individual regressions. Consumption data is available from 1/1959 to Dec/2006 and dividend yield data is available from 1/1927 to 1/2007.

	d/p	Δ cons.
intercept	0.0000	0.1670
t-stats (3lags)	0.00	9.12
t-stats (12lags)	0.00	8.23
coefficient	0.98	-0.03
t-stats (3lags)	50.32	-1.56
t-stats (12lags)	69.40	-1.40
Residual covariance (above), standard deviation (on) and Correlation (below) diagonal		
d/p	0.192	-0.008
Δ cons.	-0.086	0.509
Variable covariance (above), standard deviation (on) and Correlation (below) diagonal		
d/p	1.000	-0.030
Δ cons.	-0.059	0.510

Table 2. Regression intercepts, coefficients, t-statistics, variable variances, R-squareds: Rental Flows. The table provides estimation results for the VAR specification given in equation 9. The regression is estimated by exactly identified GMM and standard errors come from the newey-west procedure with 3 lags using monthly observations. The dividend yield (d/p) is normalized to have zero mean and unit variance for each regression. The dividend yield is the 12-month dividend yield on the value weighted NYSE,AMEX, and NASDAQ constructed using the procedure described in Fama and French (1988) using return series on the NYSE, AMEX and NASDAQ with and without dividends from the CRSP. Log rental growth is multiplied by one hundred before the regressions are run. Rent of Primary Residence Data from the Bureau of Labor Statistics is used to calculate rental growth. The data is deflated using the all-items-less-shelter CPI level. Regression R-squared's are reported in percent. The start date for rental growth observations used in the regressions is provided in the last column. All data ends in 1/2007.

Name	Intercept	Coefficient	t-stat	Variable stdev.	R^2	start date
U.S. city average	0.0148	0.01	0.41	0.43	0.061	2/1947
Northeast urban	0.0672	-0.06	-1.90	0.43	1.871	2/1987
New York-Northern New Jersey-Long Island, NY-NJ-CT-PA	0.0772	-0.08	-2.33	0.55	2.051	2/1978
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	0.0473	-0.03	-0.93	0.63	0.259	2/1978
Boston-Brockton-Nashua, MA-NH-ME-CT	0.0690	-0.12	-2.28	0.72	2.942	2/1987
Pittsburgh, PA	-0.0701	-0.06	-1.22	0.63	0.959	2/1987
Midwest urban	0.0057	-0.05	-1.76	0.40	1.422	2/1987
Chicago-Gary-Kenosha, IL-IN-WI	0.0593	-0.05	-1.36	0.60	0.696	2/1978
Cleveland-Akron, OH	0.0111	-0.02	-0.54	0.65	0.118	2/1987
Detroit-Ann Arbor-Flint, MI	-0.0102	-0.06	-1.66	0.74	0.593	2/1978
St. Louis, MO-IL	-0.1138	-0.09	-1.75	0.74	1.446	2/1987
South urban	0.0115	-0.07	-2.79	0.40	3.433	2/1987
Atlanta, GA	-0.0337	-0.12	-1.76	0.60	4.156	2/1998
Dallas-Fort Worth, TX	-0.0592	-0.12	-2.82	0.64	3.548	2/1987
Houston-Galveston-Brazoria, TX	0.0333	-0.02	-0.39	0.70	0.088	2/1987
Miami-Fort Lauderdale, FL	0.0663	-0.09	-1.89	0.72	1.632	2/1987
West urban	0.0413	-0.09	-3.26	0.42	4.890	2/1987
Los Angeles-Riverside-Orange County, CA	0.1076	-0.01	-0.30	0.57	0.028	2/1978
San Francisco-Oakland-San Jose, CA	0.0702	-0.12	-3.02	0.56	4.999	2/1987
Seattle-Tacoma-Bremerton, WA	0.0497	-0.07	-1.07	0.56	1.530	2/1998

