Housing Collateral and Consumption Insurance Across US Regions

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Abstract

Time-variation in the degree of risk-sharing induced by changes in the value of housing collateral sheds new light on the consumption correlation puzzle. If debts can only be enforced to the extent that they are collateralized by housing wealth, a decrease in the value of housing collateral endogenously increases exposure to idiosyncratic risk. This increases the cross-sectional consumption growth dispersion across regions and it reduces the amount of regional income risk shared. We investigate risk-sharing patterns for the 30 largest US metropolitan areas and find empirical support for the housing collateral channel. In times when housing collateral is scarce, the dispersion of consumption growth relative to income growth is twice as high as when collateral is abundant. A structural estimation of the model's consumption dynamics implies a time path for consumption growth dispersion that matches the one in the data. The housing collateral effect is the key element that enables this match.

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1 Introduction

Arguably the most important role of financial markets is to allocate risk across individuals. The evidence suggests that countries with good institutions tend to reduce risk faced by individuals (Gertler and Gruber (2002)). It also suggests that those same countries have better aggregate economic performance (Levine (1997)). The ability to share risk is a critical issue, not just for the welfare of individuals, but also for regions and countries. How well financial markets perform their allocative role can be measured by the correlation between consumption growth and income growth. The benchmark model, the complete markets model of Lucas (1978), predicts that individuals can perfectly diversify idiosyncratic income shocks across states of nature. Individual consumption growth only adjusts to aggregate income shocks. Consumption growth is predicted to be perfectly correlated across individuals. The data are strongly at odds with the predictions of this model. There is strong evidence against full consumption insurance at different levels of aggregation: at the household level (e.g. Attanasio and Davis (1996) and Cochrane (1991)), the regional level (e.g. Hess and Shin (1998)) and the international level (e.g. Backus, Kehoe and Kydland (1992)). The observed cross-correlation of income growth is higher than the cross-correlation of consumption growth; a stylized fact known as the 'consumption correlation puzzle'or the 'quantity anomaly'.

In this paper we show that a model that allows for a time-varying degree of risk sharing alleviates the tension between model and data. We isolate one source of time variation: movements in the *the housing collateral ratio*, defined as the value of housing wealth relative to human wealth. An increase in the ratio of housing wealth relative to human wealth coincides with a higher degree of risk sharing. In times with a low housing collateral ratio, consumption growth is predicted to be less strongly correlated across regions. We focus our empirical investigation on US metropolitan statistical areas. Indeed, in the data we find considerably less risk-sharing when housing collateral is relatively scarce. Conditioning on the housing collateral ratio makes the consumption correlation puzzle less puzzling.

We model an economy that generates time variation in the degree of risk-sharing through a collateral mechanism. We start from the Lucas endowment economy and change the environment in three ways. First, we relax the assumption that contracts are perfectly enforceable, following Alvarez and Jermann (2000). Depending on whether they have enough collateral, households sometimes cannot trade away all of their labor income risk. As in Lustig (2003), we allow households to file for bankruptcy. Second, each household owns part of the housing stock. Housing provides both utility services and collateral services. When a household chooses not to honor its debt repayments, it loses all housing collateral but its labor income is protected from creditors. Defaulting households regain immediate access to credit markets.[1] In equilibrium, all state-contingent promises are fully backed by the value of the housing stock. The lack of commitment gives rise to collateral con-

[1]The outside option of bankruptcy with the loss of all collateral assets is motivated by Chapter 7 of US personal bankruptcy legislation (Liquidation). Most other papers model the outside option upon default as exclusion from future participation in financial markets, for example Kehoe and Levine (1993), Krueger (2000), Krueger and Perri (2003), and Kehoe and Perri (2002).

straints whose tightness depends on the relative abundance of housing collateral. Third, to allow for regional variation in rental prices we introduce regional separation in rental markets: housing services are region-specific.

The key feature of the model is that the housing collateral ratio moves endogenously. It shifts the conditional distribution of household consumption growth between two benchmark economies. When the housing collateral ratio is low, households more frequently run into binding collateral constraints. To prevent a household from defaulting today, its current *and* future consumption must increase as a share of aggregate consumption. The economy is constrained in how much risk-sharing it can implement. In the limit, when the housing collateral disappears altogether, no risk sharing is possible and the economy is in autarky. In contrast, when collateralizable housing wealth is sufficiently high relative to non-collateralizable human wealth, the collateral constraints never bind. The economy achieves full insurance, like an economy without commitment problems.

