Asset Pricing and Portfolio Choice in the Presence of Housing

DISSERTATION

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By

Robert F. Sarama Jr., B.S. M.A.

Graduate Program in Economics
The Ohio State University

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Dissertation Committee:

Pok-sang Lam, Adviser
Donald R. Haurin
Mario J. Miranda
ABSTRACT

The portfolio decisions made by consumers have important implications for individual welfare and asset prices. This work addresses the frictions faced by consumers investing across asset classes and the implications those frictions have on asset prices. Specifically, I focus on the choice between housing and financial assets. Although there is a broad literature on returns to holding housing, standard structural models from the finance literature have largely been overlooked when pricing housing market returns. I argue in this line of work that by evaluating and pricing housing within the same frameworks in which equities and bonds are priced, we can better evaluate portfolio choices.

In addition to using financial economic theory to understand housing markets, we can use housing markets to gain a better understanding of other asset markets. Owner-occupied housing is unique in that it is traded in local markets, which are heterogeneous in their economic and demographic characteristics. This heterogeneity in the investor base is a source of variation from which to explore the link between asset prices and uncertainty in the expected future consumption flows of investors.

The first essay, “Pricing Housing Market Returns,” finds the housing premium to be smaller than the equity premium. Using state-level data that spans the 1983 to 2006 period, I estimate the asset pricing Euler equations from the intertemporal consumption problem faced by a representative consumer with Epstein-Zin (EZ)
preferences. EZ preferences allow the consumer to have a different level of aversion to variation in consumption across states of nature than to variation in consumption over time. The EZ Capital Asset Pricing Model captures a large proportion of the variation in housing returns over the sample period, and I find there to be heterogeneity in the structural parameter estimates across geographies. Controlling for the risk priced by the model and the consumption value of housing, I find that the housing premium is smaller than the equity premium. This result is surprising given that frictions, such as high transaction costs and borrowing constraints, affect the investor in housing more than the investor in equities. I examine institutional differences between the asset classes and find that some of the difference between the two premia may be related to differences in the tax treatment between the two asset classes.

The second essay, “Non-durable Consumption Volatility and Illiquid Assets,” finds that factors beyond the volatility of asset payoffs may significantly affect the volatility of the agent’s consumption stream. The empirical failure of consumption-based asset pricing models is often attributed to the lack of volatility in aggregate measures of consumption. However, I illustrate in this paper that frictions faced by agents may lead to much higher levels of volatility in individual consumption than we observe in the aggregate data. I identify five distinguishing characteristics of assets, and develop a life-cycle model of the consumer which incorporates these features. The consumer derives utility from non-durable consumption and stock in a risky asset: housing. A key feature of the model is that the housing adjustment costs are non-convex. These adjustment costs generate lumpy changes in the stock of the risky asset over the life-cycle. The model predicts that non-durable consumption volatility is increasing in
both the ability to borrow against the assets held in the consumer’s portfolio and in
the illiquidity of the portfolio. Because the liquidity of the investor’s portfolio may
depend on the thinness of the housing market in which the investor resides, investors
in different geographies may value the same asset differently.

The third essay, “Local and Global Risks in U.S. Housing Markets,” finds that
variation in the cross section of expected housing market returns is better explained
by a local CAPM model than by a global CAPM model. Housing is unlike many other
assets in that it is primarily traded in local markets. The 2000 U.S. Census indicates
that over 66% of housing units are owner occupied. A housing return is the combi-
nation of a capital gain and a consumption flow. In the last 30 years in the United
States, the consumption flow yield has accounted for approximately 69% of average
real return to homeownership. Frictions that prevent owners from realizing the con-
sumption flow, either directly or indirectly via renting the property, can significantly
drive down the net real return received for owning the property. For mean-variance
optimizing investors, relatively small investment costs (less than 3.5% annually) will
prevent the investor from optimally investing in housing markets in which the investor
doesn’t reside. I propose two possible models for U.S. housing markets. The local
CAPM assumes that only investors residing in the geographic region that constitutes
market \( i \) invest in housing market \( i \). The global CAPM assumes that investors who
don’t reside in the geographic region that constitutes market \( i \) have costless access
to the assets in that market. I test the ability of these models to explain the cross
section of expected real housing returns and find that smaller mean pricing errors are
associated with the local model.
This work is dedicated to my wife, Alessandra Palumbo Sarama, and my parents,

Robert and Mary Sarama.
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There are many people whose guidance and support helped to shape my work and my overall way of approaching problems in economics. Unfortunately, I cannot name them all here, but I would like to acknowledge a few who had a particularly strong impact on my work and overall growth from a student into an economist.

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Furthermore, Don actively encouraged me and the other members of the Housing Research Group at Ohio State to develop the skill set necessary to both present and critique research. While Don was not my primary adviser and despite his many other responsibilities, he was always readily available to address both major and minor issues that arose in my work while at OSU.

Mario Miranda, a member of my dissertation committee and research collaborator, worked with me as I developed my computational skills. More than just explaining approximation methods and numerical optimization, Mario taught me to formulate dynamic decision models in a way so that they are amenable to computational solutions. He spent many hours guiding me and suggesting routes I might take to overcome some of the challenges in the particular class of models I was attempting to solve.

Masao Ogaki, a member of my candidacy committee, guided me as I began the research process. He helped me to understand why the formulation of straightforward structural models is preferable to the formulation of overly detailed representations of the world. He also counseled me on econometric methods, and ways to overcome challenges that arise when working with data.

David Brasington, undergraduate adviser and co-author, gave me my first introduction to research when we worked together on “House Prices, Deed Types and Mortgage Interest Rates.” It was that project that convinced me of my interest in research, and thereby prompted me to attend graduate school in economics rather than alternative options. The patience he exhibited and guidance he provided while working with a very junior researcher helped me to build the confidence necessary to succeed in graduate school.
Bill Dupor and Belton Fleisher also provided thoughtful insight on a number of issues related to my work during my time at OSU.

I’d also like to acknowledge three Louisiana State University professors who had a significant influence on my decision to go to graduate school. R. Carter Hill’s undergraduate econometrics course sparked my interest in pursuing economics at a higher level. His guidance along with that of Doug McMillin and Eric Hillebrand were quite influential in the series of events that have led up to the completion of this dissertation.

Finally, I’d like to acknowledge all of the things I’ve learned from my brother, Michael Sarama. While most of them are not related directly to economics or finance, they nonetheless have had a major impact on the way I proceed through life and my work.

I was fortunate to have such a great group of people to guide me during the last number of years, and any shortcomings in my work can be directly attributed to me and me alone. The way in which I was mentored by the people listed above will serve as a model for how I hope to treat people I have the opportunity to mentor in the future.
VITA

February 15, 1983 ....................... Born - Monroe, Louisiana

2005 ................................. B.S. Economics with Concentration in
Empirical Analysis,
Louisiana State University

2006 ................................. M.A. Economics,
Ohio State University

PUBLICATIONS

Research Publications


FIELDS OF STUDY

Major Field: Economics
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CHAPTER 1

Pricing Housing Market Returns

The housing premium is smaller than the equity premium, yet American families give housing a substantially higher portfolio weight than equities. In this paper I estimate the asset pricing Euler equations from the intertemporal consumption problem faced by a representative consumer with Epstein-Zin (EZ) preferences, and find the risk adjusted return for holding equities to be generally higher than the risk adjusted return for holding housing. Institutional differences between assets (e.g. tax treatment) can partially explain the difference in premia. Because housing is primarily traded by investors within local markets, I use state-level data to estimate the structural parameters within the model. The estimates of the structural parameters are not uniform across geographies, suggesting that heterogeneity in the investor base has implications for consumption-based asset pricing models.

The Capital Asset Pricing Model (CAPM) is the fundamental model in financial economics that links risk to return, and I test the ability of that model to explain variation in historical housing market returns. The results of this analysis shed light on the determination of housing market price dynamics, and will thus be of interest to housing and financial economists, policymakers and asset managers. The inability of consumption-based asset pricing models to price equity returns has resulted in a
large literature in empirical asset pricing. In their widely cited paper, Mehra and Prescott (1985) revealed the so called equity premium puzzle. The equity premium puzzle is that the canonical consumption-based model of Lucas (1978) is unable to match equity return moments for empirically reasonable levels of risk aversion. More specifically, in postwar data, the amount of risk the investor must accept when owning equities isn’t high enough to justify the high risk premium yielded for owning equities.

Following Mehra and Prescott (1985), a number of papers proposed that the equity premium puzzle is a consequence of the presence of incomplete markets and various other market frictions. Aiyagari and Gertler (1991) show that the combination of incomplete markets and transactions costs imply that stocks pay a liquidity premium over bonds. They assume that households trade securities to smooth consumption in the presence of uninsurable idiosyncratic shocks to personal income. Because there are higher transaction costs associated with trading equities than with allocating funds to money market and savings accounts, the authors demonstrate that equities must pay a premium over the risk free rate. Using a life-cycle model, Constantinides, Donaldson and Mehra (2002) show that the equity premium puzzle is driven by borrowing constraints that lead to a segmentation of investors in equities markets. They argue that the attractiveness of holding equity fluctuates during the life-cycle as the correlation of equity income with consumption changes. For young households with uncertain future wages, the correlation between equity income and consumption is low; while for middle-aged households wage income is largely resolved and fluctuations in consumption are driven by fluctuations in equity income. Thus, equity is an attractive asset for young households but not for middle-aged households. However, in the presence of borrowing constraints, young households are effectively shut out of
the equities markets. The authors conclude that the marginal investor in equities is the middle-aged household, and those investors demand a premium for holding equity because of its high correlation with their consumption streams.

In this paper, I pose the question: does there exist a housing premium? The market frictions associated with housing are larger than those associated with equities, and accordingly we might expect an even higher housing premium than equity premium. Aiyagari and Gertler (1991) estimate brokerage fees for trading equities to decline monotonically from 8% to 2% for trades from $1 to $4,000, and 2% for trades from $4,000 to $200,000. The estimates of transactions costs in housing vary by study, but fall into the range of 6% for Chambers and Simonson (1989) to 12% to 13% by Malatesta and Hess (1986). A number of studies have found that down payment constraints significantly affect the tenure choices for young households. Notably, Haurin, Hendershott and Wachter (1997) find that, controlling for wealth and demographic characteristics, borrowing constrained households are much less likely to be homeowners.

Using state-level housing market returns, equity returns and bond returns as test assets, I formally estimate the structural parameters within the Euler equations that result from the intertemporal optimization problem of a representative agent with EZ preferences. The housing market returns capture both the price appreciation in housing and the service flow received from owning housing. The use of state-level data captures the fact that housing is almost entirely traded by investor bases within communities that are heterogeneous in both their economic and demographic characteristics. I find that, while the EZ-CAPM explains variation in housing returns better than in equity returns, there exists a housing market risk premium that is not
explained by the model. In general, the housing market risk premium is smaller than the risk premium associated with equities.

I identify three potential institutional explanations for the difference between the housing and equity risk premia: leverage, capital gains tax treatment and the income tax deductibility of mortgage interest payments. In the United States, it is more common to use a house rather than a portfolio of equities as collateral for loans. Using levered returns I find that, while leverage in housing increases the volatility of returns, it doesn’t consistently explain the observed gap between premia across time horizons. In fact, the use of leverage combined with poor performing housing markets leads to a widening of the gap. The tax treatment of capital gains is different for equities than it is for housing. For owner occupied housing, the capital gains tax is waived if the capital gain is less than $250,000 ($500,000) for singles (for married couples), whereas the capital gains tax on equities is charged for any size capital gain. I adjust the equity and bond return data to account for an annual payment of capital gains taxes. With this change, I observe a narrowing of the gap between the risk adjusted premium for holding housing and that for holding equities. A third institutional difference between equities and housing is the income tax deductibility of mortgage interest payments. Although I do not carry out a formal analysis of this effect, I estimate that the value of the mortgage payment deduction ranges from 0.93% to 1.80% of the house value per year for the median U.S. household. Together, the effects of differential tax treatment between the two asset classes appears to account for a large proportion of the difference in premia.

While there has been much work related to housing market returns and housing market efficiency, to my knowledge no one has structurally estimated the EZ-CAPM
so to determine the ability of the model to price housing returns. Shilling (2003) examines return expectations and finds a large risk premium associated with real estate. In a recent paper, Cannon, Miller and Pandher (2008) find a positive relation between housing market returns at the zip-code level and their risk. These authors take a cross-sectional asset pricing approach similar to that of Fama and French (1992). The seminal papers related to housing market returns and the efficiency of housing markets are Case and Shiller (1989, 1990). They find that excess housing market returns are forecastable, thereby making housing markets inefficient. An extensive literature followed these papers, examined various housing markets and came to many conflicting conclusions. Reviews of that literature can be found in Gatzlaff and Tirtiroglu (1995) and Cho (1996).

A few recent structural asset pricing papers include housing in the utility function. The two leading proponents of this approach are Lustig and Van Nieuwerburgh (2005) and Piazzesi, Schneider and Tuzel (2007). Lustig and Van Nieuwerburgh (2005) find that investors demand more compensation for risk when the housing collateral to human wealth ratio is low. Piazzesi, et al. find that when housing services and consumption are complements and returns and rental price growth are positively correlated, households demand a larger risk premium for holding assets. In recent work, Davis and Martin (2009) find that the Piazzesi et al. framework is unable to simultaneously match house prices, equity returns and the bond returns.

1.1 Model and Methodology

The approach I take to empirically evaluate the asset pricing model is the stochastic discount factor (SDF) method. This method allows me to dually test the ability
of the model to explain stock market returns and the predictive power of the model. A SDF, \( m_{t+1} \), is a variable such that the value of a financial asset \( P_t \) is equal to the expected value of the payoff of the asset in period \( t + 1 \) times the SDF\(^1\):

\[
P_t = E_t[m_{t+1}(P_{t+1} + D_{t+1})].
\] (1.1)

In this case, the payoff of the asset in the next period is equal to the price of the asset plus the dividends the asset pays. Dividing (1.1) by \( P_t \) yields an equation in terms of the SDF and asset returns \( R_{t+1} \):

\[
1 = E_t[m_{t+1}R_{t+1}].
\] (1.2)

The Euler equations that result from the optimization of an agent’s consumption and portfolio choice decisions can be expressed in this framework. Consider the representative agent model with power utility. The agent chooses the amount of assets, \( \varsigma \), (and implicitly the amount of consumption) to maximize

\[
V(W_t) \equiv U(C_t) + E_t [\beta V(W_{t+1})]
\] (1.3)

subject to

\[
U(C_t) = \frac{c_t^{1-\sigma}}{1-\sigma}
\]

\[
C_t = \omega_t - P_t\varsigma
\] (1.4)

\[
C_{t+1} = \omega_{t+1} - (P_{t+1} + D_{t+1})\varsigma
\]

\(^1\)See Cochrane (2001) for a detailed description of the SDF method.
where $\omega$ is the agent’s endowment. The first-order condition of the agent’s problem implies:

$$P_t = E_t \left[ \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} (P_{t+1} + D_{t+1}) \right]$$

or

$$1 = E_t \left[ \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} R_{t+1} \right].$$

Thus, the SDF is:

$$m_{t+1} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma}.$$

In this paper I am primarily concerned with testing a model derived by Epstein and Zin (1989) that takes advantage of nonexpected utility. The CAPM of Sharp (1964), Treynor (1961) and Lintner (1965) is the fundamental model in finance that relates risk to return. There are two distinct branches of CAPMs: the consumption-CAPM and the market-CAPM. As shown above, the consumption-CAPM says that the return on an asset is a function of the covariance between the asset return and the consumption growth rate. The market-CAPM says that the return on an asset is just a linear function of the covariance of the return on the asset with the rate of return on an optimally diversified portfolio of assets. The CAPM with EZ preferences nests both the consumption-CAPM and the market-CAPM. In this framework, the consumer chooses consumption and portfolio weights to maximize

$$V(W_t) = \left\{ (1 - \beta)C_t^\rho + \beta (E_t V(W_{t+1})^\alpha)^{\rho/\alpha} \right\}^{1/\rho}$$
subject to the budget constraint

\[ W_{t+1} = \omega_t' R_t (W_t - C_t). \] (1.9)

Here, \( W \) is the consumer’s total wealth, \( C \) is the total consumption flow, \( \omega \) is a vector of portfolio weights and \( R \) is a matrix of gross returns on assets. The EZ preference structure decouples the intertemporal elasticity of substitution parameter (EIS) from the coefficient of relative risk (CRRA). The parameter \( \beta \) is the time discount factor, \( \alpha = 1 - CRRA \), and \( \rho = (EIS - 1)/EIS \). Following the notation in Epstein and Zin (1989), I define \( \lambda = \alpha/\rho \) and \( \gamma = 1/EIS \). For \( N \) assets indexed by \( j \), the asset return Euler equations are

\[ E_t \left[ \beta^\lambda \left( \frac{C_{t+1}}{C_t} \right)^{-\lambda\gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} \right] = 1. \] (1.10)

The market Euler equation is

\[ E_t \left[ \beta^\lambda \left( \frac{C_{t+1}}{C_t} \right)^{-\lambda\gamma} R_{M,t+1}^\lambda \right] = 1. \] (1.11)

The Law of One Price together with EZ preferences imply that there exists a SDF equal to \( \beta^\lambda \left( \frac{C_{t+1}}{C_t} \right)^{-\lambda\gamma} R_{M,t+1}^{\lambda-1} \) that prices all assets in the economy. It is this proposition that is formally tested in Epstein-Zin (1991) with equity and bond returns. In this paper, I test this proposition with housing market, equity and bond returns.

To get the best fit for the proposed model I need to estimate the structural parameters to minimize the pricing errors. To do this I employ the Generalized Method of Moments (GMM). The asset pricing Euler equation implied by the EZ utility is:
\[
E \left[ \beta^\lambda \left( \frac{C_{j,t+1}}{C_{j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda - 1} R_{j,t+1} - 1 \mid I_t \right] = 0 \quad (1.12)
\]

where \( I_t \) is the available information set at time \( t \). Allowing \( z_t \) to be a vector of variables known at time \( t \), I obtain the following orthogonality conditions via the Law of Iterative Expectations:

\[
E \left[ z_t \left\{ \beta^\lambda \left( \frac{C_{j,t+1}}{C_{j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda - 1} R_{j,t+1} - 1 \right\} \right] \equiv E \left[ z_t \{ \epsilon_{t+1} \} \right] = 0 \quad (1.13)
\]

Letting the set of parameters be denoted \( \theta = (\beta, \lambda, \gamma) \), the vector of orthogonality conditions be \( \xi_{t+1}(\theta) \), and \( \phi(\theta) = \frac{1}{T} \sum_{t=1}^{T} \xi_{t+1}(\theta) \) I arrive at the following GMM estimator

\[
\hat{\theta}(\hat{W}) \equiv \arg \min_{\theta} J_T(\theta, \hat{W}) \quad (1.14)
\]

where

\[
J_T(\theta, \hat{W}) \equiv T \phi(\theta) \hat{W}_T(\theta) \phi(\theta). \quad (1.15)
\]

Hansen (1982) shows that the weight matrix is optimally chosen to be the inverse of the spectral density matrix \( \hat{S} \). Because of potential serial correlation in the data, I use the estimator of the spectral density matrix proposed by Newey and West (1987). The use of this estimator leads to efficient estimates with consistently estimated standard errors. Letting \( \hat{g}_t \) be the orthogonality condition at time \( t \) at the parameter estimates that minimize the first stage GMM criterion function, we have:

\[
\hat{S} = \hat{\rho}_0 + \sum_{k=1}^{LAGS} \omega_k (\hat{\rho}_k + \hat{\rho}'_k) \quad (1.16)
\]
where
\[ \hat{\rho}_j = \frac{1}{T} \sum_{t=k+1}^{T} \hat{g}_t \hat{g}_{t-k} \]
\[ \omega_k = 1 - \left( \frac{k}{\text{LAGS}+1} \right) \]
for \( k = 0, 1, \ldots, T - 1 \).