Table 3. GMM Estimation Results for Long Horizon Dynamics of Consumption and Rent Growth. The table reports GMM estimation results for the usual regression moment conditions obtained for long horizon regressions of the form $c_{t+T} - c_t = a_{c,T} + b_{c,T}d_t + \epsilon_{c,T}$ or $r_{t+T} - r_t = a_{r,T} + b_{r,T}d_t + \epsilon_{r,T}$ where c_t and r_t are consumption and rent values for month t. d_t is the dividend yield. The process for the dividend yield is $d_{t+1} = a_d + b_d d_t + \eta_{t+1}$. The long horizon regression intercepts and slopes are taken as implied by the monthly specification, $T = 1$. Three GMM systems are estimated using the joint moment conditions of 1 and 12, 1,12, and 24 and 1,12, 24 and 36 months. Standard errors come from the Newey-West procedure with as many lags as the longest horizon moment condition in the system.The first row of the table reports the monthly specification slope for the consumption regression, $b_{c,1}$ and the associated t-statistics. The other rows report the $b_{r,1}$ for the rental growth regressions. The dividend yield is always normalized to be mean zero and unit variance. All GMM systems are overidentified and all GMM J statistics are insignificant (unreported). The dividend yield is the 12-month dividend yield on the value weighted NYSE,AMEX, and NASDAQ constructed using the procedure described in Fama and French (1988) using return series on the NYSE, AMEX and NASDAQ with and without dividends from the CRSP. Consumption is log, real, per capita data from the table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing. Real consumption is obtained by deflating against US City Average CPI, all items from the Census Bureau and is multiplied by one hundred before the regressions are run. Consumption data is from 1/1959 to Dec/2006. Rent of Primary Residence Data from the Bureau of Labor Statistics is used to calculate rental growth. The data is deflated using the all-items-less-shelter CPI level. The consumption and rental data are multiplied by 100 before the regressions are run. The start date for rental growth observations used in the regressions is given in Table 2. All rental data ends in 1/2007. The dividend yield data is available from 1/1927 to 1/2007.

Horizons	1 and 12 months		1,12 and 24		1,12,24 and 36	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Consumption	-0.027	-1.13	-0.027	-1.159	-0.031	-1.26
U.S. city average	0.023	0.72	0.021	0.87	0.021	0.66
Northeast urban	-0.060	-2.70	-0.079	-3.99	-0.085	-4.56
New York-Northern New Jersey-Long Island, NY-NJ-CT-PA	-0.068	-1.75	-0.058	-1.40	-0.036	-0.82
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	-0.021	-0.46	-0.007	-0.18	0.005	0.12
Boston-Brockton-Nashua, MA-NH-ME-CT	-0.130	-2.46	-0.172	-5.61	-0.191	-3.84
Pittsburgh, PA	-0.047	-1.53	-0.064	-2.02	-0.080	-2.38
Midwest urban	-0.044	-2.09	-0.049	-3.67	-0.036	-3.21
Chicago-Gary-Kenosha, IL-IN-WI	-0.046	-1.29	-0.033	-0.94	-0.026	-0.88
Cleveland-Akron, OH	-0.030	-0.88	-0.020	-0.88	-0.018	-1.34
Detroit-Ann Arbor-Flint, MI	-0.050	-1.88	-0.058	-2.19	-0.053	-1.77
St. Louis, MO-IL	-0.110	-3.59	-0.173	-5.94	-0.002	-0.05
South urban	-0.068	-3.06	-0.066	-5.35	-0.043	-4.45
Atlanta, GA	-0.185	-3.92	-0.196	-6.47	-0.220	-3.12
Dallas-Fort Worth, TX	-0.084	-1.75	-0.068	-1.42	-0.002	-0.06
Houston-Galveston-Brazoria, TX	-0.005	-0.09	0.020	0.63	0.017	0.60
Miami-Fort Lauderdale, FL	-0.078	-2.22	-0.088	-2.81	-0.074	-2.25
West urban	-0.090	-3.86	-0.095	-5.68	-0.099	-5.34
Los Angeles-Riverside-Orange County, CA	-0.004	-0.13	-0.002	-0.06	0.003	0.06
San Francisco-Oakland-San Jose, CA	-0.122	-2.42	-0.120	-2.63	-0.143	-2.62
Seattle-Tacoma-Bremerton, WA	-0.121	-2.30	-0.173	-5.23	-0.255	-9.80

Table 4. Empirical Average and Standard Deviation of Price Rent Ratios and Price Appreciations The table reports the empirical means and standard deviations of the price rent ratios and the price appreciations. Campbell et. al. (2008) reports rent-price ratios for the below regions observed biannually. The table converts their ratios to monthly (see section 4.2.1.) and reports the means and the standard deviations of the monthly observed price to monthly rent ratio, (P_t/R_t), where P_t and R_t are the price and the monthly rent of the residential asset at month t. Campbell et. al. (2008) also reports house prices for the same regions regions observed biannually. Their price appreciations are disinflated by the CPI all items less shelter from BLS. The table converts their biannual price appreciations to monthly (see section 4.2.1.) and reports the means and the standard deviations of the monthly observed price appreciations. Reported are the averages of the $10^4 \times (P_{t+1}/P_t - 1)$ and standard deviation of the $10^2 \times (P_{t+1}/P_t)$. All data ends in the second half of 2007. The last four columns report for data starting at the first half of 2002.