In the empirical work, we use the following data. First, the aggregate stock of housing collateral is measured in two different ways: by the value of residential real estate owned by households (structures and land) and by the economy-wide value of residential fixed assets (structures). The housing collateral ratio is measured as the deviation from the cointegration relationship between the value of the aggregate housing collateral measure and aggregate labor income. Second, we construct a new panel data set for US metropolitan statistical areas on consumption, income and house prices. Following the convention in the literature on risk-sharing among states, we use sales data to measure non-durable consumption. In the appendix we compare our new data to other data sources that partially overlap in terms of sample period and definition. We find that they line up.

Our empirical strategy is twofold. In a first approach, we impose conditions on regional consumption shares that lead to a linear Euler equation for consumption growth. This approach allows us to make contact with a large literature that implements risk-sharing tests by estimating linear consumption growth regressions (Cochrane (1991), Mace (1991), Nelson (1994) and ensuing work). Because of the collateral constraints, regional consumption share growth is correlated with regional income share growth. However, the correct right-hand-side variable in the consumption growth regression is not the regional income share growth, but the regional income share growth interacted with the housing collateral ratio. This interaction term captures the collateral effect: Consumption share growth is more sensitive to income share growth when the housing collateral ratio is low. We reject full consumption insurance among US regions, consistent with the results of Hess and Shin (1998) and DelNegro (1998) who use state-level data. More importantly, we find that decreases in the collateral ratio increase the correlation between income growth shocks and consumption growth. The degree of insurance decreases when housing collateral is scarce. The histogram for the housing collateral ratio allows us to quantify the time variation in the degree of risk-sharing. When the housing collateral ratio is at its fifth percentile level, only thirty-five percent of regional income share shocks are insured away. In contrast, when the housing collateral ratio is at its ninety-fifth percentile level, ninety-two percent of regional income share shocks are insured away. The time-variation in the degree of risk-sharing is substantial. Using household-level data, Blundell, Pistaferri and Preston (2002) also find evidence for a degree of consumption insurance that varies over time. However, they do not take a stance on the mechanism that generates it.

In a second approach, we compare the regional consumption processes predicted by the model to the ones observed in the data. The equilibrium consumption share process follows a non-linear law of motion. A region's consumption share increases to some cutoff level when its constraint is binding, and stays constant otherwise. The cutoff level itself crucially depends on the housing collateral ratio. We generate sample paths for the consumption share of each region according to this non-linear law of motion. The model dictates the specification of the cutoff level. Starting with an initial guess for the preference and cutoff parameters, we search for the parameter vector that minimizes the distance between selected moments of the generated consumption data and the observed data. The parameter vector that minimizes this distance implies a crucial role for the collateral effect. The term in the cutoff specification that allows us to match generated and observed data closely is the interaction term of the aggregate housing collateral ratio with regional income growth. The parameter on this term is estimated to be large, it has the right sign and it is estimated precisely. The parameter estimates imply that, in times in which a region receives a positive shock to its income share, its consumption share increases. This effect is larger in times in which the housing collateral ratio is low. In such times, the regions' consumption shares drift apart and there is less risk-sharing. The parameter estimates uncover the effect predicted by the theory: The housing collateral ratio shifts the conditional distribution of household consumption shares. Quantitatively, the effects are large: We find that the ratio of consumption share dispersion to income share dispersion implied by the estimation is twice as high when the housing collateral ratio is at its lowest value in the sample as when the ratio is at its highest value in the sample. In sum, the results of this exercise provide support for the collateral mechanism. This non-linear estimation approach is closest to the work of Albarran and Attanasio (2001). They also specify a different consumption process for constrained and unconstrained households, but use a switching regression approach to estimate the Euler equations. We use a simulated method of moments approach.

The model gives rise to a degenerate cross-sectional distribution for consumption shares: All unconstrained regions face the same rate of decline in their consumption shares while all constrained regions face the same sized jump in consumption shares. In the data, the cross-sectional distribution of consumption shares is non-degenerate. We allow for measurement error in consumption in the estimation to bridge the gap between model and data.

In the model, housing wealth is efficiently distributed over the regions. The aggregate value of housing collateral is a sufficient statistic for the risk-sharing capacity of the economy and its variation over time. This efficient distribution is decentralized through a frictionless market for home-ownership. Instead, if home-ownership markets were regionally separated, the variation in the degree of risk sharing would be driven by variation in regional collateral measures. Modelling such environment is beyond the scope of the current paper. However, in the last section we look at the empirical implications of such model. Estimation results of consumption growth regressions with *regional* collateral measures, such as the regional home-ownership rate and the value of regional residential estate wealth corroborates the results found using aggregate collateral measures. We find a similar time-variation in the degree of risk-sharing. When both regional and aggregate collateral measures are used, the aggregate collateral effect drives out the regional collateral terms. Finally, we find no evidence that regional variation in bankruptcy legislation, in particular in homestead exemptions, affects the degree of risk sharing among regions.