This is a two-step procedure. In the first step, I set the weight matrix \( W_T \) to be the identity matrix. This yields first stage estimates of the parameters and model residuals. The model residuals are used to construct the spectral density matrix \( \hat{S} \). In the second stage, I set the weight matrix to be equal to the inverse of the estimated spectral density matrix. Hansen (1982) showed that this procedure leads to the GMM estimators with the lowest asymptotic variance.

The asymptotic variance evaluated at the parameter estimates is
\[
\text{ASYVAR}(\hat{\theta}(\hat{W})) = (\nabla \phi(\hat{\theta})' \hat{W} \nabla \phi(\hat{\theta}))^{-1}
\]  
(1.18)
where \( \nabla \phi(\hat{\theta}) \) is the gradient of the vector of moment conditions. The robust standard errors are just the square root of the diagonal elements of \( \text{ASYVAR}(\hat{\theta}(\hat{W})) \) divided by the sample size.

1.2 Data

So to not overwhelm the reader with data and results for all states, I limit most of the discussion to five states. The five states of focus are California, Florida, Hawaii, New Mexico and Ohio. Below, I discuss the characteristics of housing returns and demographics for each of these states.

The three variables needed to estimate the Euler equations described in the previous section are asset returns, per capita consumption and the return on an optimally
chosen portfolio of all assets in the economy. All nominal variables are converted to real 2003 dollars using the GDP deflator. The return of asset $j$ in the model is defined as

$$R_{j,t+1} = \frac{P_{j,t+1} + D_{j,t+1}}{P_{j,t}}. \quad (1.19)$$

Because part of the purpose of this work is to compare the investment performance of housing versus equities, I define housing returns in such a way that they are comparable to equity returns. Following Case and Shiller (1990) and Gatzlaff (1996) I take housing dividends to be the cost of renting a similar property. Therefore, the gross real return for housing market $j$ can be written as

$$R_{j,t+1} = \frac{\text{CAPGAIN}_{j,t+1} + \text{DIVIDEND}_{j,t+1} - \text{TAX}_j - \text{DEPRECIATION}}{P_{j,t}} \quad (1.20)$$

$P_{j,t}$ is taken to be the median value of owner-occupied units in housing market $j$ in the year $t$, and $D_{j,t}$ is the quarterly contract rent in housing market $j$ in year $t$ times a “step-up” factor. The “step-up” factor is defined to be the ratio of the average number of bedrooms in owner-occupied units in market $j$ to the average number of bedrooms in renter-occupied units market $j$. The purpose of using the “step-up” factor is to roughly adjust for the size differential between the typical house and the typical rental unit. In 1980 the average owner-occupied dwelling in the United States had 1.33 times the number of bedrooms as the average renter-occupied dwelling. Through this construction, the return definition for housing includes the consumption value of owning the house.
Because equities don’t depreciate and investors in equities don’t pay property taxes, I deduct estimates of the property tax payment and depreciation from the housing return series. I don’t have data on property taxes for each state for the entire sample period, so I use the average property tax in each state as reported by the American Community Survey in 2007. I assume annual depreciation to be 2.5% of the property value. This is in line with Harding, Rosenthal and Sirmans (2007), who find that during the 1983 to 2001 period housing depreciated at 2.5% annually.

With the returns in hand, I can calculate the gross risk premium for asset $j$ as

$$RP_{j,t+1} = \frac{R_{j,t+1}}{R_{f,t+1}}$$

(1.21)

where $R_{f,t+1}$ is the quarterly interest rate on the three month U.S. Treasury bill.

Consumption growth rates differ by market, and more importantly the covariance between the consumption growth rates and the return on the local assets may vary by market. When viewed through the CAPM these differences in covariances can translate to differences in risk exposure. For that reason, I use a measure of consumption growth that is specific to each local housing market. I use state level retail sales estimates to proxy for consumption. These estimates\(^2\) are compiled by Regional Financial Associates and are available through Moody’s data services. Retail sales account for approximately 50% of overall consumption, and therefore provide a reasonable proxy. While the consumption estimates may contain measurement error, my investigation indicates these are the best source of a state level consumption proxy.

\(^2\)See Case, Quigley and Shiller (2006) for a description of the construction of the retail sales series.
I directly address the measurement error in the consumption data with the GMM-D estimator of Alan, Attanasio, and Browning (2009). This estimator is discussed further in the Results section and Appendix A.2.

In the CAPM, the market rate of return $R_{m,t+1}$ is intended to capture the return on an optimally chosen portfolio of the investable set of assets. An important issue arises when considering this market portfolio in the presence of residential housing. Because residential housing comprises a large proportion of the consumer’s portfolio, we cannot treat the market rate of return as just the return on an index of equities. Rather, we must treat it as a weighted average between the return on an index of equities and the return on the local housing market. Therefore, the market rate of return will be unique for each market depending on both the ratio of housing wealth to equity wealth in that market, and the rate of return on the housing market. For example, housing may be a larger share of the average Californian’s portfolio than of the average Ohioan’s portfolio.

To capture the cross-sectional variation in these portfolio weights, I use data borrowed from the Case, Quigley and Shiller (2006) data set\(^3\). They constructed a quarterly measure of housing wealth and equity wealth by state over the 1983 to 1999 period. They compiled the stock wealth variable using data on mutual fund holdings by state collected from the Investment Company Institute, Flow of Funds data and the relationship between equity holding and mutual fund holding. The housing wealth variable was compiled using the 1990 Census of Population and Housing by state and weighted repeat sales indexes. While these figures may overestimate the median

\(^3\)These data were retrieved from John Quigley’s website.
equity wealth across the country, they are the best measure available to capture the cross-section variation in portfolio weights.

The sources of all the data are given in table 1.1. The analysis in this paper examines both the housing boom period (Q2 1983 to Q2 2006) and a period of relatively stable housing and equities markets (Q2 1983 to Q2 1996). The stable markets period is intended to give the reader an indication of what the relative premia for housing and equities would be if I had a longer time series of returns. The choice to examine the period that spans the second quarter of 1983 to the second quarter of 2006 was made specifically because that time period includes the housing boom. By including this period, housing has the “best chance” to have a good investment performance relative to equities. That is, if housing appears to be a poor investment compared to equities during this period that includes an unprecedented housing boom, then we can make some conclusions about housing’s relative performance over longer horizons.
Figure 1.1 plots the Freddie Mac National House Price Index against the return on the CRSP NYSE/NASDAQ/AMEX value weighted index with dividends. The notable volatility in the two series during recent years raises questions about the validity of the statistical evaluation of models that include that data.

The return characteristics and consumption growth rates of the focus states and aggregate U.S. market are given in table 1.2. The focus states each have return characteristics that make them attractive for study. California and New Mexico are the most “typical” of states in terms of return characteristics. That is, the first four moments (mean, standard deviation, skewness and kurtosis) are all within one
Table 1.2: Descriptive Statistics of the returns of the test assets and the consumption growth rates of the states.  
The p-values are in brackets.

<table>
<thead>
<tr>
<th>State</th>
<th>Returns</th>
<th>Per Capita Consumption Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>California</td>
<td>0.0672</td>
<td>0.0394</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Florida</td>
<td>0.0913</td>
<td>0.0278</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hawaii</td>
<td>0.0498</td>
<td>0.0496</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>New Mexico</td>
<td>0.0759</td>
<td>0.0299</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ohio</td>
<td>0.0525</td>
<td>0.0125</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>United States</td>
<td>0.0632</td>
<td>0.0114</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large Cap Stocks</td>
<td>0.1035</td>
<td>0.2091</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Micro Cap Stocks</td>
<td>0.0950</td>
<td>0.1473</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Month T-Bill</td>
<td>0.0252</td>
<td>0.0107</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>State</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>[0.0185]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0291]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0191]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0337]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0210]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0304]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0196]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0303]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0224]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0249]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0207]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.0228]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-</td>
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<td></td>
<td></td>
<td>-</td>
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<tr>
<td></td>
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<td>-</td>
</tr>
</tbody>
</table>
standard deviation of the average U.S. state for each moment. For a mean-variance
investor, Florida would be considered to be a good investment as its mean return is
high relative to the average market. Ohio’s return series has very few outliers, a low
return and a low variance. Thus, we can consider Ohio to be a stable investment.
However, the return distribution for Hawaii indicates that it is a poor investment.
Specifically, the Hawaii housing market realized a low return and high variance over
the sample period. Beyond California’s return series being representative of the rest of
the U.S., the state’s population accounts for roughly 12% of the total U.S. population.
Hawaii is unique in that over 70% of its population lives in a single metropolatian
statistical area. The data for the aggregate U.S. housing returns are compiled using
the average rent and house price data from the Davis, Lehnert and Martin (2008) data
set\(^4\). The variance of the aggregate return and consumption data is likely lower than
the variance of in the data from individual states due to the effects of aggregation.

Table 1.2 also contains estimates of the serial correlation in the return series.
The positive and statistically significant serial correlation coefficients for all of the
housing markets indicates a degree of predictability of housing returns. This finding
was originally discovered by Case and Shiller in their 1989 paper in the *American
Economic Review*.

Table 1.3 presents some demographic and economic characteristics of the focus
states. There is significant heterogeneity across the states in both the demographic
and economic characteristics. The demographic characteristics are from the 2000 U.S.
Census, while the economic characteristics are based on the data described above. The
variation in the age and racial composition of the population across states is notable.

\(^4\)Retrieved from [http://www.lincolninst.edu/resources](http://www.lincolninst.edu/resources)
For instance, the average age in California is 33.3 while the average age in Florida is 38.7. Furthermore, the percentage of households with members over the age of 60 or younger than the age of 18 indicates that state-by-state there may be substantial variation in the number of people at various stages of the life-cycle. The Census data indicates that while the ratio of men to women is relatively uniform across states, the race composition is not. The percentage of the population that is black or Hispanic is more than three times larger in New Mexico than it is in Ohio. The states with the most expensive housing markets (based on the average rent-to-price ratio over the 1983 to 2006 period), California and Hawaii, also have the largest household sizes. Those two states also have more people living in cities than the other three states in the study.

Perhaps due to the higher cost of housing in the California and Hawaii markets, the average housing wealth is higher than the average stock market wealth. This is not the case in the other three states. New Mexico is the only state for which the housing market return is negatively correlated with the consumption growth rate. From the perspective of the CAPM, this means that the ownership of housing in New Mexico provides a better hedge against consumption volatility than does ownership of housing in the other markets. For all states, the correlations between large cap stocks listed on the NYSE and the consumption growth rates were negative.

This observed heterogeneity between the states may have important implications for consumption-based asset pricing models. Riley and Chow (1992) and Halek and Eisenhauer (2001) find that one’s relative risk aversion rises at age 65. Halek and Eisenhauer (2001) also find that men are less risk averse than women, and that blacks and Hispanics are less risk averse than whites and other races. In an analogous way,
Table 1.3: Economic and Demographic Characteristics of States.

<table>
<thead>
<tr>
<th>Demographic Characteristic</th>
<th>California</th>
<th>Florida</th>
<th>Hawaii</th>
<th>New Mexico</th>
<th>Ohio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Age</td>
<td>33.30</td>
<td>38.70</td>
<td>36.20</td>
<td>34.60</td>
<td>36.20</td>
</tr>
<tr>
<td>HH Size</td>
<td>2.87</td>
<td>2.46</td>
<td>2.92</td>
<td>2.63</td>
<td>2.49</td>
</tr>
<tr>
<td>Urban Pop-to-Rural Pop</td>
<td>17.00</td>
<td>8.33</td>
<td>10.73</td>
<td>2.99</td>
<td>3.42</td>
</tr>
<tr>
<td>Vacant-to-Occupied Units</td>
<td>0.06</td>
<td>0.15</td>
<td>0.14</td>
<td>0.15</td>
<td>0.08</td>
</tr>
<tr>
<td>Pct of HH with 60+ old members</td>
<td>28.67%</td>
<td>37.63%</td>
<td>34.05%</td>
<td>29.06%</td>
<td>30.19%</td>
</tr>
<tr>
<td>Pct of HH with children*</td>
<td>39.73%</td>
<td>31.34%</td>
<td>37.94%</td>
<td>38.60%</td>
<td>34.50%</td>
</tr>
<tr>
<td>Pct of Black and Hispanic in POP</td>
<td>38.82%</td>
<td>30.95%</td>
<td>8.96%</td>
<td>43.76%</td>
<td>13.28%</td>
</tr>
<tr>
<td>Pct of Men in POP</td>
<td>49.82%</td>
<td>48.79%</td>
<td>50.24%</td>
<td>49.16%</td>
<td>48.55%</td>
</tr>
<tr>
<td>Economic Characteristic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing Return</td>
<td>6.72%</td>
<td>9.13%</td>
<td>4.98%</td>
<td>7.59%</td>
<td>5.25%</td>
</tr>
<tr>
<td>Housing Return STD</td>
<td>3.94%</td>
<td>2.78%</td>
<td>4.96%</td>
<td>2.99%</td>
<td>1.25%</td>
</tr>
<tr>
<td>Consumption Growth Rate</td>
<td>1.21%</td>
<td>2.38%</td>
<td>2.76%</td>
<td>2.20%</td>
<td>2.91%</td>
</tr>
<tr>
<td>Consumption Growth Rate STD</td>
<td>3.30%</td>
<td>3.57%</td>
<td>3.34%</td>
<td>3.27%</td>
<td>2.47%</td>
</tr>
<tr>
<td>Stock-to-Assets**</td>
<td>0.46</td>
<td>0.69</td>
<td>0.49</td>
<td>0.54</td>
<td>0.61</td>
</tr>
<tr>
<td>Housing-to-Assets**</td>
<td>0.54</td>
<td>0.31</td>
<td>0.51</td>
<td>0.46</td>
<td>0.39</td>
</tr>
<tr>
<td>$\rho(R^H, C)$†</td>
<td>0.08</td>
<td>0.03</td>
<td>0.12</td>
<td>-0.11</td>
<td>0.28</td>
</tr>
<tr>
<td>$\rho(R^{LCAP}, C)$‡</td>
<td>-0.20</td>
<td>-0.20</td>
<td>-0.19</td>
<td>-0.15</td>
<td>-0.05</td>
</tr>
<tr>
<td>Average Rent-to-Price Ratio</td>
<td>0.05</td>
<td>0.09</td>
<td>0.03</td>
<td>0.09</td>
<td>0.07</td>
</tr>
</tbody>
</table>

* Children are HH members 18 years old or younger.

** Assets refer to stock and housing assets only.

† Correlation between the housing return and the consumption growth rate.

‡ Correlation between the return on large cap equities and the consumption growth rate.
demographics may affect other structural parameters such as the time discount factor or the elasticity of intertemporal substitution.

Figures 1.2, 1.3 and 1.4 plot the natural logarithms of the house prices and rents for each of the focus states.

Although real house prices were still rising through the second quarter of 2006, real rents began to decline in most states around the beginning of 2006. Appendix A.1 gives an informal comparison of the rent-to-price ratios implied by the rents and prices constructed in this paper to the rent-to-price ratios constructed by Campbell, Davis, Gallin and Martin (2008).

1.3 Results

As discussed above, I separate the data into two sets. The first set contains the entire sample: the second quarter of 1983 through the second quarter of 2006. Because this period includes the housing bubble, it gives housing the best chance to achieve a good performance relative to equities. The second set contains data from the period that covers the second quarter of 1983 through the second quarter of 1996. I regard this time period as fairly placid for both housing markets and equity markets. Indeed, that period ends right at the beginning of the tech boom in equities and the bubble in residential housing markets.

The three things I examine are the overall fit of the model, the fit of the housing asset pricing Euler equations and the difference between the realized returns and the model predicted price of risk (the risk adjusted returns).

I test the overall fit of the model using a method proposed in Hansen (1982). The two step efficient estimation procedure combined with the presence of overidentifying
Figure 1.2: Log Real House Prices and Rents in California and Florida.
Figure 1.3: Log Real House Prices and Rents in Hawaii and New Mexico.
Figure 1.4: Log Real House Prices and Rents in Ohio.
conditions yields a specification test of the model restrictions. Hansen (1982) also showed that $J_T$ evaluated at the parameter estimates and the optimal weighting matrix converges to a chi-square distribution with degrees of freedom equal to the number of overidentifying conditions. A number of papers, including Hansen, Heaton and Yaron (1996), have noted that this test tends to over reject the null hypothesis of correct model specification in small samples. It will be important to keep this in mind when evaluating the results.

A second test of specific restrictions was proposed by Newey (1985) and Eichenbaum, Hansen and Singleton (1985). I use this test to determine the ability of the model to price the housing asset pricing Euler equations. I execute the test by estimating the unrestricted model with all the moment restrictions as well as a restricted model that excludes the moment restrictions of interest. The test statistic $C \equiv J_U^T - J_R^T$ converges in distribution to a chi-square with degrees of freedom equal to the number of excluded moment restrictions.

To conduct estimation, I must make decisions about the set of assets, the set of instruments and the number of Newey-West lags. I define the set of assets to be the real returns on the housing market of interest, micro cap NYSE stocks, large cap NYSE stocks and the U.S. T-bill. I use the consumption growth rate, the market rate of return, the growth rate in industrial production, the junk bond spread and a constant as the instruments. The instrument set is the set of observed instruments at period $t - 3$. This ensures that the instruments fall within the information set at time $t$. Consistent with Newey and West’s $T^{1/4}$ rule, I set the number of lags to be used in the Newey-West spectral density estimation to be equal to 3. In the analysis
of the subsets of overidentifying conditions, the unrestricted model includes the full set of four assets and the restricted model uses just the stock returns and the T-bill.

1.3.1 Epstein-Zin CAPM with a Measurement Error Corrected Estimator

The estimation of the Euler equations resulting from the first order conditions of the intertemporal optimization problem of a representative consumer with EZ preferences require consumption data, optimal portfolio return data and asset return data. While the assets that comprise the optimal portfolio have known and well measured returns, consumption is measured from survey data or estimated from retail sales tax data.

Measurement error can lead to inconsistent parameter estimates, and therefore it is important to account for the presence of it in the data. To correct for this problem, I turn to measurement error corrected estimators proposed by Alan, Attanasio, and Browning (2009). In using this estimator, I must make several assumptions about the nature of the measurement error. First, I assume the consumption measurement error is multiplicative. Second, I assume the measurement error is stationary and independent of all other variables in the model (including the instruments and expectation error).