						Start Date = 2002/1			
	Start Date	price rent Ratio		Price Appreciation		price rent Ratio		Price Appreciation	
		average	Stdev.	average	Stdev.	average	Stdev.	average	Stdev.
USA	1975/1	253.13	11.88	13.49	0.12	306.87	9.23	29.18	0.11
Northeast	1978/1	282.15	21.15	21.92	0.23	359.77	12.72	40.58	0.16
New York	1976/1	332.29	37.02	33.83	0.26	465.73	22.24	58.76	0.18
Philadelphia	1976/1	237.19	16.43	18.13	0.2	304.67	15.06	55.40	0.16
Boston	1978/1	321.57	32.31	34.94	0.29	443.02	14.54	23.53	0.22
Pittsburgh	1976/2	219.41	9.42	4.51	0.15	255.16	3.09	11.60	0.05
Midwest	1978/1	243.24	11.71	7.56	0.13	291.08	6.36	11.93	0.08
Chicago	1975/2	262.69	14.27	17.37	0.18	321.72	12.17	34.12	0.11
Cleveland	1975/2	230.77	8.27	4.88	0.16	257.15	2.21	-8.13	0.09
Detroit	1976/2	228.5	20.32	10.01	0.24	300.46	5.11	-22.83	0.15
St. Louis	1975/2	218.62	12.1	10.76	0.19	271.23	7.62	22.40	0.08
South	1978/1	232.53	8.69	7.74	0.11	266.78	8.98	32.54	0.09
Atlanta	1976/2	223.7	9.72	9.59	0.11	267.05	7.76	7.89	0.06
Dallas	1976/1	212.1	7.58	2.56	0.19	216.25	4.89	2.82	0.05
Houston	1976/1	194.21	8.51	-2.6	0.19	196.30	4.41	14.67	0.06
Miami	1978/1	239.03	29.26	28.09	0.28	364.40	29.59	101.33	0.26
West	1978/1	298.7	23.03	25.81	0.17	392.74	24.63	59.27	0.21
Los Angeles	1975/1	333.33	38.19	38.08	0.3	492.70	38.83	94.56	0.33
San Francisco	1975/2	319.29	36.66	39.91	0.27	468.43	30.93	42.77	0.22
Seattle	1975/2	232.7	26.82	35.25	0.25	342.40	22.75	57.62	0.16

Table 5. Power Utility Specification Parameter Estimates and the J-Test for System Over-Identification. The table reports region specific (*Panel A*) and jointly estimated (*Panel B*) risk aversion coefficient, γ and the time-discount parameter, δ. *Panel B* also reports the parameter standard errors and the J-Test P-value for the joint estimation. In the region specific estimation, the GMM procedure is implemented with the weighing matrix set to unity. In the joint estimation the weighing matrix is obtained by following the two-step procedure provided in Hansen and Singleton (1982). Solving for the price rent ratios in section 3.2 for Power utility, yields the model equilibrium price rent ratios as a function of the state variable: the dividend yield on the NYSE, AMEX and NASDAQ and moment conditions can be constructed using this implication, where the system is over-identified in the joint estimation (19 moment conditions, since US is aggregate is excluded and there are 2 parameters). The empirical price rent ratios are available bi-annually from Campbell et. al. (2008) and run from first half of 1978 to first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. Both the rental and consumption growth processes are allowed to be predictable using the dividend yield. In constructing the GMM weighing matrix for the joint estimation, the Newey and West (1987) procedure is used with 3 lags. Following Constantinides and Gosh (2008), the GMM system is optimized over a discrete set of values. The risk aversion coefficient is allowed to be 1.2, 1.5 and values from 2 to 10 in the increments of 1; and the time-discount parameter can be 0.95, 0.97 and 0.99 at the annual frequency. The annual time-rates of discounts are converted into the monthly by taking the 1/12th powers.

Panel A: Region Specific GMM Parameter Estimates		
	Risk Aversion	Discount Rate
US	2	0.999
Northeast	2	0.999
New York	2	0.999
Philadelphia	1.2	0.997
Boston	2	0.999
Pittsburgh	2	0.999
Midwest	2	0.999
Chicago	1.2	0.997
Cleveland	1.2	0.997
Detroit	1.2	0.997
St. Louis	1.5	0.999
South	1.2	0.997
Atlanta	2	0.999
Dallas	2	0.999
Houston	3	0.999
Miami	1.5	0.997
West	2	0.999
Los Angeles	2	0.999
San Francisco	2	0.999
Seattle	1.2	0.997
Panel B: All regions joint GMM Specification Test Results		
Parameters	2	0.999
Parameter Standard Errors	0.01	3.91
J-Test P-value	0.29	

Table 6. Power Utility Specification Model Implications for the price rent ratios and the Price Appreciations: Averages and Standard Deviations. The table reports averages and standard deviations for the price rent ratios, P_t/R_t and the price appreciations, P_t/P_{t-1}, where P_t and R_t are the price and the rent of the house at time t, respectively. The power utility specification is solved using the procedure described in 3.2 and using the model implication for the average price rent ratios, the system for the 19 regions is estimated jointly to obtain the parameter estimates for the risk aversion coefficient and the time-discount rate (see section 4.2). The results for the parameter estimates is provided in the *Panel B* of Table 5. This set of parameters is then used to calculate model implied values for the averages and standard deviations for the price rent ratios and the price appreciations (see section 3.2). The moments are calculated using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. Model parameters are estimated using biannual empirical price rent ratio data from the first half of 1978 to the first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. Both the rental and consumption growth processes are allowed to be predictable using the dividend yield.