We organize the paper as follows. Section 2 describes the environment and characterizes equilibrium allocations. Section 3 contains a discussion of our empirical strategy which bridges the theory and data. Section 4 describes the data and section 5 shows how we measure the housing collateral ratio. Our main empirical findings are reported in section 6. Section 7 discusses the empirical results using regional collateral measures. Section 8 concludes. Figures and tables are at the end of the text. Appendix A contains sources and details on the data.

2 Model

This section starts with a description of the environment in section 2.1 and market structure in 2.2. We provide a complete characterization of equilibrium allocations using stochastic consumption share processes in section 2.3. The growth rate of a region-specific weight process drives region-specific consumption growth.

2.1 Preferences and Endowments

We consider an economy with a large but finite number N of regions. Each region is populated with a continuum of identical, infinitely-lived households. Households cannot move between regions. Because we abstract from heterogeneity within a region, we use the labels 'household' and 'region' interchangeably.

We use s^t to denote the history of events $s^t = (y^t, z^t)$, where $y^t \in Y^t$ denotes the history of idiosyncratic events and $z^t \in Z^t$ denotes the history of aggregate events. $\pi(s^t)$ denotes the probability of history s^t. There are two goods. Households choose a consumption plan consisting of non-durable consumption $\{c_t(s^t)\}$ and housing services $\{h_t(s^t)\}$.

Households rank consumption streams according to

$$U(c,h) = \sum_{s^t|s^0} \sum_{t=0}^{\infty} \beta^t \pi(s^t|s^0) u(c_t(s^t), h_t(s^t)). \tag{1}$$

where β is the time discount factor, common across all regions.

The households have power utility over a CES-composite consumption good:

$$u(c_t, h_t) = \frac{1}{1-\gamma} \left[c_t^{\frac{\varepsilon-1}{\varepsilon}} + \psi h_t^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{(1-\gamma)\varepsilon}{\varepsilon-1}},$$

$\psi > 0$ converts the housing stock into a service flow. ε is the intratemporal elasticity of substitution between non-durable and housing services consumption.[2]

Each of the households is endowed with a claim to a labor income stream $\{\eta_t(y_t, z^t)\}$. The aggregate non-durable endowment $\{\eta_t^a(z^t)\}$ is the sum of the individual endowments, $\eta_t^a = c_t^a$:

$$\sum_{y_t \in Y^t} \eta_t(y_t, z^t) = c_t^a(z^t), \ \forall z^t, t \geq 0.$$

Each household is endowed with a stochastic stream of housing services $h_t^i(s^t)$. θ_0 denotes the household's initial non-labor wealth. We use Θ_0 to denote the initial distribution of non-labor wealth holdings.[3]

2.2 Trading

Trade in Sequential Markets At the start of the period, households purchase non-durable consumption goods $c(s^t)$ and housing services $h_t^r(s^t)$ in spot markets. The spot price of rental services is denoted by $\{\rho_t(s^t)\}$. Spot markets for housing services are regionally-separated: $\rho_t(s^t)$ is a region-specific price. Households in region i only trade housing services $h_t^i(s^t)$ with other households in region i. This regional separation of rental markets is the main difference with the model in Lustig and VanNieuwerburgh (2004b). The assumption of regionally separated markets brings in cross-regional heterogeneity in rental prices. This heterogeneity is an important feature of the data.

In contrast with the regionally separated rental markets, spot markets for home ownership are frictionless. Households in region i purchase $h_{t+1}^{oij}(s^t)$ units of housing in region j, at a price $p_t^{hj}(s^t)$ per unit. At the end of every period, households i receive the rental income on the housing units they own in other regions.

Although households cannot sell claims to their labor income stream $\{\eta_t(s^t)\}$, they can trade a complete set of contingent claims in financial markets to insure against idiosyncratic labor income risk. Let $a(s^t, s')$ be the quantity of a claim that pays one unit of non-durable consumption when next period's state is s' and $q_t(s^t, s')$ be the corresponding price.