The orthogonality condition used to estimate the structural parameters via GMM based on the GMM-D estimator of Alan, Attanasio and Browning (2005) is:

\[
E_t \left[ \beta^\lambda \left( \frac{C_{o,j,t+1}}{C_{j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} - \beta^{2\lambda} \left( \frac{C_{o,j,t+2}}{C_{j,t}} \right)^{-\lambda \gamma} (R_{M,t+1} R_{M,t+2})^{\lambda-1} (R_{j,t+1} R_{j,t+2}) \right] = 0
\]  

(1.22)
where $C^o$ is observed consumption.

I estimate the vector of structural parameters $\theta = [\beta \lambda \sigma]$ from the moment conditions given by equations (1.22). $\sigma$ is the elasticity of intertemporal substitution (EIS), and is equivalent to $\gamma^{-1}$ in equation (1.22). The results from the estimation of the GMM-D estimator are given in table 1.4.

Panel A of table 1.4 contains results from the period that spans the second quarter of 1983 to the second quarter of 2006 (housing boom period), and Panel B contains results from the period that spans the second quarter of 1983 to the second quarter of 1996 (stable markets period). In looking at this table, there are several things on which to focus. First, is there heterogeneity in the parameter estimates across the geographies? The estimates of time discount factor, $\beta$, are statistically close for all of the states except Ohio. That is, for California, Florida, Hawaii, New Mexico and the aggregate United States, I can’t reject the null hypothesis that the time discount factor is equal to 0.99. The estimate for Ohio is high compared to what is typically estimated. The null hypothesis that $\lambda = 1$ implies that I can’t reject the traditional consumption-based model with time separable utility. I can reject the null hypothesis of time separable utility for all states except Hawaii. Of the three estimated parameters, the EIS is the most difficult to identify. I cannot reject the null hypothesis that the EIS is equal to 0 for New Mexico and Ohio. Of the significant estimates, the sensitivity of Californians to substituting consumption across time is relatively low and similar to the 0.24 estimate of the EIS with the aggregate U.S. data. The estimate of the EIS for Florida is 0.67 and 1.15 for Hawaii. Turning to the coefficient of relative risk aversion, I can’t reject the null hypothesis of risk neutrality for California or the aggregate U.S. However, I can reject the null hypothesis of
Table 1.4: Structural parameter estimates and diagnostic statistics for EZ CAPM with GMM-D Estimator.

The four test assets (Housing market, large cap NYSE, micro cap NYSE and the three month U.S. treasury.) and the market Euler equation yield five moments. The five moments combined with the five instruments (a constant, consumption growth, the market rate of return, the growth rate in industrial production and the junk bond spread) imply twenty-five orthogonality conditions. Three parameters are estimated and thus there are twenty-two overidentifying conditions. There are five degrees of freedom for the C-statistic. In the 1983 to 2006 sample, there are 90 observations, and there are 50 observations in the 1983 to 1996 sample.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: 1983 Q2 to 2006 Q2</th>
<th>Panel B: 1983 Q2 to 1996 Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta^\dagger )</td>
<td>( \lambda^\dagger )</td>
</tr>
<tr>
<td>California</td>
<td>0.9937*</td>
<td>-0.2356*</td>
</tr>
<tr>
<td>Florida</td>
<td>0.9731*</td>
<td>-0.2387*</td>
</tr>
<tr>
<td>Hawaii</td>
<td>0.9829*</td>
<td>0.9153*</td>
</tr>
<tr>
<td>New Mexico</td>
<td>0.9708*</td>
<td>-0.2319*</td>
</tr>
<tr>
<td>Ohio</td>
<td>1.0189*</td>
<td>-0.0340*</td>
</tr>
<tr>
<td>United States</td>
<td>0.9882*</td>
<td>-0.2257*</td>
</tr>
</tbody>
</table>

Asymptotic standard errors in parentheses and p-values in brackets.

\( \dagger \) indicates estimated parameter

\( \ddagger \) indicates implied parameter

* indicates statistical significance at the 5% level.
logarithmic utility for all geographies except Ohio. The point estimates of the CRRA are 0.89 for Florida, 0.88 for Hawaii and 1.10 for New Mexico.

There is significant heterogeneity in the parameter estimates across the geographies. While it is beyond the scope of this work to formally relate the structural parameter estimates to demographic or economic characteristics of the states, I will make some broad observations. The estimate of the time discount factor indicates that Ohioans are generally more patient than residents of the other geographies. Based on the estimates of the CRRA, Californians were less averse to risk over the time period than were the residents of the other four states estimated. The estimates of the EIS indicate that Californians are more willing to substitute consumption across time than the residents of Florida and Hawaii. The variation in these parameters are likely driven by demographic and economic characteristics of the populations of the respective states, and in future work it may be fruitful to consider using a panel of geographies to explore the drivers of the variation in structural parameters across space.

Second, do we observe different parameter estimates across time? Campbell and Cochrane (1999) is a prominent paper in a line of financial economics papers to posit that time-varying risk aversion may help to explain the equity premium puzzle. There is some limited evidence that the parameters vary across time. Statistically, the time discount factor for Ohio is higher during the housing boom period than during the stable markets sub-period. The EIS was significantly higher for both California and the aggregate U.S. during the sub-period than it was during the full period. While the CRRA was larger for Hawaii during the sub-period than it was during the housing boom period, it was smaller for New Mexico during the sub-period.
The number of degrees of freedom associated with the J-statistic is 22 while it is 5 for the C-statistic. At the 5% level of significance, the chi-square critical values for 22 and 5 degrees of freedom are 33.92 and 11.07, respectively. The model performed better over the stable markets period than it did over the housing boom period. That is, I cannot reject the null hypothesis that model is properly specified. In general, the overall model had a similar performance across states; however, the C-statistic provides evidence that the variation in the housing asset returns was captured worse for Ohio than the other states. A comparison of the J-statistic with the C-statistic for each state indicates that the pricing errors associated with the housing market assets are smaller than those associated with the equities.

Under the assumption that gross consumption and gross returns are jointly log-normally distributed, I can derive:

\[
\log E_t \left( \frac{R_{i,t+1}}{R_{f,t+1}} \right) = \lambda \gamma Cov_t(x_{t+1}, r_{i,t+1}) + (1 - \lambda) Cov_t(r_{m,t+1}, r_{i,t+1}) = \lambda \gamma Cov_1 + (1 - \lambda) Cov_2 \tag{1.23}
\]

where \( x \) is the log of gross consumption growth, \( r_m \) is the log gross rate of return on the market, \( r_i \) is the log gross rate of return on an asset and \( R_f \) is the gross risk free return. Therefore, given estimates of \( \lambda, \gamma, Cov_1 \), and \( Cov_2 \) I can evaluate the unconditional risk premium implied by the model. In table 1.5 I report the risk adjusted premium implied by the data and the model. I calculate the risk adjusted premium by subtracting the model predicted premium from the premium observed in the data.

In table 1.5 we can see that there does exist a housing premium, but that the premium is generally smaller than the equity premium. Furthermore, during the stable markets period both the housing premium and the large cap equities premium
Table 1.5: Risk adjusted premia for benchmark data. Epstein-Zin CAPM estimated with the GMM-D measurement error corrected estimator.

<table>
<thead>
<tr>
<th></th>
<th>1983 Q2 to 2006 Q2</th>
<th>1983 Q2 to 1996 Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HOUSING</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>California</td>
<td>4.09%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Florida</td>
<td>6.51%</td>
<td>2.42%</td>
</tr>
<tr>
<td>Hawaii</td>
<td>2.40%</td>
<td>0.95%</td>
</tr>
<tr>
<td>New Mexico</td>
<td>4.96%</td>
<td>3.39%</td>
</tr>
<tr>
<td>Ohio</td>
<td>2.66%</td>
<td>2.28%</td>
</tr>
<tr>
<td>United States</td>
<td>3.74%</td>
<td>2.25%</td>
</tr>
<tr>
<td><strong>EQUITIES</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large Cap†</td>
<td>6.36%</td>
<td>3.48%</td>
</tr>
<tr>
<td>Micro Cap†</td>
<td>5.55%</td>
<td>7.05%</td>
</tr>
</tbody>
</table>

The risk adjusted premium is the difference in the average observed premium in the data and the premium predicted by the model.
† Average across geographies.

were significantly smaller than they were during the housing boom period. I discuss this table further in the next section.

1.3.2 The Puzzle

A popular explanation of the equity premium puzzle is that, in a world of incomplete markets, market frictions can drive the premium. That is, high transactions costs or borrowing constraints may prevent subsets of the population from investing in equities. These frictions, it is argued, can explain the gap between the return earned for owning equities versus the yield on the risk free asset. Aiyagari and Gertler (1991) argue that investors demand a liquidity premium for owning equities because they are relatively more costly to trade than money market funds. Constantinides, Donaldson, and Mehra (2002) posit that the desirability of an asset to the marginal investor in that asset determines the asset’s premium. They argue that equities are
undesirable to the marginal investor (middle aged households) because equity income is highly correlated with consumption for that age group.

Relative to housing, equities are liquid. Where equities can be purchased in small amounts with low transactions costs, the purchase of housing often involves large brokerage fees and thin markets. The literature on the impact of down payment constraints on tenure choice seems to indicate that there might be an even larger segmentation in the market for housing than there is in the market for equities. Thus, given the incomplete market explanations of the equity premium, we might expect housing to command a larger risk premium than equities.

The puzzling result can be found in table 1.5. The national housing market boom that ended in 2006 was the most prominent in United States history. Even with the inclusion of this boom in the sample, the performance of housing is mediocre compared to the performance of equities over the same time period. The Florida housing market earned the highest risk adjusted premium at 6.51% annually. During the same time period, large cap and small cap equities earned annual risk adjusted premia of 6.36% and 5.55% respectively. In terms of the statistical characteristics of returns, California and New Mexico are most like the median U.S. housing market. Over the 1983 to 2006 period, the California market earned a risk adjusted premium of 4.09% and the New Mexico market earned a rate of 4.96%: respectively, that is 227 and 140 basis points below the risk adjusted returns on the largest firms in the NYSE! The risk adjusted premium of housing for the aggregate U.S. data was 262 basis points below the premium on large cap equities. The premia for all assets except micro cap NYSE stocks are lower during the stable markets sample period. The highest housing premium during the stable markets period was New Mexico at
3.39%, which was slightly below the 3.48% premium on large cap equities. The risk adjusted premium for the aggregate U.S. data was 123 basis points below the premium on large cap equities.

In the Data section, I made the point that the distribution of housing returns in California and New Mexico are representative of the distribution of returns for the average state in the U.S. The difference between the annual risk adjusted premium for California and the annual risk adjusted premium for large cap equities was 227 basis points. Over a long horizon, this difference in risk adjusted return would yield a significant difference in wealth growth. For illustrative purposes, suppose one could invest $100,000 in each of the two assets and receive the risk adjusted return. Over a twenty year period, the investment in the California market would be worth $222,936 while the investment in large cap equities would be worth approximately $343,215.

Recall that the housing returns are measured to include the consumption flow from owning housing. I measure returns in this way so that I can directly compare the investment value of housing to the investment value of equities. Why, then, would investors accept a lower risk adjusted return for housing than for equities? In general equities, and certainly large cap equities, are more liquid than housing. Furthermore, where a housing investment is generally a large proportion of a consumer’s wealth, equity investments may be as small as a few dollars. Thus, equities presumably provide a diversification benefit that is not present in housing. Finally, the brokerage fees associated with transacting in housing markets are generally larger than those associated with transacting in equities markets. While one may pay a real estate agent in the range of 6.0% of the value of the house for a round-trip transaction, equities market transactions may be completed for small fixed costs.
1.4 Possible Explanations

There are a few institutional characteristics that differentiate housing from equities that are not controlled for in the above analysis. I refer to them as institutional because they are determined by legislative policy. First, retail investors can use leverage to purchase housing in a way that is either not possible or much more costly for equities. In some countries, such as Canada, there are laws that specify the minimum size of a down payment. Second, there are differences in the tax treatment of capital gains on housing and equities. Third, the mortgage interest payments are deductible from taxable income in the United States. In the first three parts of this this section I explore the extent to which these characteristics may be able to explain the puzzle. In the fourth part of this section, I make note of a non-institutional characteristic of housing that may be able to explain the puzzle.

1.4.1 Leverage

One way in which housing differs from stock as an investment is in the ability consumers have to borrow to purchase the asset. In the United States, consumers often only pay a small fraction of the house value at the time of purchase. The rest of the value is lent to the consumer by a financial institution, and the house is the collateral for the loan. This ability to borrow against the house relaxes the consumer’s borrowing constraints, and thus may increase the value of a house as an investment.

I take the an approach similar to that in Case and Shiller (1990) to calculate levered returns. Formally, a levered return is

\[
R_{j,t+1}^L = \frac{P_{j,t+1} + D_{j,t+1}}{(1 - \omega)P_{j,t}} - \frac{(1 + \omega MTG_t)}{(1 - \omega)} - TAX_j - DEPRECIATION \quad (1.24)
\]
where $\omega$ is the amount borrowed and $MTG$ is the average prevailing rate on a 30-year fixed rate mortgage.

Figure 1.5 illustrates the effects of mortgage interest rates and the amount of leverage on the average annualized levered return on an asset that yields 5.00% annually. When mortgage rates are very low or the asset return is very high, the rewards for financing the investment are high. However, when the mortgage rate is high or the asset return is low, the magnification of the return is in the negative direction. While leverage can increase the value of an asset substantially when net returns are high, it can magnify the destruction of value when net returns are low. Thus, ceteris paribus, when leverage is used returns will be more volatile.

The relationship in figure 1.5 is also important because it illustrates the benefits of borrowing to finance an investment when the investor expects future returns to be high. If expectations for future returns to housing were to become irrationally high, my hypothesis is that the loan-to-value ratios in the residential housing sector would become unsustainably high. I leave it to future work to test this hypothesis.

I choose the leverage rate to be 50%. The loan-to-value ratio in the United States increased over the sample period: 36% in 1978, 50% in 1989 and 73% in 2003. The 50% rate I use assumes that the housing debt-to-housing equity ratio is a constant 50%. Since some homeowners do accumulate equity in their house beyond the down payment and approximately one-third of people own their homes outright, I consider 50% to be at the upper end of the reasonable parameterizations for $\omega$.

Table 1.6 reports the risk adjusted premia for the two time periods when I account for a leverage rate of 50%. With leverage included, some of the housing markets outperform equities during the 1983 to 2006 period. In particular, leverage propelled
Figure 1.5: Effect of leverage and mortgage rate on levered returns.
Table 1.6: Risk adjusted premia with levered housing returns.
Epstein-Zin CAPM estimated with the GMM-D measurement error corrected estimator. Leverage rate assumed to be 50%.

<table>
<thead>
<tr>
<th></th>
<th>1983 Q2 to 2006 Q2</th>
<th>1983 Q2 to 1996 Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HOUSING</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>California</td>
<td>5.44%</td>
<td>-3.00%</td>
</tr>
<tr>
<td>Florida</td>
<td>10.42%</td>
<td>1.78%</td>
</tr>
<tr>
<td>Hawaii</td>
<td>1.82%</td>
<td>-1.32%</td>
</tr>
<tr>
<td>New Mexico</td>
<td>7.14%</td>
<td>3.64%</td>
</tr>
<tr>
<td>Ohio</td>
<td>3.20%</td>
<td>2.21%</td>
</tr>
<tr>
<td>United States</td>
<td>1.88%</td>
<td>-1.37%</td>
</tr>
<tr>
<td><strong>EQUITIES</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large Cap†</td>
<td>6.34%</td>
<td>3.61%</td>
</tr>
<tr>
<td>Micro Cap†</td>
<td>5.59%</td>
<td>7.18%</td>
</tr>
</tbody>
</table>

The risk adjusted premium is the difference in the average observed premium in the data and the premium predicted by the model.
† Average across geographies.

the housing premium in Florida to 10.42%. Yet, for Hawaii and the aggregate U.S. the housing premium fell with the use of leverage. During the stable markets period, the low returns on housing combined with the leverage actually drove the risk adjusted premium to be negative for several markets. The levered return housing premium on the aggregate U.S. data was lower for both periods than the premium on the unlevered returns over both periods.

1.4.2 Effects of Capital Gains Tax

The wedge between the housing and equities premia may simply be attributed to the difference in the tax treatment of the two asset classes. While I have already adjusted housing for the approximate property taxes in the respective states, I have ignored taxes on the equities. An obvious difference in tax treatment between owner
occupied housing and equities is the capital gains tax. As a result of the Taxpayer Relief Act of 1997, the capital gains tax for owner-occupied housing is waived if the capital gain is less than $250,000 ($500,000) for singles (for married couples), whereas the capital gains tax on equities is charged for any size capital gain. Prior to 1997, owners could defer the capital gains tax payment on housing related capital gains as long as their next home purchase had a higher value than the home they sold. Furthermore, after the age of 55 homeowners received a one-time exemption on capital gains up to $125,000. So, prior to 1997, as long as a homeowner remained a homeowner and didn’t downsize before the age of 55, they remained exempt from capital gains taxes. According to Burman (2008), in 1993 there were $50.5 billion dollars in capital gains on home sales in the United States, and $48 billion was exempt through the tax law at the time.

To evaluate whether this channel has the ability to explain the wedge between the premia, I adjust returns on equities and bonds to account for capital gains taxes paid at a turnover rate of 40%. In this case, I assume that no capital gains taxes are paid on housing and that capital gains taxes are paid each year on 40% of equity and bond holdings. I choose the turnover rate based on estimates in the literature. Aiyagari and Gertler (1991) report a turnover rate of 50% for all U.S. equities. However, the majority of transactions in their aggregate calculation are executed by institutional investors. Analysis by Agnew, Balduzzi and Sunden (2003) indicates that the turnover rate within 401(k) accounts by individual investors is around 16% while Barber and Odean (2000) report the turnover rate on online brokerage accounts to be around 75%. Given that online brokerage accounts did not exist for much of the sample
Table 1.7: Risk adjusted premia with capital gains tax adjusted equity and bond returns.
Epstein-Zin CAPM estimated with the GMM-D measurement error corrected estimator. Portfolio turnover rate assumed to be 40%.

<table>
<thead>
<tr>
<th></th>
<th>1983 Q2 to 2006 Q2</th>
<th>1983 Q2 to 1996 Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HOUSING</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>California</td>
<td>4.50%</td>
<td>0.57%</td>
</tr>
<tr>
<td>Florida</td>
<td>6.94%</td>
<td>2.97%</td>
</tr>
<tr>
<td>Hawaii</td>
<td>2.73%</td>
<td>1.46%</td>
</tr>
<tr>
<td>New Mexico</td>
<td>5.40%</td>
<td>3.91%</td>
</tr>
<tr>
<td>Ohio</td>
<td>3.08%</td>
<td>2.88%</td>
</tr>
<tr>
<td>United States</td>
<td>4.15%</td>
<td>2.78%</td>
</tr>
<tr>
<td><strong>EQUITIES</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large Cap†</td>
<td>5.25%</td>
<td>2.96%</td>
</tr>
<tr>
<td>Micro Cap†</td>
<td>4.63%</td>
<td>6.54%</td>
</tr>
</tbody>
</table>

The risk adjusted premium is the difference in the average observed premium in the data and the premium predicted by the model.
† Average across geographies.

period, I consider a 40% turnover rate to be a conservatively high parameterization for this study.