	price rent Ratio		Price Appreciation	
	Average	Stdev.	Average ($\times 10^4$)	Stdev. ($\times 10^2$)
US	252.34	6.91	1.74	0.72
Northeast	288.87	0.57	6.82	0.43
New York	297.47	1.69	7.89	0.58
Philadelphia	274.10	3.18	4.96	0.68
Boston	292.98	6.73	7.28	0.86
Pittsburgh	207.24	0.20	-6.81	0.63
Midwest	245.29	1.45	0.66	0.42
Chicago	283.11	1.52	6.11	0.60
Cleveland	249.78	3.84	1.36	0.71
Detroit	236.83	0.60	-0.75	0.74
St. Louis	190.25	1.62	-11.08	0.77
South	248.62	0.99	1.23	0.41
Atlanta	224.24	4.78	-3.07	0.76
Dallas	212.37	4.42	-5.62	0.78
Houston	264.68	4.25	3.62	0.77
Miami	289.83	3.09	6.92	0.75
West	268.75	2.90	4.25	0.48
Los Angeles	329.74	6.80	11.03	0.72
San Francisco	292.56	6.74	7.30	0.74
Seattle	275.03	0.54	5.13	0.56

Table 7. Epstein-Zin-Weil Specification Parameter Estimates and the J-Test for System Over-Identification. The table reports region specific (*Panel A*) and jointly estimated (*Panel B*) risk aversion coefficient, γ and the time-discount parameter, δ and the Elasticity of Intertemporal Substitution (EIS), ϕ. *Panel B* also reports the parameter standard errors and the J-Test P-value for the joint estimation. In the region specific estimation, the GMM procedure is implemented with the weighing matrix set to unity. In the joint estimation the weighing matrix is obtained by following the two-step procedure provided in Hansen and Singleton (1982). Solving for the price rent ratios in section 3.2 for Epstein-Zin-Weil utility, yields the model equilibrium price rent ratios as a function of the state variable: the dividend yield on the NYSE, AMEX and NASDAQ and moment conditions can be constructed using this implication, where the system is over-identified in the joint estimation (19 moment conditions, since US is aggregate is excluded and there are 3 parameters). The empirical price rent ratios are available bi-annually from Campbell et. al. (2008) and run from first half of 1978 to first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. Both the rental and consumption growth processes are allowed to be predictable using the dividend yield. In constructing the GMM weighing matrix for the joint estimation, the Newey and West (1987) procedure is used with 3 lags. Following Constantinides and Gosh (2008), the GMM system is optimized over a discrete set of values. The risk aversion coefficient is allowed to be 1.2, 1.5 and values from 2 to 10 in the increments of 1; and the time-discount parameter can be 0.95, 0.97 and 0.99 at the annual frequency. The annual time-rates of discounts are converted into the monthly by taking the 1/12th powers. EIS can be from 0.3 to 1.5 in the increments of 0.3.

Panel A: Region Specific GMM Parameter Estimates			
	Risk Aversion	Discount Rate	EIS
US	10	0.997	0.9
Northeast	8	0.997	0.9
New York	6	0.997	1.5
Philadelphia	10	0.997	0.6
Boston	1.2	0.997	1.2
Pittsburgh	3	0.997	1.2
Midwest	10	0.997	0.9
Chicago	1.2	0.997	0.9
Cleveland	1.2	0.997	0.9
Detroit	8	0.997	0.9
St. Louis	10	0.997	1.5
South	1.2	0.997	0.9
Atlanta	10	0.997	0.9
Dallas	10	0.997	0.9
Houston	10	0.999	0.3
Miami	10	0.997	0.6
West	10	0.997	1.2
Los Angeles	10	0.997	0.9
San Francisco	1.2	0.997	1.2
Seattle	10	0.997	0.6
Panel B: All regions joint GMM Specification Test Results			
Parameters	6	0.997	0.9
Parameter Standard Errors	0.12	18.18	58.97
J-Test P-value	0.14		