The household problem is to maximize utility over non-durable consumption and housing services (1) subject to the following wealth constraints and collateral constraints:

$$c_t^i + \rho_t^i h_t^{ir} + \sum_{s'} q_t(s') a_t^i(s') + \sum_{j=1}^{N} p_t^{hj} h_{t+1}^{oij} \leq W_t^i.$$

[2]The preferences belong to the class of homothetic power utility functions of Eichenbaum and Hansen (1990). Special cases are separability ($\gamma\varepsilon = 1$) and Cobb-Douglas preferences ($\varepsilon = 1$). The cross-derivative $u_{ch} > 0$ for $\gamma\varepsilon < 1$ and $u_{ch} < 0$ for $\gamma\varepsilon > 1$. We say that there is complementarity when $\varepsilon < 1$. Substitutability arises when $\varepsilon > 1$.

[3]In this setup, housing is the only collateralizable asset. We abstract from financial assets or other kinds of capital (such as cars) that households may use to collateralize loans. We make this choice to keep the model as simple as possible. Also, in the data, 75 percent of household borrowing in the data is collateralized by housing wealth (Flow of Funds data).

Next period wealth in state s' is:

$$W_{t+1}^{i}(s') = \eta_{t+1}^{i}(s') + a_{t}^{i}(s') + \sum_{j=1}^{N} h_{t+1}^{oij}\left[p_{t+1}^{hj}(s') + \rho_{t+1}(s')\right].$$

All of a household's state-contingent promises are backed by the cum-dividend value of its housing h_{t+1}^{oij}, owned at the end of period t. For each state s', households face a separate *collateral constraint*:

$$-a_{t}^{i}(s') \leq \sum_{j=1}^{N} h_{t+1}^{oij}\left[p_{t+1}^{hj}(s') + \rho_{t+1}^{j}(s')\right]. \tag{2}$$

The collateral constraints prevent bankruptcy because households are not allowed to borrow more in a given state than the cum-dividend value of the housing stock in that state.

Because it will turn out to be easier to characterize equilibrium allocations, we describe an Arrow-Debreu economy where all trade takes place at time zero.

Trade in Time Zero Markets Because it will be easier to characterize equilibrium consumption rules, we continue to work with an economy where all trade takes place at time zero. We denote the present discounted value of a stream $\{x\}$ after a history s^t as $\Pi_{s^t}\left[\{x_t(s^t)\}\right]$, defined by $\sum_{s^\tau|s^t}\sum_{\tau=0}^{\infty}\left[p_{t+\tau}\left(s^\tau|s^t\right)x_{t+\tau}\left(s^\tau|s^t\right)\right]$, where $p(s^t)$ denotes the Arrow-Debreu price of a unit of non-durable consumption in history s^t.

Households purchase a complete, state-contingent consumption plan $\{c(\theta_0, s_0), h(\theta_0, s_0)\}$ subject to a single, time zero budget constraint:

$$\Pi_{s_0}\left[\{c(\theta_0, s_0) + \rho h(\theta_0, s_0)\}\right] \leqslant \theta_0 + \Pi_{s_0}\left[\{\eta\}\right], \tag{3}$$

In a time zero economy, the collateral constraints take the form of solvency constraints. They restrict the value of a household's consumption claim net of its labor income claim to be non-negative:

$$\Pi_{s^t}\left[\{c_t(s^t) + \rho_t(s^t)h_t(s^t)\}\right] \geq \Pi_{s^t}\left[\{\eta_t(s^t)\}\right].$$

The effectiveness of the risk sharing technology that the economy is endowed with depends on the ratio of total housing wealth to human wealth. We call this ratio the housing collateral ratio my:

$$my_t(z^t) = \frac{\Pi_{z^t}\left[\sum_{y_t}\{\rho_t(y_t, z^t)h_t(y_t, z^t)\}\right]}{\Pi_{z^t}\left[\{c_t^a(z^t)\}\right]}$$

The housing collateral ratio depends on the Arrow-Debreu prices for non-durable consumption through the pricing functional $\Pi_{s^t}[\cdot]$. Suppose the households in this economy derive no utility from housing services, then there is no collateral in this economy and my is zero. All the solvency constraints necessarily bind at all nodes and households are in autarchy. As my increases, perfect risk sharing becomes feasible.

In anticipation of our empirical results, we note that the housing collateral ratio my is a sufficient statistic for the degree of risk sharing of this economy.[4] The reason that the *aggregate* housing collateral ratio indexes the degree of risk sharing is that the stock of collateral is allocated efficiently across regions in a stationary equilibrium.[5] Shocks to my change the conditional distribution of consumption across regions. The next section explains exactly how shocks to my impinge on allocations and prices.