I apply this treatment by evaluating the nominal returns on the equity market and bond market assets each year. If the nominal return in a given year is positive, the capital gains tax is calculated and deducted evenly from the four quarters of nominal returns. If the nominal return is negative, no changes are made to the quarterly returns in that year. With the tax adjusted return series for non-housing assets in hand, I estimate the model with the measurement error adjusted estimator. The risk adjusted premia for the two time periods are given in table 1.7.

Taking capital gains taxes into account, the Florida and New Mexico housing markets outperformed large cap equities during both samples periods. The difference
in capital gains tax treatment almost entirely narrows the gap between the housing premium on the aggregate U.S. data and the premium on large cap equities during the stable markets period. During the housing boom period, the 217 basis point difference in premia between the Ohio housing market and large cap equities was the largest. The observation of the gap narrowing for all geographies implies that the differences in capital gains tax treatment may be an important component of the explanation of the puzzle.

1.4.3 Tax Deductibility of Mortgage Interest Payments

For residents of the United States, the tax deductibility of mortgage interest payments is also a source of value accruing to the homeowner but not to the owner of equities. I have not carried out the formal analysis for this potential explanation because the amount of value the homeowner gains is dependent on several variables: (1) the income tax bracket into which they fall; (2) the size of their outstanding mortgage debt; (3) the prevailing interest rate when they borrowed the money; and (4) whether or not the deduction fell entirely into one tax bracket. I leave it to future work to complete a rigorous examination of this unique institutional characteristic of housing. However, I can do some simple calculations to get an idea of the value a homeowner might expect to gain from this provision.

According to the Current Population Survey, median household income in 2000 was $42,100. In that year, the median household would have fallen into the 28% income tax bracket. Suppose that the median household bought a home that was valued at $126,300, or three-times their income, with a 20% down payment. The prevailing 30-year fixed rate mortgage in 2000 was 8.05%. Now, I will assume two
things: (1) they pay the mortgage debt over the course of 30 years; and (2) they remain in the 28% income tax bracket.

The tax savings as a percentage of the house value falls over time as the household pays the debt. Over a 30-year period, the average annual tax savings would be 0.93% of the value of the house in the year of purchase. If the household maintained only 20% equity in the house, their annual tax savings on mortgage interest rate deductions would be 1.80% of the value of the house in the year of purchase. So, for the median household, the value of the tax deductability of mortgage interest payments is approximately in the range of 93 to 180 basis points per year. Because there is no tax in the U.S. on imputed rental income\(^5\), for most homeowners the true benefit from the mortgage payment tax deduction is likely near the upper end of the range reported above. However, it is important to note that the median household does not itemize deductions. According to a report by the Tax Foundation, the overall itemization rate in the United States in 2005 was only 35.61%. Thus, the benefits from the mortgage payment tax deduction are not likely being realized by the median household.

1.4.4 Housing’s Value as a Hedge Against Rental Risk

In addition to the institutional characteristics of housing, there may be additional sources of value accrued from owing housing that I have failed to capture in this paper. In their 2005 *Quarterly Journal of Economics* article, Sinai and Souleles show that there is value in homeownership as a hedge against rental price risk. Although, one might argue that equity ownership can provide even more value as a hedge against other risks faced by the consumer. For example, ownership of oil service equities

\(^5\)See Follain and Ling (1991) for a detailed description of the implications of this provision
hedges the consumer against fluctuations in gasoline prices. Likewise, ownership of
countercyclical companies provides the consumer with a hedge against income risk.
However, an investigation of the ability of a rental hedge premium to resolve the
puzzle is merited.

1.5 Conclusion and Extensions

In this paper, I test the ability of the CAPM with EZ preferences to price housing
and equity returns. I find statistically significant differences in the structural param-
eter estimates across geographies, and this suggests that heterogeneity in the investor
base has implications for consumption-based asset pricing models. The model prices
housing market returns better than equity returns across different time horizons, and
yields a price of risk that, along with realized returns, can be used to compute the
model risk adjusted premium of holding various asset classes. I find that the model
risk adjusted premium is generally lower for housing than it is for equities. That
is, the investor in equities was compensated at a higher risk adjusted rate than the
investor in housing. This result is puzzling for two reasons. First, the 2007 Survey
of Consumer Finance indicates American families hold approximately fifty percent of
their assets in real estate and only ten percent in risky financial assets, yet the in-
vestment performance of equities appears to dominate that of housing. Second, if the
theoretical explanations for the equity premium puzzle (based on incomplete markets
and market frictions) are accurate, an even larger premium would be expected for
housing than for equities. This follows from the large transactions costs associated
with housing transactions and the documented effects that borrowing constraints have
on tenure choice.
I investigate three potential explanations of the observed gap related to the institutional characteristics of the two asset classes: leverage, capital gains tax treatment and the income tax deductibility of mortgage interest payments. In the United States, it is more common to use a house rather than a portfolio of equities as collateral for loans. While leverage in housing increases the volatility of returns, it doesn’t consistently explain the observed gap across time horizons. In fact, the use of leverage combined with poor performing housing markets leads to a widening of the gap. The tax treatment of capital gains is different for equities than it is for housing. For owner occupied housing, the capital gains tax is waived if the capital gain is less than $250,000 ($500,000) for singles (for married couples), whereas the capital gains tax on equities is charged for any size capital gain. I adjust the equity and bond return data to account for annual payment of capital gains taxes. With this change, I observe a narrowing of the gap between the risk adjusted premium for holding housing and that for holding equities. A third institutional difference between equities and housing is the income tax deductibility of mortgage interest payments. Although I do not carry out a formal analysis of this effect, I estimate the value of the mortgage payment deduction to range from 0.93% to 1.80% of the house value per year for the median U.S. household. However, it is important to note that the median household does not itemize deductions. According to a report by the Tax Foundation, the overall itemization rate in the United States in 2005 was only 35.61%. Thus, the benefits from the mortgage payment tax deduction are not likely being realized by the median household. In sum, the tax benefits of homeownership appear to account for at least part of the documented difference in premia between housing and equities.
In the absence of the tax benefits to holding housing, the asset class yields a significantly lower risk adjusted premium to investors than do equities. Given the incomplete markets explanations of the equity premium puzzle, this finding is puzzling. A robust asset pricing model must simultaneously explain (1) the low risk free rate; (2) the high equity premium; and (3) the housing premium that falls somewhere between the risk free rate and the equity premium. The mechanisms invoked in the incomplete markets versions of the Lucas (1978) model imply an even higher premium for housing than for equities, and thus fail to explain the three puzzles. A better model may retain the important pricing features of assets that are in the incomplete market versions of the Lucas model while explicitly accounting for the differences in the quality of the information the investor has about different asset classes. Epstein and Schneider (2008) show that ambiguity-averse investors demand a higher premium for holding assets for which the information quality is low. Investors may perceive the information they collect regarding their local housing markets to be of better quality than the information they receive about publicly traded companies.

This paper points toward a couple of potentially fruitful paths of future research. First, in the absence of legislative intervention, it appears that the incomplete market explanations of the equity premium puzzle would not be robust to the inclusion of housing as an asset. The models that include housing in the utility function, such as Piazzesi, Schneider and Tuzel (2007) have performed poor empirically. Researchers should investigate whether models with ambiguity-averse investors are capable of simultaneously explaining the low risk free rate, the high equity premium and the housing premium that lies somewhere between the risk free rate and the equity premium. Second, the heterogeneity in the estimates of the preference parameters across
geographies implies that different investor bases may value the same asset differently. A panel study that links the preference parameters to demographic and economic characteristics of the population would be an important contribution.
CHAPTER 2

Non-durable Consumption Volatility and Illiquid Assets

There are two reasons why consumers choose to hold assets: (1) they derive utility from holding the asset and (2) the expected discounted marginal utility from holding the asset for a certain time period is greater than the current marginal utility from consuming. The types of assets they hold are differentiated along five dimensions. First, assets can be solely investment vehicles or they can serve the dual role of an investment vehicle and a consumption good. Second, assets have different expected returns. Third, assets have different risk profiles. Fourth, the degree to which an asset may be levered is not uniform. Finally, the liquidity of assets differs across asset classes and even within asset classes.

This paper investigates the influence that asset liquidity and the degree to which an asset may be levered have on non-durable consumption and portfolio choice in a life-cycle setting. Portfolio choice models often assume that an agent may switch costlessly between risky and risk-free assets. Samuelson (1969) and Merton (1971) are the two seminal examples. Their assumption that markets are complete and the two-fund separation theorem imply that agents can satisfy mean-variance preferences in each period.
In the data, however, there is evidence that agents are not always able to costlessly alter their allocations of risky and risk-free assets. Heaton and Lucas (1997) and Cocco, Gomes, and Maenhout (2002) note that market incompleteness hinders investors from insuring against labor income risk. Further, they conclude that under certain conditions, labor income acts as a substitute for risk-free asset holdings. Beyond market incompleteness, transitioning from one financial asset to another often requires a brokerage fee. Yet there are still many cases, such as IRAs, in which the brokerage fee is minimal or even nonexistent. Campbell (2007) reports that a majority of public equity held by investors is in mutual funds or retirement accounts.

Even in cases in which the brokerage fees are trivial, the agent faces a cost of acquiring the information necessary to make an optimal financial decision. For the more financially astute agents, the cost is merely the time it takes to acquire information and analyze the decision. However, for those less confident in making financial decisions, the aid of financial consultants is often necessary. Indeed, Calvet, Campbell, and Sodini (2007) find that poor and less educated households are more likely to make “investment mistakes” than wealthier, higher educated households. They characterize “investments mistakes” as: (1) Nonparticipation in risky asset markets, (2) Underdiversification of risky portfolios, and (3) Failure to exercise options to refinance mortgages. Whatever the reason may be, investor behavior provides some evidence that there exist barriers to participation in asset markets.

To capture barriers to participation in asset markets in this paper, I assume that all financial transactions in risky markets incur strictly positive transaction costs. The size of the transaction cost in the context of different asset classes is debatable, and for that reason I will focus on housing in this paper. With respect to fixed transactions
costs, housing adjustment costs likely represent the upper limit of those incurred by a typical consumer in his or her life. Given the assumption about the existence of fixed transaction costs, agents are unable to optimally rebalance their portfolios in each period. One of the goals of this work is to gain a better understanding of these non-convex transactions costs affect non-durable consumption.

The model predicts that consumption volatility is decreasing in the liquidity of the asset. I also find that consumption volatility increases as the ability to borrow against the asset increases. Large fixed transaction costs cause there to be lumpy adjustment in the stock of the asset. When this effect is combined with borrowing constraints, it causes the agent’s consumption to become very volatile around the adjustment points. This effect is discussed further in section 4 of the paper. I find evidence in consumption data retrieved from the Consumer Expenditure Survey to support the prediction of the model.

In context, this work most closely relates to that of Grossman and Laroque (1990) and Flavin and Nakagawa (2008). Grossman and Laroque introduce non-convex transactions costs, and show that even with the transaction costs it is optimal for the consumer to hold a mean-variance efficient portfolio at all times. Further, they find that consumers appear to be more risk averse after purchasing a house, and less risk averse before purchasing the house. Flavin and Nakagawa extend the model of Grossman and Laroque to include housing in the utility function. They also allow the price process of the house being sold to differ from the price process of the house being purchased.

The model used in this paper is most closely related to models used by Cocco (2005) who studies portfolio choice over the life-cycle, Yao and Zhang (2005a,2005b),
and Li and Yao (2007) who study the life-cycle effects of housing tenure. Yao and Zhang allow renting in their models, and they find that the adjustment cost generates a no adjustment region for housing. They also find that the investor holds more liquid portfolios when he or she is near the boundary of the adjustment region. Li and Yao find that non-housing consumption is less responsive to changes in housing wealth when the transaction cost is included. On the theoretical side, Chetty and Szeidl (2004) and Vereshchagina (2007) examine the effect of consumption commitments in dynamic decision models.

2.1 Model

I formulate a discrete-time, dynamic decision model of a finitely-lived representative agent who derives utility from consuming a non-durable good and from owning a durable asset. For the first $T$ years of her life, the agent receives a deterministic flow of labor income, which she allocates among consumption of the non-durable good, cash savings held in an interest-bearing account, and investment in the durable asset. At the beginning of year $T+1$, the agent retires, makes no further adjustments to her stock of the durable asset, and converts her cash balances into an annuity that will provide her with a fixed annual payment with which to finance consumption of the non-durable good over the remaining $N$ years of her life.

2.1.1 Household Problem

Entering each pre-retirement period $t$, the agent observes the current price of the durable asset $P_t$, her current cash holdings $S_t$ and her current stock of the durable asset $K_t$. She then decides how much of the non-durable good to consume $C_t$ and how much stock of the durable asset to purchase or sell $A_t$, deriving utility
\[
\begin{align*}
\quad u(C_t, K_t) &= \frac{(C_t^\alpha (K_t + A_t)^{(1-\alpha)})^{1-\beta}}{1-\beta}.
\end{align*}
\] (2.1)

Note that the agent’s utility function is a constant relative risk aversion (CRRA) function, within which is nested a Cobb-Douglas consumption function. The period marginal rate of substitution between non-durable and durable consumption is \(\frac{\alpha}{1-\alpha} \frac{C}{K}\).

In any given period, the agent’s allocation decisions are restricted by three constraints. Total addition to (deduction from) savings in period \(t\) must be equal to the agent’s realized income in period \(t\) less the amount she spends on consumption of the non-durable good and the amount she adds to (deducts from) her durable asset holdings in that period. For any changes made to the durable asset holdings, the agent incurs a transaction cost which is a proportion of the total value of the durable asset held entering period \(t\) plus a proportion of the value of the durable asset held at the end of the period. When we take the asset to be a house, the transaction cost setup is analogous to requiring the agent pay a transaction cost on the sale of her old house and on the purchase of her new house. From this point forward, I will talk about the durable asset as if it is a house. The budget constraint described here is formalized in the following equation:

\[
\begin{align*}
X_t &= Y_t - P_t A_t - C_t - \tau D_t P_t (K_t + (K_t + A_t)).
\end{align*}
\] (2.2)

Here, \(Y_t\) is the agent’s income in period \(t\), \(X_t\) is the addition (deduction) to cash holdings in period \(t\), \(D_t\) is a discrete choice variable which takes a value of one when the agent decides to change houses and a value of zero when the agent chooses to stay in the same house:
This non-convex transaction cost prevents the consumer from making small, regular changes to housing stock. Figure 2.1 gives a visual depiction of the transaction cost. Given $K_t = 10$ and $\tau = 0.03$, the figure shows the actual amount of the cost for values of $A_t$ ranging from -10 to 10. Because housing transactions typically incur a large fixed cost (from brokerage fees and search costs), non-convex adjustment costs are appropriate. The interpretation behind the above transaction cost is that the agent pays $\tau$ times the sale price of the old house plus $\tau$ times the purchase price of the new house. It is debatable whether transactions in other asset markets incur fixed costs. In equity and bond markets there are costs associated with acquiring the information necessary to adjust the stock appropriately in these assets. It may be reasonable to view these as fixed costs rather than variable.

For simplicity, I assume that the agent’s lifetime income stream is deterministic and known by the agent from the beginning of her working life. The agent is allowed to borrow and lend at a rate of $r$, however she is restricted to only being able to borrow $\theta$ proportion of the value of her house. I restrict $\theta$ to be zero in period $T$ so that the agent doesn’t retire with debt. The agent’s borrowing constraint in period $t$ for $t = 1, ..., T - 1$ is:

$$
X_t \geq -(S_t + \theta P_t K_t).
$$

(2.4)
Figure 2.1: Transactions Costs for Changes in Housing Stock
We may think of $\theta$ as a measure of the degree to which the asset may be levered. For a typical consumer their housing assets are likely to have a higher $\theta$ than their other financial assets.

Finally, the agent is not allowed to be short of housing. Therefore, I invoke a nonnegativity constraint:

$$A_t \geq -K_t \quad (2.5)$$

### 2.1.2 State Variables

Entering period $t$ the agent observes her relative stock of saving or debt $S_t$ and chooses to change this stock by an amount $X_t$. If the agent has net savings after the choice of $X_t$, she earns an interest rate $r$ on the savings account holdings. Otherwise, the agent pays the interest rate $r$ on the total debt she holds. The law of motion for savings is formalized as:

$$S_{t+1} = (1 + r)(S_t + X_t) \quad (2.6)$$

As discussed above, the agent enters period $t$ with some stock of housing $K_t$. She then decides to remain in the same house, or to move to a new house of size $K_t$ plus $A_t$. The stock in the house depreciates annually at a rate of $\gamma$. Specifically,

$$K_{t+1} = (1 - \gamma)(K_t + A_t) \quad (2.7)$$

The house price $P_t$ follows a first order mean reverting Markov process. The evolution of the logarithm of this price $p_t$ is given by:
\[ p_{t+1} = \mu + \phi(p_t - \mu) + \tilde{\epsilon}_{t+1} \] (2.8)

Here, \( \mu \) is the long-run average price, \( \phi \) is the mean reversion parameter and \( \tilde{\epsilon}_t \) is i.i.d. Normal(0,\( \sigma^2 \)). \( \sigma \) corresponds to the average per-period volatility of the durable asset price process.