Table 8. Epstein-Zin-Weil Utility Specification Model Implications for the price rent ratios and the Price Appreciations: Averages and Standard Deviations. The table reports averages and standard deviations for the price rent ratios, P_t/R_t and the price appreciations, P_t/P_{t-1}, where P_t and R_t are the price and the rent of the house at time t, respectively. The Epstein-Zin-Weil utility specification is solved using the procedure described in 3.2 and using the model implication for the average price rent ratios, the system for the 19 regions is estimated jointly to obtain the parameter estimates for the risk aversion coefficient and the time-discount rate (see section 4.2). The results for the parameter estimates is provided in the *Panel B* of Table 7. This set of paremeters is then used to calculate model implied values for the averages and standard deviations for the price rent ratios and the price appreciations (see section 3.2). The moments are calculated using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. Model parameters are estimated using biannual empirical price rent ratio data from the first half of 1978 to the first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. Both the rental and consumption growth processes are allowed to be predictable using the dividend yield.

	price rent Ratio		Price Appreciation	
	Average	Stdev.	Average ($\times 10^4$)	Stdev. ($\times 10^2$)
US	246.17	4.15	1.64	0.55
Northeast	275.71	2.37	6.83	0.47
New York	280.71	4.53	7.95	0.67
Philadelphia	263.72	0.30	4.93	0.63
Boston	275.74	9.17	7.40	1.00
Pittsburgh	200.69	1.83	-6.79	0.66
Midwest	236.48	1.04	0.66	0.42
Chicago	270.83	1.39	6.12	0.62
Cleveland	242.04	1.20	1.32	0.65
Detroit	227.85	1.76	-0.73	0.76
St. Louis	183.83	3.36	-11.01	0.85
South	238.07	3.38	1.28	0.51
Atlanta	213.32	6.66	-2.95	0.91
Dallas	203.18	6.23	-5.50	0.92
Houston	255.90	1.42	3.58	0.70
Miami	274.86	5.79	6.99	0.84
West	255.32	5.38	4.33	0.62
Los Angeles	317.82	3.11	10.95	0.61
San Francisco	274.07	9.12	7.43	0.90
Seattle	261.81	3.23	5.17	0.63

Table 9. Power Utility Specification Parameter Estimates and the J-Test for System Over-Identification, IID Rental Growth. The table reports region specific (*Panel A*) and jointly estimated (*Panel B*) risk aversion coefficient, γ and the time-discount parameter, δ. *Panel B* also reports the parameter standard errors and the J-Test P-value for the joint estimation. In the region specific estimation, the GMM procedure is implemented with the weighing matrix set to unity. In the joint estimation the weighing matrix is obtained by following the two-step procedure provided in Hansen and Singleton (1982). Solving for the price rent ratios in section 3.2 for Power utility, yields the model equilibrium price rent ratios as a function of the state variable: the dividend yield on the NYSE, AMEX and NASDAQ and moment conditions can be constructed using this implication, where the system is over-identified in the joint estimation (19 moment conditions, since US is aggregate is excluded and there are 2 parameters). The empirical price rent ratios are available bi-annually from Campbell et. al. (2008) and run from first half of 1978 to first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. The rental growth is calibrated as IID, while consumption growth processes are allowed to be predictable using the dividend yield. In constructing the GMM weighing matrix for the joint estimation, the Newey and West (1987b) procedure is used with 3 lags. Following Constantinides and Gosh (2008), the GMM system is optimized over a discrete set of values. The risk aversion coefficient is allowed to be 1.2, 1.5 and values from 2 to 10 in the increments of 1; and the time-discount parameter can be 0.95, 0.97 and 0.99 at the annual frequency. The annual time-rates of discounts are converted into the monthly by taking the 1/12th powers.

Panel A: Region Specific GMM Parameter Estimates		
	Risk Aversion	Discount Rate
US	2	0.999
Northeast	1.2	0.997
New York	2	0.999
Philadelphia	1.5	0.997
Boston	2	0.999
Pittsburgh	1.2	0.997
Midwest	1.2	0.997
Chicago	1.2	0.997
Cleveland	1.2	0.997
Detroit	1.2	0.997
St. Louis	2	0.999
South	1.2	0.997
Atlanta	2	0.999
Dallas	2	0.999
Houston	3	0.999
Miami	1.5	0.997
West	2	0.999
Los Angeles	1.2	0.997
San Francisco	2	0.999
Seattle	2	0.999
Panel B: All regions joint GMM Specification Test Results		
Parameters	1.2	0.997
Parameter Standard Errors	0.00	0.23
J-Test P-value	0.29	

Table 10. Power Utility Specification Model Implications for the price rent ratios and the Price Appreciations: Averages and Standard Deviations, IID Rental Growth. The table reports averages and standard deviations for the price rent ratios, P_t/R_t and the price appreciations, P_t/P_{t-1}, where P_t and R_t are the price and the rent of the house at time t, respectively. The power utility specification is solved using the procedure described in 3.2 and using the model implication for the average price rent ratios, the system for the 19 regions is estimated jointly to obtain the parameter estimates for the risk aversion coefficient and the time-discount rate (see section 4.2). The results for the parameter estimates is provided in the *Panel B* of Table 9. This set of parameters is then used to calculate model implied values for the averages and standard deviations for the price rent ratios and the price appreciations (see section 3.2). The moments are calculated using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. Model parameters are estimated using biannual empirical price rent ratio data from the first half of 1978 to the first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. The rental growth is calibrated as IID, while consumption growth processes are allowed to be predictable using the dividend yield.

	price rent Ratio		Price Appreciation	
	Average	Stdev.	Average ($\times 10^4$)	Stdev. ($\times 10^2$)
US	228.52	3.18	1.62	0.52
Northeast	259.72	3.70	6.86	0.51
New York	266.81	3.88	7.91	0.61
Philadelphia	247.48	3.44	4.98	0.70
Boston	262.41	3.69	7.22	0.79
Pittsburgh	191.70	2.62	-6.78	0.68
Midwest	223.82	3.13	0.69	0.48
Chicago	254.96	3.68	6.14	0.65
Cleveland	227.20	3.19	1.35	0.70
Detroit	216.88	3.01	-0.71	0.79
St. Louis	177.03	2.41	-11.07	0.77
South	226.72	3.17	1.27	0.49
Atlanta	205.95	2.84	-3.15	0.66
Dallas	195.82	2.66	-5.68	0.70
Houston	239.47	3.38	3.61	0.75
Miami	260.41	3.68	6.94	0.78
West	243.30	3.43	4.26	0.51
Los Angeles	291.05	4.18	10.98	0.64
San Francisco	262.17	3.73	7.22	0.63
Seattle	248.62	3.53	5.16	0.62

Table 11. Epstein-Zin-Weil Specification Parameter Estimates and the J-Test for System Over-Identification, IID Rental Growth. The table reports region specific (*Panel A*) and jointly estimated (*Panel B*) risk aversion coefficient, γ and the time-discount parameter, δ and the Elasticity of Intertemporal Substitution (EIS), ϕ. *Panel B* also reports the parameter standard errors and the J-Test P-value for the joint estimation. In the region specific estimation, the GMM procedure is implemented with the weighing matrix set to unity. In the joint estimation the weighing matrix is obtained by following the two-step procedure provided in Hansen and Singleton (1982). Solving for the price rent ratios in section 3.2 for Epstein-Zin-Weil utility, yields the model equilibrium price rent ratios as a function of the state variable: the dividend yield on the NYSE, AMEX and NASDAQ and moment conditions can be constructed using this implication, where the system is over-identified in the joint estimation (19 moment conditions, since US is aggregate is excluded and there are 3 parameters). The empirical price rent ratios are available bi-annually from Campbell et. al. (2008) and run from first half of 1978 to first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. The rental growth is calibrated as IID, while consumption growth processes are allowed to be predictable using the dividend yield. In constructing the GMM weighing matrix for the joint estimation, the Newey and West (1987b) procedure is used with 3 lags. Following Constantinides and Gosh (2008), the GMM system is optimized over a discrete set of values. The risk aversion coefficient is allowed to be 1.2, 1.5 and values from 2 to 10 in the increments of 1; and the time-discount parameter can be 0.95, 0.97 and 0.99 at the annual frequency. The annual time-rates of discounts are converted into the monthly by taking the 1/12th powers. EIS can be from 0.3 to 1.5 in the increments of 0.3.

Panel A: Region Specific GMM Parameter Estimates			
	Risk Aversion	Discount Rate	EIS
US	10	0.997	0.9
Northeast	5	0.997	0.9
New York	8	0.997	1.2
Philadelphia	10	0.997	0.6
Boston	2	0.997	1.2
Pittsburgh	1.5	0.997	1.2
Midwest	7	0.997	0.9
Chicago	1.2	0.997	0.9
Cleveland	1.2	0.997	0.9
Detroit	4	0.997	0.9
St. Louis	8	0.997	1.5
South	1.2	0.997	0.9
Atlanta	8	0.997	0.9
Dallas	9	0.997	0.9
Houston	10	0.999	0.3
Miami	10	0.996	1.5
West	4	0.997	1.2
Los Angeles	10	0.997	0.9
San Francisco	5	0.997	1.2
Seattle	10	0.997	0.6
Panel B: All regions joint GMM Specification Test Results			
Parameters	7	0.997	0.9
Parameter Standard Errors	0.08	30.80	39.08
J-Test P-value	0.14		

Table 12. Epstein-Zin-Weil Utility Specification Model Implications for the price rent ratios and the Price Appreciations: Averages and Standard Deviations, IID Rental Growth. The table reports averages and standard deviations for the price rent ratios, P_t/R_t and the price appreciations, P_t/P_{t-1}, where P_t and R_t are the price and the rent of the house at time t, respectively. The Epstein-Zin-Weil utility specification is solved using the procedure described in 3.2 and using the model implication for the average price rent ratios, the system for the 19 regions is estimated jointly to obtain the parameter estimates for the risk aversion coefficient and the time-discount rate (see section 4.2). The results for the parameter estimates is provided in the *Panel B* of Table 11. This set of paremeters is then used to calculate model implied values for the averages and standard deviations for the price rent ratios and the price appreciations (see section 3.2). The moments are calculated using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. Model parameters are estimated using biannual empirical price rent ratio data from the first half of 1978 to the first half of 2007. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. The rental growth is calibrated as IID, while consumption growth processes are allowed to be predictable using the dividend yield.