### 2.1.3 Retirement

At the beginning of year \( T + 1 \), the agent retires, makes no further adjustments to her stock of durable asset and converts her cash balances into an annuity that will provide her with a fixed annual payment with which to finance consumption of the non-durable good over the remaining \( N \) years of her life. In particular, for \( t = T + 1, T + 2, \ldots, T + N, k_t = k_T \) and

\[ C_t = \frac{1 - (1 + r)^{-1}}{1 - (1 + r)^{-N}} S_{T+1}. \] (2.9)

### 2.1.4 Dynamic Decision Problem Formulation

Assuming that the agent maximizes the present value of utility discounted at an annual subjective rate \( \delta \), her dynamic decision problem will be characterized by the Bellman equation

\[
V_t(P_t, S_t, K_t) = \max_{A_t, X_t, D_t} \left\{ u(A_t, X_t, D_t) + \delta E_t V_{t+1}(P_{t+1}, S_{t+1}, K_{t+1}) \right\} \\
C_t = Y_t - P_t A_t - X_t - \tau D_t P_t (K_t + (K_t + A_t)) \\
C_t \geq 0 \\
X_t \geq -(S_t + \theta P_t K_t) \\
A_t \geq -K_t \\
S_{t+1} = (1 + r)(S_t + X_t) \\
K_{t+1} = (1 - \gamma)(K_t + A_t) \\
p_{t+1} = \mu + \phi(p_t - \mu) + \tilde{\epsilon}_{t+1} \] (2.10)
for $t \leq T$, subject to the terminal condition

$$V_{T+1}(P_{T+1}, S_{T+1}, K_{T+1}) = u\left(\frac{r}{1+r}S_{T+1}, K_{T+1}\right).$$  \hfill (2.11)

In the way the model is specified, the transactions costs are discontinuous at $A_t = 0$. The implication of this is that the Bellman equation will have nondifferentiable points between states in which it is optimal to purchase a new house and those in which it is optimal to stay in the same house. I address this by employing a strategy in which I find two conditional value functions. $V_{0t}$ is the conditional value function given the discrete choice of not adjusting, and $V_{1t}$ is the conditional value function given the discrete choice to adjust housing stock. Specifically, the conditional value functions are:

$$V_{0t}(P_t, S_t, K_t) = \max_{X_t, A_t} \{u(X_t) + \delta E_t \max(V_{0t+1}(P_{t+1}, S_{t+1}, K_{t+1}), V_{1t+1}(P_{t+1}, S_{t+1}, K_{t+1}))\}$$

s.t. \hspace{1cm} $C_t = Y_t - X_t$

$C_t \geq 0$

$X_t \geq -(S_t + \theta P_t K_t)$

$A_t = 0$

$S_{t+1} = (1 + r)(S_t + X_t)$

$K_{t+1} = (1 - \gamma)(K_t + A_t)$

$p_{t+1} = \mu + \phi(p_t - \mu) + \epsilon_{t+1}$

(2.12)

and

$$V_{1t}(P_t, S_t, K_t) = \max_{X_t, A_t} \{u(X_t, A_t) + \delta E_t \max(V_{0t+1}(P_{t+1}, S_{t+1}, K_{t+1}), V_{1t+1}(P_{t+1}, S_{t+1}, K_{t+1}))\}$$

s.t. \hspace{1cm} $C_t = Y_t - P_t A_t - X_t - \tau P_t((K_t + A_t) + K_t)$

$C_t \geq 0$

$X_t \geq -(S_t + \theta P_t K_t)$

$A_t \neq 0$

$S_{t+1} = (1 + r)(S_t + X_t)$

$K_{t+1} = (1 - \gamma)(K_t + A_t)$

$p_{t+1} = \mu + \phi(p_t - \mu) + \epsilon_{t+1}$

(2.13)
These conditional value functions are related to the Bellman equation by the following function:

\[ V_t(P_t, S_t, K_t) = \max \{ V_0(P_t, S_t, K_t), V_1(P_t, S_t, K_t) \}. \] (2.14)

Because this model cannot be solved analytically, I use the numerical techniques discussed in Miranda and Fackler (2002) to find a solution.\textsuperscript{6} There are two advantages to using the approach sketched above. First, the optimands of the maximization problem embedded in the conditional value functions will be continuous. Second, the conditional value functions will be differentiable. This property enables us to approximate the conditional value functions using smooth Chebychev polynomials.

\subsection*{2.2 Calibration}

Table 2.1 summarizes both the general parameter restrictions and the baseline parameterization.

I set the per-period interest rate \( r \) to approximately 100 basis points below the average annualized post-World War II real return on U.S. T-bills. The 100 basis point departure from the real T-bill return is meant to capture an asset that is relatively more liquid than the T-bill. The coefficient of relative risk aversion, \( \beta \), of 1.5 is fairly standard in the literature. In the 2006 survey of consumer finances, it is reported that housing makes up somewhere between 30 and 40 percent of household expenditure. Therefore, I set the non-durable consumption utility weight, \( \alpha \), equal to 0.7. I set the durable asset depreciation rate, \( \gamma \), equal to 0.03 and the collateral requirement, \( \theta \),

\textsuperscript{6}Details in the Appendix
Table 2.1: Model Parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Restriction</th>
<th>Parameterization</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r )</td>
<td>per-period interest rate</td>
<td>( 0 \leq r \leq 0.02 )</td>
<td></td>
</tr>
<tr>
<td>( \delta )</td>
<td>subjective discount factor</td>
<td>( 0 \leq \delta \leq 1 )</td>
<td>0.97</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>durable asset depreciation rate</td>
<td>( 0 \leq \gamma \leq 1 )</td>
<td>0.02</td>
</tr>
<tr>
<td>( \theta )</td>
<td>collateral requirement</td>
<td>( 0 \leq \theta \leq 1 )</td>
<td>0.80</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>non-durable consumption utility weight</td>
<td>( 0 \leq \alpha \leq 1 )</td>
<td>0.70</td>
</tr>
<tr>
<td>( \beta )</td>
<td>coefficient of relative risk aversion</td>
<td>( 0 \leq \beta \leq 1 )</td>
<td>1.5</td>
</tr>
<tr>
<td>( \mu )</td>
<td>long-run mean return</td>
<td>( 0 \leq \mu \leq 1 )</td>
<td>1.0</td>
</tr>
<tr>
<td>( \phi )</td>
<td>mean reversion parameter</td>
<td>( 0 \leq \phi \leq 1 )</td>
<td>0.90</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>standard deviation of durable asset price process</td>
<td>( 0 \leq \sigma \leq 0.06 )</td>
<td></td>
</tr>
<tr>
<td>( \tau )</td>
<td>transaction cost</td>
<td>( 0 \leq \phi \leq 1 )</td>
<td>0.03</td>
</tr>
<tr>
<td>( T )</td>
<td>number of time periods</td>
<td>( 0 \leq T \leq 45.0 )</td>
<td></td>
</tr>
</tbody>
</table>

equal to 0.80. In addition to the parameters in table 2.1, there is also a deterministic income process \( I_t \), specified as:

\[
Y_t = Y_0(1 + r)^t
\]  

(2.15)

2.3 Results

The purpose of that paper is to study the effects that asset characteristics have on consumption decisions. In the following analysis I solve the model specified above using numerical methods. Each time I solve the model, I vary a single parameter. Then I run Monte Carlo simulations to generate optimal paths for agents. In the present study, I am interested in understanding what the model predicts at different levels of asset liquidity \( (\tau) \) and at different levels of asset leverage \( (\theta) \).
2.3.1 Asset liquidity

Liquidity of assets held by consumers is not constant. The relative thickness or thinness of asset markets is affected by business cycles and aggregate shocks. Additionally, individual real estate markets are not all homogeneous in their liquidity. I examine different levels of asset liquidity ranging from no transactions costs to $\tau = 0.05$ to determine if degree to which the intertemporal changes in liquidity and the heterogeneity between consumers portfolio liquidity affects consumption. Note that at a $\tau = 0.05$, say, the ‘round-trip’ transaction cost of selling the old house and purchasing a new one is ten percent. I choose to be somewhat agnostic about what the ‘correct’ level of transaction cost should be. Indeed, I intend for the adjustment cost in this setting to not only capture brokerage fees but also the relative thickness of the market and the cost of the agent to acquire information about the new asset. In this sense transactions costs likely differ by market, and depend on whether the agent goes from thin market to thin market, thin market to thick market, et cetera.

Figure 2.2 depicts the relationship between asset liquidity, leverage ability, and non-durable consumption volatility. As can be seen in the figure, consumption volatility is decreasing in the liquidity of the asset. For perfectly liquid assets ($\tau = 0.0$), the average time series consumption volatility for 1000 Monte Carlo draws is 0.178 for the baseline $\theta = 0.8$. When the transaction cost increases, the consumption volatility increases. At the highest transaction cost I explore ($\tau = 0.05$) the average consumption volatility predicted by the model is 0.24. In section 4.3, I will give some intuition about the mechanism driving this effect.
Figure 2.2: Consumption Volatility in Liquidity and Leverage
2.3.2 Asset leverage

Some assets may be leveraged more than others. For example, it may be easier to borrow using a house as collateral rather than a portfolio of equities. There are institutional differences between countries and states that cause the degree to which nearly identical or identical assets may be levered to be different. Government regulation of credit markets can directly affect the degree to which an asset may be levered. I examine how degrees of asset leverage ability ranging from $\theta = 0.4$ to $\theta = 1.0$ affect consumption volatility.

Returning to figure 2.2, we can see that consumption volatility is increasing in the degree to which the asset may be levered. At the baseline transaction cost of $(\tau = 0.03)$, the average time series consumption volatility for 1000 Monte Carlo draws is merely 0.19 at $\theta = 0.4$. Increasing the leverage ability to 100%, a reasonable level in modern U.S. mortgage markets, the average consumption volatility increases to 0.242.

2.3.3 The Mechanism

In order to get some intuition about the mechanism driving the model predictions above, figure 2.3 plots the consumption path and housing stock path for three randomly chosen Monte Carlo draws using the baseline calibration.

The fixed transaction cost makes it suboptimal for the consumer to adjust in each period. This feature of the model, generates $(s, S)$ bounds on housing stock similar to those in Grossman and Laroque (1990). That is, at any given time the consumer prefers to be at a housing stock level equal to $S$. However, because there is a high fixed cost associated with adjustment the agent waits until her housing stock
Figure 2.3: Consumption and Housing Stock
has deviated sufficiently far from \( S \) to justify incurring the transaction cost. The lower and upper bounds at which the agent will chose to adjust are defined \( s \) and \( \bar{s} \) respectively. On the right hand side of figure 2.3, we can see how the agent waits until the asset depreciates a certain amount before adjusting. In each of the draws displayed here, the agent adjusts housing six times during the forty-five year period. When transactions costs are eliminated (not shown here), the agents adjust housing in every period.

On the left hand side of figure 2.3, we observe that consumption becomes more volatile around the adjustment points. This is driven by the liquidity constraints that the consumer faces around the purchasing points. Under convex adjustment costs, these liquidity constraints would not bind as often because the agents are able to accumulate housing stock gradually over time. The liquidity constraints also bind early in the life-cycle as the consumer attempts to smooth consumption. However, liquidity constraints binding early in the life-cycle are not unique to this model and are not related to the specification of the transactions costs. The utility specification dictates that durable and non-durable consumption are nonseparable. Bernanke (1985) notes that this nonseparability in the utility function causes spillover effects between non-durable and durable consumption. Indeed, we observe these spillover effects. When the consumer enters a period in which it is optimal to adjust housing, non-durable consumption falls. This is the result of the consumer spending a larger proportion of her budget on durable consumption in that period. It is the combination of the non-convex transactions costs, liquidity constraints and the nonseparable utility function that drive the results above.
Some aspects of the model setup cause problems in the approximation of the value function in certain limited parts of the state space. Thus, the simulated consumption paths of individual agents should be taken with some degree of caution. It is my view that the approximation problems are effectively smoothed out through the use of Monte Carlo methods to produce the results in figure 2.2. Future versions of this model are aimed at rectifying the approximation issues.

2.4 Data

Given limitations of the data, finding conclusive tests of the model predictions is a challenge. I have settled upon an exercise in which I separate out non-durable consumption of homeowners from that of non-homeowners in the Consumer Expenditure Survey (CEX). I perform two observational exercises to determine whether there might be any justification for the model results in the data. First, I use actual response data from the CEX to identify which households own homes. Second, I separate out non-durable consumption from homeowners who do not own equities from those who do.

After the delineations are made, I examine the time series properties of the consumption of the groups. I have acquired the data extracts of the CEX from the National Bureau of Economic Research (NBER) website. These extracts were assembled by Ed Harris and John Sabelhaus. This data is a pseudo panel spanning 1981 to 2001, and contains detailed information on consumption of households. More details about the data are provided in Appendix B. Table 2.2 provides a description of the consumption categories used in this study.
Table 2.2: Consumption Categories

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>Includes expenditures on alcohol, tobacco, food consumed at home, work, and in restaurants.</td>
</tr>
<tr>
<td>Utilities</td>
<td>Includes expenditures on electricity, gas for home, water, and telephone.</td>
</tr>
<tr>
<td>Clothes</td>
<td>Includes expenditures on clothes, tailors, jewelry, and personal care products.</td>
</tr>
<tr>
<td>Car</td>
<td>Includes expenditures on car servicing, gasoline, parts, and auto insurance.</td>
</tr>
<tr>
<td>Health</td>
<td>Includes expenditures on drugs, doctor visits, hospital visits, health insurance, and orthopedic products.</td>
</tr>
</tbody>
</table>
The categories were chosen specifically to capture non-durable household consumption. For this reason, I don’t include furniture, appliances, housing, or car purchases. The reader is encouraged to take note that the category car only includes maintenance costs and fuel costs for automobile transportation. Although the variables used in this study are not exhaustive, I believe they provide a reasonable sample of the representative household’s non-durable consumption bundle. Other studies, such as Mankiw and Zeldes (1991) look only at food consumption spending from the Panel Survey of Income Dynamics. Attanasio, et al. (2002) look at total non-durable consumption from the British Family Expenditure survey. Their conclusions were that consumption is more volatile for stockholders than for non-stockholders.

Taking consumption growth rates to be the log difference of consumption from one year to the next, I define consumption volatility to be the standard deviation of time series of consumption growth rates. Formally, given a consumption series $C_t$ I let the natural logarithm be denoted as $c_t$. Then the growth rate of consumption in any period is:

$$\Delta c_t \equiv c_t - c_{t-1}$$

(2.16)

The consumption volatility is just the standard deviation of the vector $\Delta c$.

2.4.1 Analysis of Actual Homeowners

Table 2.3 was generated by using house value data provided in the CEX extract data set. If the reported house value for a household is greater than zero, I code that household as a homeowner. This table provides some limited evidence that consumption volatility is higher for homeowners than for non-homeowners. In three of
Table 2.3: Standard Deviation of Actual Homeowners

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>PERCENT OF 2005 EXPENDITURES</th>
<th>CONSUMPTION VOLATILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>HOMEOWNERS</td>
</tr>
<tr>
<td>Food</td>
<td>14.75</td>
<td>0.0238</td>
</tr>
<tr>
<td>Car</td>
<td>8.98</td>
<td>0.0291</td>
</tr>
<tr>
<td>Utilities</td>
<td>6.89</td>
<td>0.0309</td>
</tr>
<tr>
<td>Health</td>
<td>5.92</td>
<td>0.0442</td>
</tr>
<tr>
<td>Clothes</td>
<td>5.31</td>
<td>0.0640</td>
</tr>
</tbody>
</table>

the five categories (Food, Utilities, and Clothes), the consumption volatility is higher for homeowners than for non-homeowners. Of the other two categories, the volatility of consumption on health care services and products is substantially lower for homeowners than non-homeowners. Using data from the 2005 CEX, I find that the weighted average of consumption volatility of the five categories is slightly higher for homeowners than non-homeowners. However, it should be noted that the consumption volatility of homeowners is not statistically significantly larger than that of non-homeowners.

While this exercise does not contradict the model results in section 2.3, the conclusions I can make are weak. However, the second exercise provides better evidence for the central finding in section 2.3: that consumption volatility is higher for consumers who hold less liquid assets that may be levered to a high degree. For the most part, equities are more liquid than houses. Samples of intra day trade data provide evidence that large cap equity common stock is traded multiple times per minute, while small cap equity data may be traded as infrequently as weekly. Houses often stay on the market for weeks or even months before the market settles on a price.
Table 2.4: Consumption Volatility of Stockholders and Non-Stockholders

<table>
<thead>
<tr>
<th>CATEGORY</th>
<th>Percent of 2005 Expenditures</th>
<th>Consumption Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Non-Stockholders</td>
</tr>
<tr>
<td>Food</td>
<td>14.75</td>
<td>0.0297</td>
</tr>
<tr>
<td>Car</td>
<td>8.98</td>
<td>0.0413</td>
</tr>
<tr>
<td>Utilities</td>
<td>6.89</td>
<td>0.0294</td>
</tr>
<tr>
<td>Health</td>
<td>5.92</td>
<td>0.0624</td>
</tr>
<tr>
<td>Clothes</td>
<td>5.31</td>
<td>0.0818</td>
</tr>
</tbody>
</table>

Also, for a typical household, houses are easier to borrow against than equity portfolios. Therefore a test case might be to separate out the households who just own houses from those who just own equities. Unfortunately, the set of households that own equity buy not houses is empty for a majority of our sample period. Therefore, I separate the set of homeowners into two groups: those who own equities and those who do not.

We can think of the household portfolio as being a weighted average of all the assets it owns. The properties of the household portfolio (liquidity, leverage ability, expected return, etc.) can similarly be taken to be a weighed average. Consider two households (A and B) whose portfolios are of equal value, but household A holds equities and a house while household B only holds the house. The liquidity household A’s asset portfolio will be higher than that of household B. Likewise, the ability ability for household A to lever its portfolio will be less than household B. Therefore, ceteris paribus, I propose that households who own houses and equities will have lower consumption volatility than households that only hold houses. This provides the framework for the exercise carried out in table 2.4.
To construct the groups of stockholders and non-stockholders in table 2.4, I start with the set of homeowners used in table 2.3. Within that set, I define households as stockholders if the securities variable in the CEX Extract data set is greater than zero. For four of the five consumption categories, consumption volatility is higher for non-stockholders than for stockholders. The consumption of utilities is the one exception, with stockholders utility consumption volatility being higher than non-stockholders. Using data from the 2005 CEX, I find that the weighted average of consumption volatility of the five categories is modestly higher for non-stockholders than stockholders. This is in line with the model prediction that consumption volatility is higher for households that hold less liquid, highly leveragable asset portfolios.

Caution should be taken when reading these results as they are merely observational. The data doesn’t lend itself to a formal statistical analysis, and I have not controlled for outside factors that may influence consumption volatility. If data becomes available, it will be fruitful for a future study to examine this issue in a more rigorous way.

2.5 Conclusion

This paper presents a model that helps us to understand the effects that leverage and portfolio liquidity have on agent’s intertemporal consumption paths. I find that consumption volatility is higher for consumers who hold asset portfolios that are less easily levered and less liquid. The mechanism that drives the predictions of the model is rooted in non-convex adjustment cost which creates regions of inaction with respect to portfolio adjustment within the agent’s state space. When these non-convex transactions are combined with the liquidity constraints that arise from secured borrowing
requirement, household consumption is very volatile around adjustment points. This volatility in consumption arises from the liquidity constraints binding around the adjustment points.

The model is flexible to the extent that it allows one to vary the parameters governing the liquidity (τ), leverage ability (θ), and volatility (σ) of the asset. The expected return of the asset can be changed by allowing the long run average price parameter (µ) to be time-varying. One can move the asset in and out of the utility function simply by changing the Cobb-Douglas weight on non-durable consumption (α) to one. In short, although this study specifies the risky asset to be a house, the model presented in this paper has the ability to examine all five characteristics of assets identified in the introduction.

Future work on this topic will explore how correlation between stochastic labor income and risky asset returns affect portfolio choice and consumption decisions in the life-cycle. Another offshoot of this project is to take the partial equilibrium model presented here to a general equilibrium setting with many heterogeneous agents. By specifying a general equilibrium model with heterogeneous agents, I will be able to endogenize the asset price process. Endogenous asset prices are more reasonable than exogenous asset prices in both household portfolio choice models with housing and in institutional portfolio choice models with small cap equities, over-the-counter derivatives and other assets that trade in thin markets.
CHAPTER 3

Local and Global Risks in U.S. Housing Markets

Why do housing returns differ across geographies? If we take housing markets to simply be portfolios of assets within the broader set of assets in the economy, the differences in returns across geographies should just be related to the differences in the risk exposures of the individual housing markets to the return to aggregate wealth. However, if there are frictions that prevent investors from making investments in housing markets in which they do not reside, then cross sectional differences in housing returns will be a function of their risk exposure to both global and local risks.