	price rent Ratio		Price Appreciation	
	Average	Stdev.	Average ($\times 10^4$)	Stdev. ($\times 10^2$)
US	247.10	3.20	1.61	0.51
Northeast	283.91	3.77	6.85	0.50
New York	290.48	3.94	7.91	0.60
Philadelphia	268.94	3.48	4.97	0.69
Boston	288.80	3.78	7.21	0.78
Pittsburgh	205.06	2.62	-6.78	0.67
Midwest	241.74	3.15	0.69	0.47
Chicago	277.86	3.75	6.13	0.64
Cleveland	245.71	3.21	1.35	0.69
Detroit	233.15	3.01	-0.72	0.78
St. Louis	188.22	2.39	-11.08	0.77
South	245.00	3.19	1.26	0.48
Atlanta	220.55	2.83	-3.15	0.65
Dallas	209.71	2.66	-5.68	0.69
Houston	259.84	3.43	3.60	0.74
Miami	285.76	3.76	6.93	0.77
West	264.48	3.47	4.26	0.49
Los Angeles	322.55	4.31	10.97	0.64
San Francisco	286.52	3.80	7.22	0.62
Seattle	269.86	3.57	5.16	0.61

Table 13. Cross Sectional Regressions of the Difference between Empirical and Theoretical price rent Ratios on the Measures of Subprime Activity. The table reports coefficients and the t-statistics for the cross sectional regressions where the dependent variable is the difference between logs of empirical and theoretical price rent ratios for the 20 regions considered in this paper. The independent variable is the log of the subprime activity measure for the same 20 regions. Both the independent and the dependent variables are normalized to zero mean and unit variance before the regressions are run. The regressions are estimated using exact identified GMM with no Newey-West correction. The empirical price rent ratios are from the unconditional average of the price rent ratios from the first half of 2002 to second half of 2007. The theoretical price rent ratios are the unconditional average price rent ratios implied by the four specifications considered: Power and Epstein-Zin-Weil Utilities with i.i.d. and predictable rental processes. The theoretical unconditional averages are taken using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. There are a total of 13 subprime activity measures considered and they constitute the first column of the table. The activity measures are taken from the website of the Federal Reserve Bank of New York and are provided by the FirstAmerican CoreLogic Inc. using the Loan Performance Data. Loan Performance data is available at a finer geographic resolution than the 20 regions provided by the BLS. To calculate the measure for any BLS region we use the following procedure. Each area of the Loan Performance data is associated with a state indication and for each of the 20 BLS regions we calculate the weighted average of the subprime measures using the total number of housing units in the area. The subprime activity measures are expressed as a percent of subprime loans, with the exception of the first row which simply is the percentage subprime loans in the universe of all outstanding loans.

	Power Utility				Epstein-Zin-Weil Utility			
	pred.		i.i.d.		pred.		i.i.d.	
	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
subprime loans	0.26	1.58	0.28	1.65	0.26	1.59	0.26	1.55
with FICO $<$ 600	-0.67	-4.63	-0.70	-5.11	-0.68	-4.68	-0.68	-4.75
with FICO $>$ 660	0.68	4.95	0.71	5.45	0.69	4.96	0.69	5.05
high LTV and FICO $<$ 620	-0.67	-4.69	-0.70	-5.19	-0.68	-4.66	-0.68	-4.77
low LTV and FICO $\geq$ 620	0.58	4.43	0.62	4.89	0.59	4.43	0.59	4.49
originated in 2007	0.55	2.62	0.57	2.74	0.56	2.71	0.56	2.65
originated in 2006	0.58	3.05	0.61	3.23	0.59	3.17	0.59	3.06
originated in or before 2005	-0.54	-2.58	-0.56	-2.72	-0.55	-2.68	-0.54	-2.59
no or low documentation	0.54	4.91	0.58	5.33	0.56	5.05	0.55	4.94
purchases	-0.51	-2.23	-0.51	-2.29	-0.49	-2.15	-0.51	-2.25
cash-out refinances	0.74	3.89	0.75	4.20	0.73	3.83	0.74	3.96
loans used for other purpose	-0.63	-2.98	-0.66	-3.17	-0.64	-3.08	-0.63	-2.98
ARM loans	0.66	3.27	0.66	3.39	0.65	3.25	0.66	3.30