A key difference between housing and other assets is that housing is primarily traded in local markets. That is, a majority of the owners of residential real estate in communities across the United States live in those communities. According to the 2000 U.S. Census, over 66% of housing units are owner-occupied. The reasons for this home-bias in housing markets are likely related to the costs associated with owning real estate investments in different localities. These costs, while variable by case, can be substantial. It is important to note that the return to real estate is not simply the capital gain on the asset, but also the cumulative value of the consumption flow from owning the property. An investor who does not reside in a property that she owns must either rent the property or forgo the returns associated with the consumption
flow from the property for time in which she does not take residence there. During
the period spanning the first quarter of 1980 to the fourth quarter of 2009, the real
average annual capital gain on housing in the United States was 2.17% and the real
average annual rent yield was 4.8%. Thus, over this time period, approximately
69% of the value generated by the investment was derived from the consumption flow
component. The inability to take advantage of the consumption flow component and
the fees associated with monitoring and renting a property in a region in which the
investor does not reside can have a substantial impact on the expected net return of
the asset.

Given that housing is largely owned by investors who live and earn within the
geographic region within which the house is located and that there may exist sub-
stantial costs associated with investing in outside housing markets, is it reasonable to
assume that housing is priced in perfect global capital markets like other assets such
as stocks and bonds? On the other hand, given that at least some housing within
markets is owned by outside investors, is a model assuming that all investors are
local too restrictive? I find evidence to support the hypothesis that housing markets
are priced locally rather than globally. That is, a local capital asset pricing model
(CAPM) is better able to explain variation in the cross section of housing returns
than a global CAPM. This finding implies that the cost of accessing housing markets
for investors residing in other housing markets is, in general, high enough to drive
away outside investment. In this sense, housing markets are not traded frictionlessly
by global investors, and thus they are disproportionately priced by investors residing
within the market.

7 These figures do not account for taxes or depreciation.
There are several recent papers that look at housing markets through the prism of financial economic models. Sarama (2010) uses state-level data to examine the ability of the Capital Asset Pricing Model with Epstein-Zin preferences to explain variation in historical housing market returns. Although market frictions that are commonly used to explain the large equity premium are larger for housing than for equities, the paper finds the housing premium is smaller than the equity premium. Institutional differences between the assets (e.g. tax treatment) can partially explain the difference in premia. Case, Cotter and Gabriel (2010) use MSA-level data to examine the relationship between various risk factors and housing market returns. They characterize the return to wealth as the return on the aggregate U.S. housing market and find that the covariance between the U.S. housing market and local housing markets is a priced risk factor. Cannon, Miller and Pandher (2008) find a positive relation between housing market returns at the zip-code level and their risk. These authors take a cross-sectional asset pricing approach similar to that of Fama and French (1992).

A number of papers in international asset pricing have examined whether equities are disproportionately priced by agents in the country in which the company is domiciled. Stulz (1981) proposed a model of asset pricing that allows for differences in consumption opportunity sets across countries. His model results in an asset pricing equation in which the real expected excess return on an asset is just proportional to the covariance between the return on that asset and changes in the world real consumption rate. Karolyi and Stulz (2002) examined how international factors affect expected returns. They find evidence that while the home bias increases the importance of local risk factors, cross-country correlations increase the importance of global risk factors.
In this paper, I ask whether housing is priced locally or globally. The methodological approach taken in this paper is most similar to that taken by Case, Cotter and Gabriel, but extends the analysis along several dimensions. First, I utilize the conditional asset pricing tests proposed by Harvey (1991) to examine the risk-return relationships. This approach allows for time variation in the conditional covariances - this is important given evidence from the data that there is time variation in housing market premia. Second, I include a measure of the consumption flow of housing in my construction of housing returns. To the extent that there is volatility in rental markets, making home ownership a hedge against volatility in shelter expenditures (as suggested by Sinai and Souleles (2005)), the inclusion of the consumption flow in the housing return series is an important source of variation. Finally, I characterize the return to wealth as a weighted average between the return on the housing market and the return on stocks. That the return on the aggregate U.S. housing market alone is a priced factor for local housing returns may have important implications. However, in the context of the CAPM, the return to wealth for the median consumer is likely to be more highly correlated with a weighted average between the consumer’s local housing market and the aggregate stock market.

3.1 Models and Methodology

I consider a Capital Asset Pricing Model (CAPM) in which investors have exponential utility and consumption is normally distributed. The utility function is:

\[ E[u(c)] = E[-e^{-\lambda c}] \] (3.1)
where $\alpha$ is the coefficient of relative risk aversion. Given the assumption that consumption is normally distributed, I can rewrite the expectation on the right hand side as:

$$E[u(c)] = -e^{-\lambda E(c) + \frac{\lambda^2}{2} \sigma^2(c)}. \quad (3.2)$$

The investor splits her wealth between a risk free asset and a set of risky assets yielding the budget constraint:

$$c = y^f R^f + y^r R \quad (3.3)$$

The only source of uncertainty in the budget constraint is the vector of expected returns of the risky assets. Thus, I can rewrite equation (1) as:

$$E[u(c)] = -e^{-\lambda y^f R^f + y^r E(R) + \frac{\lambda^2}{2} y^r \Sigma y}. \quad (3.4)$$

Maximizing (4) with respect to $y^f$ and $y$ and re-arranging the first order conditions, I arrive at the following relationship implied by the capital asset pricing model:

$$E[R_i] - R^f = \lambda \text{Cov}[R_i, R_W]. \quad (3.5)$$

That is, the excess return on asset $i$ is just a proportion of the covariance between the return on asset $i$ and the return to wealth $R_W$. The specification of the return to wealth is the primary concern of this paper, and we can study the implications of different specifications of the variable using two extreme cases.
3.1.1 Local Model

The local model assumes that housing in market $i$ is *only* traded by investors residing in market $i$. This is an extreme case, given that at least some proportion of owner-occupied housing stock is owned by investors who reside in other areas. Thus, the model is inherently wrong as it assumes that housing is priced by a subset of investors that is a degree smaller than the actual set of investors.

The return to wealth in the local model in market $i$, $R_{iW}$, is taken to be the weighted average between MSA $i$’s excess housing market return and the excess value weighted stock market return:

$$R_{iW,t} = \omega_i^S R_{iSTOCK}^t + \omega_i^H R_{i,t}^H.$$  \hspace{1cm} (3.6)

If this model is correct, then the CAPM implies:

$$E[R_i^H] - R_f = \lambda L Cov[R_i, R_{iW}].$$  \hspace{1cm} (3.7)

However, if some of the housing in market $i$ is priced by outside investors, the model will be incorrect and the relationship in equation (3.7) will not hold. The mispricing caused by outside investor participation can be captured in a non-zero intercept term $\alpha_i$. Thus the augmented local model is:

$$E[R_i^H] - R_f = \alpha_i + \lambda L Cov[R_i, R_{iW}].$$  \hspace{1cm} (3.8)

where $\alpha_i$ is the pricing mistake driven by omitted risk factors and the restrictive assumption that the asset is only priced by local investors.
3.1.2 Global Model

The global model assumes that housing market $i$ is actively traded by all investors. This model is an extreme case in that it assumes that agents encounter no costs or frictions to invest in markets in which they do not reside. To the extent that there exist investment frictions between markets, this model is wrong.

The return to wealth in the global model $R^G_L$ is the weighted average between the excess housing market return in the United States and the excess value weighted stock market return:

$$R^G_{W,t} = \omega^S R^S_{STOCK,t} + \omega^H R^H_{t}. \quad (3.9)$$

If this model is correct, then the CAPM implies:

$$E[R^H_i] - R^f = \lambda^G Cov[R_i, R^G_{W}]. \quad (3.10)$$

However, if there exist investment frictions that prevent outside investors from investing in housing in market $i$, the model will be incorrect and the relationship in equation (3.10) will not hold. This raises the question over whether investment frictions could possibly be large enough to prevent investors from investing in outside markets. To investigate this, I employ a model of mean-variance optimizing investors who can pick a portfolio from a set of assets that includes the aggregate stock market and the ten largest MSAs in the United States.

Formally, the agents choose a vector of portfolio weights, $\omega$ to maximize:

$$U(\omega) = \omega' E[\tilde{R}] - \frac{1}{\phi} \omega' \Sigma_R \omega \quad (3.11)$$
where \( \phi \) is the investor’s risk tolerance, \( E[\tilde{R}] \) is a vector of expected returns net of investment costs and \( \Sigma_R \) is the variance-covariance matrix of the returns. Knowing portfolio weights in stock and risk free assets, I can compute measures of risk tolerance for investors residing in each MSA. I solve the model for different levels of the cost associated with investing in a housing market in which the investor does not reside. Figure 3.1 plots the proportion of the investors’ portfolios invested in stocks and the local housing market as a function of the investment cost: a value of 1 indicates that none of the portfolio would be optimally invested in housing markets outside of the one in which the agent resides.

All optimal portfolios converge to 100% investment in stocks and the local market with an investment frictions of around 3.4%. Given that the real average annual rent yield during this period was 4.8%, investors would need to receive at least 29% of the consumption flow from the property on average to justify investment in outside markets. Over this horizon, the performance of the Philadelphia housing market was very close to the mean-variance frontier. Mean-variance optimizing investors in that market find it optimal to invest none of their portfolio in outside markets - even if there is no cost associated with doing so. Investors in the Dallas and Los Angeles markets required the highest investment cost to prevent them from investing in outside markets. Over the time horizon studies, Dallas had the lowest mean return while Los Angeles had the highest return volatility.

It should be noted that investors do not need to directly invest in housing to at least partially access the returns to housing in markets other than that in which they reside. For instance, investment in region specific residential REITs and homebuilders give the investor a return that is correlated to some degree with the return
Figure 3.1: Optimal Portfolio Weights for Different Investment Costs.
received from direct real estate investment. However, in purchasing equity in a REIT or homebuilder the investor is buying the levered capital of the firm. The type and amount of capital and leverage is determined by the management and board of directors of the firm. To the extent that the individual investor does not influence management decisions, the total return also includes a return to the talent of the managers. One delineation of the claim of an equity owner in such a firm is: a long position in the capital (real estate), a short position in bonds (leverage) and a long position in management talent. Such a delineation makes it clear that equity in a regional REIT may be quite a different asset than a direct investment in the housing market. Furthermore, homeownership rates above 55% indicate that a majority of homes are owned by investors residing within the MSA.

In the presence of such investment frictions, the prices in respective housing markets will be determined disproportionately by investors residing in that market. The mispricing associated with pricing the model assuming perfect access to market \( i \) is captured by a non-zero intercept term \( \tau_i \). The augmented global model is:

\[
E[R^{H}_i] - R^f = \tau_i + \lambda_L Cov[R_i, R^G].
\] (3.12)

### 3.1.3 Hypothesis Tests

The objective of this paper is to determine the relative abilities of the two models to explain the cross section of expected returns in the United States. If the local CAPM is the correct model, the estimates of \( \alpha \) for each market will be statistically indistinguishable from zero. On the other hand, I can’t reject the global CAPM as
being the correct model if the estimates of τ for each market statistically not different from zero.

It may simply be the case that the CAPM, in either the local or global form, isn’t capable of explaining expected returns. In the empirical equities pricing literature, many studies have found that other risk factors play a significant role in explaining the cross section of expected returns.\(^8\) If this is true, neither the α’s nor τ’s will be equal to zero. However, we can still learn about the relative abilities of the two models to explain expected returns by comparing the magnitude of the estimates of the constants in the respective geographic regions.\(^9\)

\[ H_0 : \alpha_i = 0 \]

The null hypothesis that the intercepts from the local model are zero implies that expected returns can be explained as just a proportion of the covariance of the asset return with the local return to wealth. Thus, failure to reject the hypothesis would imply a failure to reject the hypothesis that the market is priced locally.

\[ H_0 : \tau_i = 0 \]

The null hypothesis that the intercepts from the global model are zero implies that the expected returns can be explained as a proportion of the covariance between the asset return and the aggregate return to wealth. A failure to reject this hypothesis indicates for market \(i\) indicates that there are relatively small frictions associated with an outside investor investing in market \(i\).

\(^8\)For example, Fama and French (1992), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Bansal and Yaron (2004).

\(^9\)Technically, I can’t directly compare the equivalence of \(\tau_i\) and \(\alpha_i\) because I’m estimate the models separately. Thus I don’t know the correlation between the errors of the estimates.
3.1.4 Estimation Methodology

The conditional asset pricing approach utilized in this paper was first proposed by Harvey (1989). Let $\Omega_{t-1}$ be the information set available in period $t - 1$, and we can proxy for this set with a matrix of observed information $Z_{t-1}$. Then, the model implication is:

$$E[R_{i,t}|Z_{t-1}] = \lambda \text{Cov}[R_{i,t}, F_t|Z_{t-1}].$$  (3.13)

Here, $R_{i,t}$ is the return on asset $i$ in period $t$ and $F_t$ is a factor. When $F_t$ is the return to wealth, this is the restriction implied by the market CAPM. When I assume that the reward-to-risk is constant across time, I can represent the expected conditional return of asset $i$ in period $t$ as:

$$E[R_{i,t}|Z_{t-1}] = \lambda E[(R_{i,t} - E[R_{i,t}|Z_{t-1}]) (F_t - E[F_t|Z_{t-1}])|Z_{t-1}].$$  (3.14)

In other words, I have the pricing error:

$$\epsilon_{i,t} = R_{i,t} - \lambda (R_{i,t} - E[r_{i,t}|Z_{t-1}]) (F_t - E[F_t|Z_{t-1}]).$$  (3.15)

The conditional expectations of the asset return and the factor can be replaced by any model, but for simplicity I will take the model to be a linear regression of the return or factor on the set of instrumental variables. That is:

$$\eta_{i,t}^R = R_{i,t} - Z_{t-1} \delta^i$$  (3.16)

and
\[ \eta^F_t = F_t - Z_{t-1}\delta^F. \] (3.17)

Given this, the local model can be re-written as:

\[ \epsilon^L_{i,t} = R_{i,t} - \alpha_i - \lambda_L(R_{i,t} - Z_{t-1}\delta^i)(R^i_{W,t} - Z_{t-1}\delta^W). \] (3.18)

This can be simplified to\(^{10}\):

\[ \epsilon^L_{i,t} = R_{i,t} - \alpha_i - \lambda_L R_{i,t}(R^i_{W,t} - Z_{t-1}\delta^W). \] (3.20)

Similarly, the moment condition for the global model is:

\[ \epsilon^G_{i,t} = R_{i,t} - \tau_i - \lambda_G R_{i,t}(R^G_{W,t} - Z_{t-1}\delta^G). \] (3.21)

The moments from the two models can be stacked into a vectors of the form

\[ m^L_t = (\eta^R_{i,t} \epsilon^L_{i,t}) = \left( \begin{array}{c} R^i_{W,t} - Z_{t-1}\delta^W \\ R_{i,t} - \alpha_i - \lambda_L R_{i,t}(R^i_{W,t} - Z_{t-1}\delta^W) \end{array} \right), \] (3.22)

and

\[ m^G_t = (\eta^R_t \epsilon^G_{i,t}) = \left( \begin{array}{c} R^G_{W,t} - Z_{t-1}\delta^W \\ R_{i,t} - \tau_i - \lambda_G R_{i,t}(R^G_{W,t} - Z_{t-1}\delta^W) \end{array} \right). \] (3.23)

This system can be efficiently estimated using the two-step generalized method of moments proposed by Hansen (1982).

\(^{10}\)Harvey (1991) shows that this simplification follows from:

\[
\begin{align*}
E[\eta^F_t \eta^R_{i,t} | Z_{t-1}] &= E[\eta^F_t (R_{i,t} - Z_{t-1}\delta^i)|Z_{t-1}] \\
&= E[\eta^F_t R_{i,t} | Z_{t-1}] - E[\eta^F_t Z_{t-1}\delta^i]|Z_{t-1}] \\
&= E[\eta^F_t R_{i,t} | Z_{t-1}] - E[\eta^F_t | Z_{t-1}] Z_{t-1}\delta^i \\
&= E[\eta^F_t R_{i,t} | Z_{t-1}] \\
\end{align*}
\] (3.19)
3.2 Data

The data are quarterly and span the second quarter of 1984 to the third quarter of 2009. Excess housing market returns are taken to be:

\[ R_{i,t+1} = \frac{P_{i,t+1} - P_{i,t} + D_{i,t+1}}{P_{i,t}} - \text{DEPRECIATION} - R_{f,t+1} \]  

(3.24)

Where \( P_{i} \) is the median house price in market \( i \), \( D_{i} \) is the median quarterly rent in market \( i \), \( \text{DEPRECIATION} \) is set to be 2.5% annually and the \( r_{f} \) is the quarterly holding period yield on a 30-day Treasury bills. The choice of 2.5% follows a paper by Harding, Rosenthal and Sirmans (2007) that estimates the depreciation rate on U.S. real estate to be 2.5% during the 1983 to 2001 period. To construct the median house prices, I use the Freddie Mac all transactions indexes to compute a price growth series. I then use median house price data from the 1990 Census for each MSA to trace a series of quarterly price levels. I employ a similar method with the rent levels. For the rent growth series, I utilize the Bureau of Labor Statistics semi-annual MSA owner’s equivalent rent series. I use a cubic spline interpolation procedure to transform the semi-annual series into a quarterly series, and then I compute a quarterly rent growth series. These series, combined with 1990 Census median rent data, enable me to create a time series of quarterly rent levels in each MSA.

The returns are available for 23 cities, and the limitation to 23 cities is due to the limitation of high quality data on rents. I limit the analysis in this paper to the 10 largest MSAs in the sample because of dimensionality issues in the estimation procedure. Those MSAs are: New York, Los Angeles, Chicago, Boston, San Francisco, Philadelphia, Detroit, Dallas, Miami and Houston. The correlations between the
housing market returns, the stock market return and the aggregate U.S. housing market return are given in table 3.1. In general, the housing market returns are uncorrelated with the stock market return. Chicago's housing market return is most highly correlated with the aggregate U.S. market return with a correlation coefficient of 0.88, while Houston has the lowest correlation of 0.09. Some of the markets that are geographically close to each other have some of the highest intermarket housing return correlation. The correlation between Boston and New York is 0.84 and it is 0.82 between New York and Philadelphia. The correlation between Los Angeles and San Francisco is 0.80. Although the relationship is not as strong between Dallas and Houston, which have a correlation coefficient of only 0.57. The Dallas and Houston housing markets share a relatively low correlation with housing markets outside of the state of Texas. The Houston market has a correlation coefficient of 0.15 or less with every market except Dallas. In fact, the Houston housing market has a significantly negative correlation with the Boston and New York markets. Perhaps the unique housing price dynamics in Houston are related to the fact that a large proportion of the prosperity of the city is derived from the price of energy: a commodity for which the price is inversely related with the profitability of many industries. Dallas has a correlation coefficient below 0.15 for all the markets excluding New York, Boston, Houston and Miami.