Table 14. Cross-Sectional Regressions of the Absolute Value of Percentage Nominal House Price Fall on the Difference between Empirical and Theoretical price rent Ratios. The table reports coefficients and the t-statistics for the cross sectional regressions where the dependent variable is the absolute value of the percentage nominal house price fall for the 20 regions considered in this paper. The start date of house price measurement is provided in the first column and the end date of measurement is always the third quarter of 2008. The independent variable is the difference between logs of empirical and theoretical price rent ratios for the same 20 regions. Both the independent and the dependent variables are normalized to zero mean and unit variance before the regressions are run. The regressions are estimated using exact identified GMM with no Newey-West correction. The empirical price rent ratios are from the unconditional average of the price rent ratios from the first half of 2002 to second half of 2007. The theoretical price rent ratios are the unconditional average price rent ratios implied by the four specifications considered: Power and Epstein-Zin-Weil Utilities with i.i.d. and predictable rental processes. The theoretical unconditional averages are taken using the unconditional distribution of the dividend yield on the NYSE, AMEX and NASDAQ. The house price measures are taken from the website of the National Association of Realtors (NAR) and are provided at a finer geographic resolution than the 20 regions from the BLS used in the paper. To calculate the price fall for any BLS region we use the following procedure. All geographic areas of NAR are associated with a state indication, and for each of the state indications of the 20 regions we take the median of the NAR area values.

	Power Utility				Epstein-Zin-Weil Utility			
	pred.		i.i.d.		pred.		i.i.d.	
Start Date	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
2006	0.53	3.08	0.55	3.14	0.53	2.99	0.53	3.06
2007	0.57	3.19	0.59	3.28	0.56	3.12	0.58	3.20
2008	0.34	1.98	0.34	2.03	0.32	1.80	0.34	2.01
2007 4th Quarter	0.58	3.02	0.60	3.13	0.57	2.96	0.58	3.04

Table 15. Regional Closing Cost Rates and Lower Bounds of House price rent Ratios with Calibrated Parameter Values: Power and Epstein-Zin-Weil Utility Specifications. The table reports the lower bounds of House price rent ratios where the bounds are implied by the analysis in He and Modest (1995). The proportional trading cost of the house is taken conservatively at a quarter of the empirical closing cost rate in the regions. In particular the Euler equations in equations 5 and 6 are replaced by the euler inequalities in equations 7 and 8. A linearly equally spaced grid with 100 nodes between the upper limit and the lower limit is used the resulting equal number of euler equations are solved with the same technique in section 3.2 but replacing the unity value on the right hand side with the grid node value. The lower bound is obtained when the euler equation is evaluated at the upper limit of the euler inequality. Parameter estimates for the Power and Epstein-Zin-Weil utilities come from the *Panel B* of Tables 5 and 7, respectively. The rental processes come from the Rent of Primary Residence data from the Bureau of Labor Statistics and the statistics of the rental processes are reported in Table 2. The consumption process used to construct the pricing kernel is log, real and per capita from table 2.3.5U from the Bureau of Economic Analysis (BEA), nondurables and services less housing and the statistics of the consumption process are reported in Table 1. Both the rental and consumption growth processes are allowed to be predictable using the dividend yield. The table also reports mortgage closing costs as a percentage of the mortgage amount. Closing costs include Origination fees (application, commitment, document preparation, funding, origination or lender, processing, tax service, underwriting and wire transfer), and Title and Closing fees (appraisal, attorney, closing or settlement, credit report, flood certification, pest, other inspection, postage/courier, survey, title insurance and title work). We use data from www.bankrate.com which provides state by state closing cost dollar figures for a two hundred thousand dollar mortgage. For each of the geographic classifications used in the paper, the associated states indicated by the BLS is looked up and the total closing cost as a percentage of the mortgage amount is calculated. The data is collected by Bankrate.com during the year 2008. For the geographical areas that have more than one state associated, we used the median percent closing costs of the associated states.

	Percent Cost Rate	Power Utility	Epsten-Zin-Weil Utility
US	1.53	85.56	84.77
Northeast	1.56	88.40	87.17
New York	1.71	83.46	82.15
Philadelphia	1.63	84.22	83.21
Boston	1.51	90.62	89.05
Pittsburgh	1.71	74.46	73.62
Midwest	1.44	88.15	87.00
Chicago	1.44	92.77	91.44
Cleveland	1.66	80.87	80.02
Detroit	1.60	81.53	80.46
St. Louis	1.41	80.96	79.83
South	1.55	84.33	83.14
Atlanta	1.45	84.96	83.46
Dallas	1.99	67.82	66.94
Houston	1.99	72.44	71.74
Miami	1.84	78.54	77.48
West	1.53	87.42	86.03
Los Angeles	1.63	89.13	88.19
San Francisco	1.63	86.16	84.62
Seattle	1.51	88.79	87.42