Descriptive statistics for the excess housing market returns for the ten MSAs are given in the first panel of table 3.2. The period covered includes the record housing boom that began around the second quarter of 1996, and the collapse of the subprime mortgage and housing markets between 2007 and 2009. The Philadelphia market exhibited the highest excess return over this period at 1.01% quarterly, while Dallas
Table 3.1: Asset Return Correlations Between MSAs.
The sample covers the period 1984Q2 to 2009Q3.

<table>
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<tr>
<th></th>
<th>NY</th>
<th>LA</th>
<th>CHI</th>
<th>BOS</th>
<th>SF</th>
<th>PHI</th>
<th>DET</th>
<th>DAL</th>
<th>MIA</th>
<th>HOU</th>
<th>Stock</th>
<th>US Housing</th>
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<td>-0.01</td>
<td>0.01</td>
<td>-0.04</td>
<td>0.05</td>
<td>0.01</td>
<td>0.11</td>
<td>0.01</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>US Housing</td>
<td>0.75</td>
<td>0.83</td>
<td>0.88</td>
<td>0.60</td>
<td>0.72</td>
<td>0.82</td>
<td>0.60</td>
<td>0.18</td>
<td>0.73</td>
<td>0.09</td>
<td>-0.05</td>
<td>1.00</td>
</tr>
</tbody>
</table>

had the lowest excess return at 0.31%. Among the most volatile markets were Los Angeles, Miami, San Francisco and Boston. Housing prices in California and Florida experienced some of the strongest growth during the boom and also a precipitous fall during the collapse of the subprime mortgage market. Dallas, Chicago and Houston were among the most stable markets during the period spanning the second quarter of 1984 and the third quarter of 2009.

The nine columns on the right hand side of table 3.2 give the return autocorrelations at various lag lengths. The first eight lags show significant autocorrelation in housing returns, while the autocorrelation coefficient at a lag length of twelve quarters is negative for many of the MSAs. The patterns tend to suggest that there is substantial short run momentum in house prices, but that mean reversion exists at longer horizons.

In the models outlined above, I utilize both global and local risk measures. The covariance between the risk measures and the portfolio returns comprise the risk
Table 3.2: Descriptive Statistics.

The sample covers the period 1984Q1 to 2009Q3. The statistics for the ten housing markets are given in Panel A. The statistics for the local and U.S. returns to wealth are in Panel B, and the statistics for the instruments are in Panel C. In addition to the mean, standard deviation, skewness and kurtosis of the series, the table includes the first eight autocorrelation coefficients and the autocorrelation coefficients for twelve quarters.

### Panel A: Returns

<table>
<thead>
<tr>
<th>City</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>(\rho_1)</th>
<th>(\rho_2)</th>
<th>(\rho_3)</th>
<th>(\rho_4)</th>
<th>(\rho_5)</th>
<th>(\rho_6)</th>
<th>(\rho_7)</th>
<th>(\rho_8)</th>
<th>(\rho_{12})</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York</td>
<td>0.0079</td>
<td>0.0224</td>
<td>0.3103</td>
<td>2.5092</td>
<td>0.80</td>
<td>0.79</td>
<td>0.77</td>
<td>0.69</td>
<td>0.61</td>
<td>0.54</td>
<td>0.45</td>
<td>0.37</td>
<td>-0.03</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.0063</td>
<td>0.0301</td>
<td>-0.0321</td>
<td>3.8315</td>
<td>0.85</td>
<td>0.76</td>
<td>0.69</td>
<td>0.60</td>
<td>0.55</td>
<td>0.50</td>
<td>0.40</td>
<td>0.30</td>
<td>-0.14</td>
</tr>
<tr>
<td>Chicago</td>
<td>0.0074</td>
<td>0.0128</td>
<td>-0.4968</td>
<td>5.1632</td>
<td>0.73</td>
<td>0.61</td>
<td>0.72</td>
<td>0.72</td>
<td>0.54</td>
<td>0.43</td>
<td>0.33</td>
<td>0.29</td>
<td>-0.24</td>
</tr>
<tr>
<td>Boston</td>
<td>0.0075</td>
<td>0.0239</td>
<td>0.2084</td>
<td>2.7396</td>
<td>0.78</td>
<td>0.70</td>
<td>0.73</td>
<td>0.66</td>
<td>0.61</td>
<td>0.53</td>
<td>0.42</td>
<td>0.39</td>
<td>0.06</td>
</tr>
<tr>
<td>San Francisco</td>
<td>0.0076</td>
<td>0.0239</td>
<td>0.2321</td>
<td>2.3398</td>
<td>0.79</td>
<td>0.70</td>
<td>0.65</td>
<td>0.54</td>
<td>0.44</td>
<td>0.32</td>
<td>0.26</td>
<td>0.15</td>
<td>-0.17</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>0.0101</td>
<td>0.0171</td>
<td>0.7110</td>
<td>3.1727</td>
<td>0.63</td>
<td>0.43</td>
<td>0.60</td>
<td>0.80</td>
<td>0.76</td>
<td>0.40</td>
<td>0.60</td>
<td>0.62</td>
<td>0.54</td>
</tr>
<tr>
<td>Detroit</td>
<td>0.0058</td>
<td>0.0184</td>
<td>-1.6413</td>
<td>6.3931</td>
<td>0.57</td>
<td>0.48</td>
<td>0.59</td>
<td>0.48</td>
<td>0.39</td>
<td>0.31</td>
<td>0.24</td>
<td>0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>Dallas</td>
<td>0.0031</td>
<td>0.0120</td>
<td>-1.0071</td>
<td>3.6139</td>
<td>0.57</td>
<td>0.48</td>
<td>0.59</td>
<td>0.48</td>
<td>0.39</td>
<td>0.31</td>
<td>0.24</td>
<td>0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>Miami</td>
<td>0.0085</td>
<td>0.0285</td>
<td>-1.0065</td>
<td>5.6095</td>
<td>0.80</td>
<td>0.73</td>
<td>0.71</td>
<td>0.70</td>
<td>0.66</td>
<td>0.53</td>
<td>0.38</td>
<td>0.22</td>
<td>-0.44</td>
</tr>
<tr>
<td>Houston</td>
<td>0.0058</td>
<td>0.0157</td>
<td>-1.6558</td>
<td>5.7341</td>
<td>0.64</td>
<td>0.56</td>
<td>0.49</td>
<td>0.46</td>
<td>0.39</td>
<td>0.33</td>
<td>0.35</td>
<td>0.44</td>
<td>0.25</td>
</tr>
</tbody>
</table>

### Panel B: Return to Wealth

<table>
<thead>
<tr>
<th>City</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>(\rho_1)</th>
<th>(\rho_2)</th>
<th>(\rho_3)</th>
<th>(\rho_4)</th>
<th>(\rho_5)</th>
<th>(\rho_6)</th>
<th>(\rho_7)</th>
<th>(\rho_8)</th>
<th>(\rho_{12})</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York</td>
<td>0.0108</td>
<td>0.0316</td>
<td>-0.2550</td>
<td>3.4237</td>
<td>0.30</td>
<td>0.21</td>
<td>0.22</td>
<td>0.22</td>
<td>0.12</td>
<td>0.12</td>
<td>0.01</td>
<td>0.16</td>
<td>-0.20</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.0096</td>
<td>0.0354</td>
<td>-0.4295</td>
<td>3.3069</td>
<td>0.41</td>
<td>0.35</td>
<td>0.29</td>
<td>0.22</td>
<td>0.13</td>
<td>0.08</td>
<td>0.02</td>
<td>0.15</td>
<td>-0.22</td>
</tr>
<tr>
<td>Chicago</td>
<td>0.0112</td>
<td>0.0341</td>
<td>-0.5768</td>
<td>3.6883</td>
<td>0.09</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
<td>-0.02</td>
<td>0.03</td>
<td>-0.10</td>
<td>0.12</td>
<td>-0.10</td>
</tr>
<tr>
<td>Boston</td>
<td>0.0113</td>
<td>0.0367</td>
<td>-0.2377</td>
<td>3.4069</td>
<td>0.20</td>
<td>0.17</td>
<td>0.16</td>
<td>0.09</td>
<td>0.07</td>
<td>0.13</td>
<td>0.01</td>
<td>0.15</td>
<td>-0.09</td>
</tr>
<tr>
<td>San Francisco</td>
<td>0.0106</td>
<td>0.0319</td>
<td>-0.2912</td>
<td>3.2790</td>
<td>0.29</td>
<td>0.27</td>
<td>0.23</td>
<td>0.16</td>
<td>0.10</td>
<td>0.08</td>
<td>-0.05</td>
<td>0.08</td>
<td>-0.18</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>0.0127</td>
<td>0.0329</td>
<td>-0.3017</td>
<td>3.3068</td>
<td>0.11</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
<td>0.00</td>
<td>0.07</td>
<td>-0.08</td>
<td>0.12</td>
<td>-0.15</td>
</tr>
<tr>
<td>Detroit</td>
<td>0.0109</td>
<td>0.0465</td>
<td>-0.5631</td>
<td>3.7155</td>
<td>0.12</td>
<td>0.09</td>
<td>0.07</td>
<td>0.07</td>
<td>0.02</td>
<td>0.05</td>
<td>-0.06</td>
<td>0.15</td>
<td>-0.03</td>
</tr>
<tr>
<td>Dallas</td>
<td>0.0102</td>
<td>0.0442</td>
<td>-0.4910</td>
<td>3.9239</td>
<td>0.01</td>
<td>-0.03</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.04</td>
<td>-0.02</td>
<td>-0.12</td>
<td>0.13</td>
<td>-0.03</td>
</tr>
<tr>
<td>Miami</td>
<td>0.0110</td>
<td>0.0339</td>
<td>-1.0632</td>
<td>5.3333</td>
<td>0.39</td>
<td>0.27</td>
<td>0.28</td>
<td>0.29</td>
<td>0.15</td>
<td>0.12</td>
<td>-0.05</td>
<td>0.17</td>
<td>-0.31</td>
</tr>
<tr>
<td>Houston</td>
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<td>-0.4796</td>
<td>3.8847</td>
<td>0.00</td>
<td>-0.06</td>
<td>-0.04</td>
<td>-0.04</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.14</td>
<td>0.12</td>
<td>-0.02</td>
</tr>
<tr>
<td>United States</td>
<td>0.0105</td>
<td>0.0341</td>
<td>-0.4761</td>
<td>3.6216</td>
<td>0.06</td>
<td>0.04</td>
<td>0.03</td>
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<td>-0.03</td>
<td>0.02</td>
<td>-0.11</td>
<td>0.12</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

### Panel C: Instruments

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>(\rho_1)</th>
<th>(\rho_2)</th>
<th>(\rho_3)</th>
<th>(\rho_4)</th>
<th>(\rho_5)</th>
<th>(\rho_6)</th>
<th>(\rho_7)</th>
<th>(\rho_8)</th>
<th>(\rho_{12})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock</td>
<td>0.0172</td>
<td>0.0870</td>
<td>-0.5095</td>
<td>3.7598</td>
<td>0.01</td>
<td>-0.04</td>
<td>-0.03</td>
<td>0.02</td>
<td>-0.06</td>
<td>0.00</td>
<td>-0.12</td>
<td>0.14</td>
<td>-0.03</td>
</tr>
<tr>
<td>Housing</td>
<td>0.0063</td>
<td>0.0103</td>
<td>-0.1701</td>
<td>4.2466</td>
<td>0.84</td>
<td>0.69</td>
<td>0.77</td>
<td>0.78</td>
<td>0.66</td>
<td>0.49</td>
<td>0.39</td>
<td>0.31</td>
<td>-0.22</td>
</tr>
</tbody>
</table>
factors, with the price of each factor being determined by the parameter $\lambda$. The risk measures are intended to capture the return to wealth in the various markets. The global risk measure is the weighted average between the excess return on the CRSP value weighted NYSE/AMEX/NASDAQ index and the excess return on the aggregate U.S. housing market. The weights are determined using data from the 2005 to 2009 Consumer Finance Monthly surveys on the value of stock investments and housing investments in Americans' portfolios. Likewise, the local risk measures are the weighted average between the excess return on the CRSP value weighted NYSE/AMEX/NASDAQ index and the excess return on the local housing market. Again, the weights for each MSA were calculated using data from the Consumer Finance Monthly survey. Descriptive statistics for the return to wealth across the various geographies are given in the second panel of table 3.2. Interestingly, participants in the Dallas market have one of the highest portfolio allocations to stock. The Dallas housing market exhibited the lowest volatility over the period, thus holding risk preferences constant we would expect participants in the Dallas housing market to have more of their portfolios weighted toward equities.

While a wide variety of instruments were considered, some preliminary analysis led to the choice of a parsimonious set of just two variables and a constant. In addition to the constant, I include: (1) a quarter lag of the excess return to U.S. housing and (2) a quarter lag of the excess return on the CRSP value weighted NYSE/AMEX/NASDAQ index. Descriptive statistics for the instruments are given in the third panel of table 3.2.
Table 3.3: Return to Global and Local Risk - Unrestricted Models.

This table contains the results of the two-step GMM procedure for the respective sets of moments:

\[ m^L_t = \left( R^i_{W,t} - Z_{t-1} \delta^L_t - \left( R^i_{W,t} - Z_{t-1} \delta^L_t \right) \right). \]  

(3.25)

and

\[ m^G_t = \left( R^G_{W,t} - Z_{t-1} \delta^G_t - \left( R^G_{W,t} - Z_{t-1} \delta^G_t \right) \right). \]  

(3.26)

The asymptotic standard error of the estimate for the \( \lambda \) is given in parentheses.

<table>
<thead>
<tr>
<th>Local Model</th>
<th>Global Model</th>
<th>( \alpha )</th>
<th>( \tau )</th>
<th>( \alpha = 0 )</th>
<th>( \tau = 0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York</td>
<td>New York</td>
<td>0.0003</td>
<td>0.0056</td>
<td>Can’t Reject</td>
<td>Reject</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0023)</td>
<td>(0.0020)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Los Angeles</td>
<td>Los Angeles</td>
<td>-0.0042</td>
<td>0.0027</td>
<td>Can’t Reject</td>
<td>Can’t Reject</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0028)</td>
<td>(0.0029)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chicago</td>
<td>Chicago</td>
<td>0.0071</td>
<td>0.0062</td>
<td>Reject</td>
<td>Reject</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>(0.0009)</td>
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</tr>
<tr>
<td>Boston</td>
<td>Boston</td>
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<td>0.0062</td>
<td>Can’t Reject</td>
<td>Reject</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0031)</td>
<td>(0.0024)</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>San Francisco</td>
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<td>0.0046</td>
<td>Can’t Reject</td>
<td>Can’t Reject</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0024)</td>
<td>(0.0026)</td>
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<td></td>
</tr>
<tr>
<td>Philadelphia</td>
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<td>0.0077</td>
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<td>Reject</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0016)</td>
<td>(0.0014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detroit</td>
<td>Detroit</td>
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<td>0.0064</td>
<td>Can’t Reject</td>
<td>Reject</td>
</tr>
<tr>
<td></td>
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<td>(0.0014)</td>
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<tr>
<td>Dallas</td>
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<td>0.0032</td>
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</tr>
<tr>
<td></td>
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<td>(0.0009)</td>
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</tr>
<tr>
<td>Miami</td>
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<td>0.0013</td>
<td>0.0083</td>
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<td>Reject</td>
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<td>(0.0012)</td>
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<td></td>
</tr>
<tr>
<td>Houston</td>
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<td>0.0055</td>
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<td>Reject</td>
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<td></td>
<td>(0.0021)</td>
<td>(0.0011)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.3 Results

The results from of the two-step GMM estimation of the system outlined in the equations above are given in table 3.3. The two columns on the left side of the table give the parameter estimates for the local and global models, respectively, while the two columns on the right hand side of the table give the results of the hypothesis tests outlined in section 2 above.
First, looking at the parameter estimates, it is of note that the price of local risk \( \lambda_L \) is 34.60 while the price of global risk \( \lambda_G \) is a statistically insignificant -7.04. I can’t reject the null hypothesis that this model is true if I can’t reject that intercept estimates are equal to zero.

In every market, except Chicago, the point estimate of the intercept is greater for the global model than for the local model. The average of the point estimates of the \( \alpha \)’s from the local model is 0.0014, which is less than a quarter of the average of the point estimates of the \( \tau \)’s from the global model 0.0057. In annual terms, this means that on average 0.55% of the expected returns are not explained by the local CAPM compared to 2.28% not explained by the global CAPM. While I can’t formally test the hypothesis that the estimate of \( \alpha \) for market \( i \) is smaller the corresponding market estimate of \( \tau \), the evidence suggests that this may indeed the the case.

Turning to the hypothesis tests, I can reject the null hypothesis that \( \tau \) is equal to zero for all markets except Los Angeles and San Francisco. Los Angeles and San Francisco have some of the lowest homeownership rates in the United States. To the extent that these markets also have higher investments from outside investors, we would expect the global CAPM to have a good performance relative to the local CAPM. Given that the Census data suggest that upwards of 66% of investors in U.S. housing live within the geographic region in which the asset is located, it isn’t entirely surprising that the global CAPM fails for most markets. The general failure of the global model is likely due to the fact that investment frictions prevent investors who reside outside of a market from investing in that market. Thus, effectively, there are different investment opportunity sets across geographies.
In the case of the local CAPM, I can only reject the hypothesis that the model explains expected returns for Chicago and Philadelphia. The failure of the local model in this context may stem from two factors. First, it may be that the assumption that these markets are priced solely by local investors is too restrictive. Second, it may simply be the case that the CAPM is unable to capture the risks born by investors in Chicago and Philadelphia.

Now, I directly estimate the local and global CAPMs without the intercept term. Estimating these restricted models gives me a direct way to measure the ability of the two models to explain variation in the cross section of expected housing returns. The results of the estimations are given in table 3.4.

By estimating the restricted model, I get a true measure of the price of covariance risk. The difference in the two specifications of the CAPM is the way in which I specify the covariance risk. In the local model the risk is the covariance between the local return to wealth and the local housing return, while in the global model the risk is the covariance between the aggregate return to wealth and the local housing return. The price of the local covariance risk is 60.87 and the price of the global risk is 13.04. Again, the independent estimation of the models precludes me from conducting a hypothesis test that the prices of risk are different. However, the high precision of the estimates yields sufficient evidence that the investors demand more compensation for local covariance risk than for global covariance risk.

This observation that of a higher price for local risks may be because local risks are more highly correlated with the pricing agent’s labor income stream than are the global risks. In table 3.5 I report the pair-wise correlations between local household disposable income growth and the different measures of the return to wealth. The
Table 3.4: Return to Global and Local Risk - Restricted Models.
This table contains the results of the two-step GMM procedure for the respective sets of moments:

\[
m^L_t = \left( \begin{array}{c}
R^i_{W,t} - Z_{t-1}\delta^L_i \\
R_{i,t} - \lambda^L_i R_{i,t}(R^i_{W,t} - Z_{t-1}\delta^L_i)
\end{array} \right),
\]
and

\[
m^G_t = \left( \begin{array}{c}
R^G_{W,t} - Z_{t-1}\delta^G_i \\
R_{i,t} - \lambda^G_i R_{i,t}(R^G_{W,t} - Z_{t-1}\delta^G_i)
\end{array} \right).
\]

The asymptotic standard error of the estimate for the \(\lambda\) is given in parentheses.

<table>
<thead>
<tr>
<th>MSA</th>
<th>Mean Return</th>
<th>Mean Error</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York</td>
<td>0.0079</td>
<td>-0.0002</td>
<td>0.13</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.0063</td>
<td>-0.0004</td>
<td>0.27</td>
</tr>
<tr>
<td>Chicago</td>
<td>0.0074</td>
<td>0.0001</td>
<td>0.02</td>
</tr>
<tr>
<td>Boston</td>
<td>0.0075</td>
<td>-0.0004</td>
<td>0.06</td>
</tr>
<tr>
<td>San Francisco</td>
<td>0.0076</td>
<td>-0.0007</td>
<td>0.19</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>0.0101</td>
<td>-0.0002</td>
<td>-0.02</td>
</tr>
<tr>
<td>Detroit</td>
<td>0.0058</td>
<td>-0.0005</td>
<td>0.07</td>
</tr>
<tr>
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<td>0.0031</td>
<td>-0.0005</td>
<td>0.00</td>
</tr>
<tr>
<td>Miami</td>
<td>0.0085</td>
<td>-0.0008</td>
<td>0.34</td>
</tr>
<tr>
<td>Houston</td>
<td>0.0058</td>
<td>0.0001</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>MSA</th>
<th>Mean Return</th>
<th>Mean Error</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.17</td>
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<tr>
<td>Los Angeles</td>
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<td>-0.0055</td>
<td>0.35</td>
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<td>Chicago</td>
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<td>0.21</td>
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<tr>
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<tr>
<td>San Francisco</td>
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<td>Philadelphia</td>
<td>0.0101</td>
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<tr>
<td>Detroit</td>
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<td>0.15</td>
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<tr>
<td>Dallas</td>
<td>0.0031</td>
<td>0.0027</td>
<td>0.03</td>
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<tr>
<td>Miami</td>
<td>0.0085</td>
<td>-0.0022</td>
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</tr>
<tr>
<td>Houston</td>
<td>0.0058</td>
<td>0.0050</td>
<td>0.02</td>
</tr>
</tbody>
</table>

90
Table 3.5: Correlations Between Household Disposable Income Growth and Return to Wealth.
The first column contains the correlations between the change in household disposable income growth for MSA $i$ and the return to wealth in MSA $i$. The second column contains the correlations between the change in household disposable income growth for MSA $i$ and the global return to wealth.

<table>
<thead>
<tr>
<th>City</th>
<th>Local</th>
<th>Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York</td>
<td>0.240</td>
<td>0.176</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>0.207</td>
<td>0.153</td>
</tr>
<tr>
<td>Chicago</td>
<td>0.121</td>
<td>0.128</td>
</tr>
<tr>
<td>Boston</td>
<td>0.045</td>
<td>0.013</td>
</tr>
<tr>
<td>San Francisco</td>
<td>0.168</td>
<td>0.122</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>0.141</td>
<td>0.131</td>
</tr>
<tr>
<td>Detroit</td>
<td>0.154</td>
<td>0.160</td>
</tr>
<tr>
<td>Dallas</td>
<td>-0.001</td>
<td>-0.014</td>
</tr>
<tr>
<td>Miami</td>
<td>0.267</td>
<td>0.202</td>
</tr>
<tr>
<td>Houston</td>
<td>-0.023</td>
<td>-0.042</td>
</tr>
</tbody>
</table>

The first column contains the correlation of the local measures of return to wealth with the second column contains the correlation with the global measure. It is of note that the correlations with the local measures of return to wealth are higher in most geographies. These higher correlations would prompt consumption smoothing agents to demand a higher compensation for taking on such risk: a higher value of $\lambda$.

Table 3.4 also contains a couple of measures of the model fit. The first measure is the mean error of the model:

$$\bar{\epsilon}_i = \frac{1}{T} \sum_{t=1}^{T} \epsilon_{i,t}$$

Because the CAPM is intended to model variation in the cross section of excess returns as opposed to variation in the time series of returns, the mean error is a particularly useful measure of the fit of the model. As an example, take the New York housing market. Looking at the mean error and the mean return, we know that the model predicted the mean quarterly return in New York to be 0.81% while the
global model predicted 0.66%. In general, the mean errors for the global model are further from zero than the mean errors for the local model. For the local model, most of the mean errors are negative. That is, the model predicts a marginally larger return than was realized in all housing markets except Chicago and Houston.

Another measure of the model fit is the adjusted coefficient of determination of the regression of the model errors on the information set. A good fit of the model would imply that the errors are uncorrelated with the information set. For the local model, the coefficient of determination is within 0.10 of zero for Chicago, Boston, Philadelphia, Detroit, Dallas and Houston. In the case of the global model, the same criterion is only true for Boston, Dallas and Houston. However, these measures seem to indicate in general that both models do a poor job of explaining variation in the time series of housing market returns.

The CAPM says that the expected excess return of an asset is just a proportion of the covariance between the excess return of that asset and the return to wealth. If the model is correct, then there should be a clear linear relationship between excess returns and the mean conditional covariance from the conditional CAPMs outlined above. The panels in figure 3.2 plot the mean excess returns from the ten housing markets versus the mean conditional covariances of the local and global models respectively.

The green lines in the figure plot the fitted CAPM for the local and global models respectively. As can be seen in the top panel, there is a clear linear relationship between the mean excess returns and the mean conditional covariances of the assets with the local return to wealth. However, such a relationship does not exist between the mean excess returns and the mean condition covariances implied by the global
Figure 3.2: Model Performance
Thus, the local CAPM appears to explain the cross section of housing market returns reasonably well, while the global CAPM does not.

In a final specification of the model, I include both the local and global market returns as independent risk factors. Because there is reasonably high correlation between the local market covariance risk and the global market covariance risk, I can’t say a lot about the relative magnitude of the parameter estimates. However, the existence of multicollinearity does not preclude me from drawing conclusions about the overall fit of the model. The parameter estimates, mean returns, mean errors and coefficients of determination of the regression of the model errors on the information set are reported in table 3.6. In general, the absolute sizes of the model errors are larger for this specification than for the local model and smaller for this specification than the global model. The model predicted average excess returns are larger than the realized returns for most MSAs. While this model does not explain the cross section of expected returns as well as the local model, the coefficients of determination from the regression of the model errors on the information set indicate that the joint specification explains variation in the time series of returns better than the local model.

3.4 Summary and Extensions

This paper addresses a key problem associated with pricing housing: is housing priced locally or globally? Housing is unlike many other assets in that it is primarily traded in local markets. The 2000 U.S. Census indicates that over 66% of housing units are owner occupied - implying that at most 34% of housing units are owned by investors residing in a different geographic region. A housing return is the combination
Table 3.6: Return to Global and Local Risk - Restricted Models.

This table contains the results of the two-step GMM procedure for the respective sets of moments:

\[
m_t^L = \left( \begin{array}{c}
R_{W,t}^i - Z_{t-1}^L \\
R_{G,t}^i - Z_{t-1}^G \\
R_{i,t} - \lambda_L R_{i,t}(R_{W,t}^i - Z_{t-1}^L) - \lambda_G R_{i,t}(R_{G,t}^i - Z_{t-1}^G)
\end{array} \right). \tag{3.30}
\]

The asymptotic standard error of the estimate for the \( \lambda \)'s is given in parentheses.

<table>
<thead>
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<td>0.09</td>
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<td>0.0007</td>
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<td>-0.0015</td>
<td>0.03</td>
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<tr>
<td>Philadelphia</td>
<td>0.0101</td>
<td>0.0004</td>
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<tr>
<td>Detroit</td>
<td>0.0058</td>
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<tr>
<td>Dallas</td>
<td>0.0031</td>
<td>-0.0008</td>
<td>0.00</td>
</tr>
<tr>
<td>Miami</td>
<td>0.0085</td>
<td>-0.0017</td>
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</tr>
<tr>
<td>Houston</td>
<td>0.0058</td>
<td>-0.0006</td>
<td>0.01</td>
</tr>
</tbody>
</table>

of a capital gain and a consumption flow. In the last 30 years in the United States, the consumption flow yield has accounted for approximately 69% of average real return to homeownership. Frictions that prevent owners from realizing the consumption flow, either directly or indirectly via renting the property, can significantly drive down the net real return received for owning the property. For mean-variance optimizing investors, relatively small investment costs (less than 3.5% annually) will prevent the investor from optimally investing in housing markets in which the investor doesn’t reside.

I propose two possible models for U.S. housing markets. The local CAPM assumes that only investors residing in the geographic region that constitutes market \( i \) invest in housing market \( i \). The global CAPM assumes that investors who don’t reside in the geographic region that constitutes market \( i \) have costless access to the assets in
that market. I test the ability of these models to explain the cross section of expected real housing returns in the U.S.

The mean errors of the local CAPM are, in general, an order of magnitude less than the mean errors of the global CAPM. For most markets, I can’t reject the null hypothesis that the excess real housing market return is just proportional to the covariance between the housing market return and the local return to wealth. However, there does not appear to be a consistent relationship between excess housing returns and the covariance between the local market and the global return to wealth.

The analysis in this paper was restricted in the sense that I assumed either housing is priced only by local investors or that there are no frictions associated with outside investment in the local market. In the data, we observe both investment by outside investors and positive frictions associated with that investment. Thus, a general model that allows for imperfect access to the local housing market by outside investors would advance this line of work.
APPENDIX A

Appendix: Pricing Housing Market Returns

A.1 Informal Comparison of Rent-to-Price Ratios

The two key components of my constructed housing market returns are housing rents and housing prices. I constructed these series following the approach of Case and Shiller (1990) by using indexes combined with quality adjusted base rent price level and base housing price level. In a recent paper, Campbell, Davis, Gallin and Martin (2008) (CDGM) constructed returns and rent-to-price ratios for 23 metropolitan areas.\footnote{They have made this data publicly available at \url{http://morris.marginalq.com/whatmoves.html}}. Although the methodology used to construct rents and prices in their paper differs from that used in this paper, the sources of the data are similar. Both papers use the OFHEO house price index. I construct the rent index from the Fair Market Rent data available through the Office of Housing and Urban Development (HUD), whereas CDGM use data reported by renters to the Bureau of Labor Statistics.

Among other differences in the two sets of data, my data are at the state level but the CDGM data are at the MSA level. Thus, while I do not expect my rent-to-price ratios to match those of CDGM, I do expect the series to be highly correlated and exhibit similar sample moments. I keep only states for which the sum of the population of the MSAs available in the CDGM data is greater than 50% of the
state population over the 1983 to 1999 period. Those states are: Missouri, Illinois, Minnesota, Massachusetts, Pennsylvania, Colorado, Hawaii and Oregon.

Table A.1 gives the first four sample moments of each series, and the correlations between the series.

First, note that all the correlations fall above 0.9 with half of them falling above 0.95. While the means are not identical, it appears that similar cross-sectional patterns emerge in the means of the series. The other three sample moments display similar patterns, in general, across the states.
A.2 Derivation of the GMM-D Estimator

This section contains the derivation of the GMM-D estimator of Alan, Attanasio and Browning (2009). To derive the estimator, I must make several assumptions about the nature of the measurement error. First, I assume the consumption measurement error is multiplicative. Second, I assume the measurement error is stationary and independent of all other variables in the model (including the instruments and expectation error).

If I let \( C^*_j,t \) be the actual consumption (exclusive of measurement error) in state \( j \) at time \( t \), then the Asset Pricing Euler Equation is

\[
E \left[ \beta^\lambda \left( \frac{C^*_{j,t+1}}{C^*_j,t} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} - 1 \mid I_t \right] = 0
\] (A.1)

Taking \( \epsilon_{t+1} \) to be the expectation error, I re-express (A.1) as

\[
\beta^\lambda \left( \frac{C^*_{j,t+1}}{C^*_j,t} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} = \epsilon_{t+1}
\] (A.2)

where \( E_t[\epsilon_{t+1}]=1 \).

By the assumption of multiplicative measurement error, I can write observed consumption in state \( j \) at time \( t \) as \( C^o_{j,t} = C^*_j,t \eta_t \). Using this identity, I can rewrite (A.2) as

\[
\beta^\lambda \left( \frac{C^o_{j,t+1}}{C^o_{j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} = \epsilon_{t+1} \left( \frac{\eta_{j,t+1}}{\eta_{j,t}} \right)^{-\lambda \gamma}
\] (A.3)

Utilizing the independence assumption and taking the expectation of (A.4) I get

\[
E_t \left[ \beta^\lambda \left( \frac{C^o_{j,t+1}}{C^o_{j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} \right] = E_t \left[ \epsilon_{t+1} \right] E_t \left[ \left( \frac{\eta_{j,t+1}}{\eta_{j,t}} \right)^{-\lambda \gamma} \right].
\] (A.4)
By the stationarity assumption, \((\eta_{j,t+1}/\eta_{j,t})^{-\lambda \gamma}\) is a constant. Therefore, (A.4) is equivalent to

\[
E_t \left[ \beta^\lambda \left( \frac{C_{o,j,t+1}}{C_{o,j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} \right] = \kappa.
\]

Likewise, the asset pricing Euler equation that links consumption at period \(t\) to consumption at period \(t+2\) is expressed as

\[
E_t \left[ \beta^{2\lambda} \left( \frac{C_{o,j,t+2}}{C_{o,j,t}} \right)^{-\lambda \gamma} (R_{M,t+1} R_{M,t+2})^{\lambda-1} (R_{j,t+1} R_{j,t+2}) \right] = \kappa.
\]

Taking the difference between equations (A.5) and (A.6) I arrive at the orthogonality condition used to estimate the structural parameters via GMM:

\[
E_t \left[ \beta^\lambda \left( \frac{C_{o,j,t+1}}{C_{o,j,t}} \right)^{-\lambda \gamma} R_{M,t+1}^{\lambda-1} R_{j,t+1} - \beta^{2\lambda} \left( \frac{C_{o,j,t+2}}{C_{o,j,t}} \right)^{-\lambda \gamma} (R_{M,t+1} R_{M,t+2})^{\lambda-1} (R_{j,t+1} R_{j,t+2}) \right] = 0
\]

\(\text{A.7}\)
APPENDIX B

Appendix: Non-durable Consumption Volatility and Illiquid Assets

B.1 Data Appendix

The CEX Interview Survey is a pseudo panel that follows households for four quarters, and asks questions about some 600 income and expenditure categories. The CEX Extracts, assembled by Ed Harris and John Sabelhaus, are available for download on the NBER data website. The purpose of the extracts is to make the data more accessible by eliminating noise and combining some of the consumption categories. In the household data, the four quarterly files are merged into one annual file. Many questions within the survey are asked about ‘The previous year’s...’, and therefore it simplifies things to aggregate quarterly variables up to the annual level. Of course the downside to doing this is the loss of information.

The annual files, ranging from 1981 to 2001, also contain demographic information about the households, asset holding information, and other income information. I eliminate households that did not respond in all four quarters, and households for the head of the household did not directly respond to the survey. The average sample size after the eliminations for the 1981 to 2001 period is 2191.76.
For the first exercise, I separate out the homeowners from the non-homeowners. The average number of homeowners over the twenty year sample is 1173.43, while the average number of non-homeowners is 1018.33. So, homeowners comprise on average 53.54 percent of the sample.

In the second exercise, we take the set of homeowners and separate out the stockholders from the non-stockholders within that set. The average number of stockholders over the twenty year period is 324.29 or 27.6 percent of the homeowners.
B.2 Model Solution

I solve this finite horizon dynamic programming problem via backward recursion from time $T$ to the beginning. Specifically, in period $t$ the agent chooses a vector $\mathbf{x} = [X_t \ A_t]'$ to maximize conditional value functions $V_i^t$ for $i = 0, 1$ a state vector $\mathbf{s}$ and approximation coefficients $a$:

$$V_i^t(\mathbf{s}) = \max_{\mathbf{x}} \left\{ u_t(\mathbf{x}, \mathbf{s}) + \beta \int \hat{V}_t(s'; a) dF(s'|s, \mathbf{x}) \right\}$$  \hspace{1cm} (B.1)

I use the collocation method to approximate the unknown functional equation $\hat{V}$ using a linear combination of known basis functions. For this application, we use spectral methods to approximate the function using $N$ Chebychev polynomials evaluated at $N$ Chebychev nodes within the three dimensional state space. Rivlin’s Theorem states that Chebychev-node polynomial interpolants are nearly optimal polynomial approximants. To pin down the polynomial coefficients, I require that the value function approximant equal the actual value function at the $N$ state nodes. Therefore, I seek to solve a system of $N$ nonlinear equations in the $N$ unknown coefficients.

I map the conditional value functions into the Bellman equation by evaluating the following relationship at each of the $N$ collocation nodes.

$$V_t = \max \left\{ V_0^t(\mathbf{s}, x_{0t}^*), V_1^t(\mathbf{s}, x_{1t}^*) \right\}$$  \hspace{1cm} (B.2)

Here, $x_{0t}^*$ and $x_{1t}^*$ are the vectors of choice variables that maximize the respective conditional value functions given state $\mathbf{s}$.

An issue with this type of model, where I both allow the consumer to accumulate savings and stock in the risky asset and approximate the value function using
polynomials, is that we must allow the state space to grow over time. The curse of dimensionality implies that we must be judicious in the number of collocation nodes/basis functions that we use to approximate the value function. The tighter I am able to keep the state space, the better approximation we can achieve with a limited number of nodes. For this reason, I don’t want to set the boundaries state space in every period $t$ to be at the absolute maximum and absolute minimum of period $T$. Therefore, the size of our state space will be time dependent. This poses a problem because the boundaries of the state space must be set ex ante. If the state space is too small, I risk evaluating the polynomial interpolant at points beyond the predesignated boundaries. Chebychev polynomial approximants are known to behave poorly when the state variables extrapolate beyond their bounds. Setting the size of the state space ex ante is cumbersome. However, the finite horizon setting allows us to use this method rather than restricting our parameters to meet the sometimes economically implausible ‘impatience constraints.’

B.3 Simulation

The solution to the model generates to matrices of control variables at the pre-specified state nodes. I simulate $M$ individual ‘agent’ paths by randomly generating $M$ T-by-1 vectors of house price shocks. I evaluate the evolution of our state periods in each time period, yielding a vector of evaluated states $\mathcal{F}_t \equiv [\tilde{P}_t \tilde{K}_t \tilde{S}_t]$. Typically, I would interpolate between the nodes to find the control value relating the evaluated states $\mathcal{F}_t$. However, because of the presence of the discrete choice, interpolation between the three state points $\mathcal{F}_t$ yields incorrect results. A second best
approach is adopted. In this approach, I chose the control value by identifying the set of prespecified state nodes that are closest to the evaluated states.

Unfortunately, the approach adopted here generates quite a bit of noise. However, I can reduce the noise to an arbitrarily small number by simply increasing the number of prespecified state nodes. Because I am making comparisons between different calibrations of the same model while using the same simulation approach, I believe that the noise generated by the simulation approach does not influence the main result of this paper.
BIBLIOGRAPHY