2.3 Equilibrium Consumption

We first discuss equilibrium allocations in the model where preferences over non-durable consumption and housing services are separable ($\gamma\varepsilon = 1$). This is conceptually the easiest case. We then allow for non-separability in preferences ($\gamma\varepsilon \neq 1$).

Separable Preferences A household's consumption share is defined as the ratio of its consumption to aggregate consumption. In equilibrium, household consumption shares follows a simple pattern. As long as a household does not switch to a state in which the solvency constraint binds, the household's consumption share decreases. When the household enters a state in which the solvency constraint binds, its consumption share jumps up. Binding constraints preclude perfect risk-sharing.[6]

We use consumption weights ω to characterize the equilibrium prices and allocations. The new consumption weight of a households that enters the period with consumption weight ω is denoted $\widetilde{\omega}_t(\omega, s^t)$. The new consumption weight is equal the old weight as long as the agent does not switch to a state with a binding constraint. However, when a household's constraint binds, its new weight $\widetilde{\omega}_t(\omega, s^t)$ is set to a cutoff weight $\underline{\omega}_t(y_t, z^t)$. This is the weight at which the solvency constraint holds with equality. We compute the aggregate consumption weight by integrating over the new household weights at aggregate node z^t:

$$\xi_t^a(z^t) = \sum_{j=1}^{N} \widetilde{\omega}_t^j(\omega, s^t)\Phi_t^j(\omega; z^t), \tag{4}$$

where $\Phi_t(\cdot; z^t)$ is the cross-sectional distribution over weights at the start of period t and this distribution depends on the entire aggregate history z^t. The aggregate consumption weight $\xi_t^a(z^t)$ is a non-decreasing stochastic process. At the end of the period we re-normalize the consumption weights so that they integrate to one. We store the household's consumption share $\omega = \frac{\widetilde{\omega}_t(\omega,s^t)}{\xi_t^a(z^t)}$ as its identifying label.

[4] In general, the degree of risk-sharing also depends on the entire aggregate history of the economy. In computation and estimation, it turns out that keeping track of the housing collateral ratio and just one lag of the aggregate state captures almost all time variation in the degree of risk-sharing.

[5] In the language of the economy with sequential trade: As long as the ownership market for housing is not regionally separated, the extent of cross-regional risk sharing depends on the *aggregate* housing collateral ratio.

[6] When a household is not in a state with a binding constraint today, it may still face a binding constraint in some state tomorrow.

The equilibrium consumption share of an household equals the ratio of his individual stochastic consumption weight to the aggregate consumption weight:

$$c_t(\omega, s^t) = \frac{\widetilde{\omega}_t(\omega, s^t)}{\xi_t^a(z^t)} c_t^a(z^t). \tag{5}$$

This risk sharing rule clears the market for non-durable consumption by construction. In a stationary equilibrium, each household's consumption share is drifting downwards as long as it does not switch to a state with a binding constraint. The consumption share for the constrained households jumps. The rate of decline of the consumption share for the unconstrained households is equal to $g_t = \xi_t^a / \xi_{t-1}^a$.

The aggregate weight shock g_t depends on the housing collateral ratio my. When my is low, the solvency constraints are tight, many households are highly constrained and the remainder experience large consumption share drops. The consumption share at which the solvency constraint holds with equality increases:

$$\frac{\underline{\omega}_t(y_t, z^t)}{\xi_t^a(z^t)} \nearrow \text{ as } my \searrow,$$

The lower the collateral ratio, the larger the increase in its consumption share when it switches to a state with a binding solvency constraint. The other households experience steeper declines in their consumption shares. As a result, the cross-sectional dispersion of consumption shares increases; there is less risk-sharing. Put differently, when my is low, the risk-free rate is low, inducing households to decrease assets at a high rate. For low housing collateral ratios, a household's consumption share growth becomes very sensitive to shocks to its income share. In the limit, when there is no housing collateral at all, the cutoff level for the consumption share equals the household's labor income share $\widehat{\eta}(y_t, z_t)$, where $\widehat{\eta}(y_t, z_t)$ is the labor income share relative to the total non-durable endowment. In the other extreme, when housing collateral is sufficiently abundant (my is high enough), none of the households are constrained and interest rates are high.

Non-Separable Preferences The equilibrium relative price of housing services (the rental price) equals the marginal rates of substitution between consumption and housing services:

$$\rho_t(s^t) = \frac{u_h(c_t(s^t), h_t(s^t))}{u_c(c_t(s^t), h_t(s^t))}. \tag{6}$$

Because of regional separation in rental markets, the housing services consumption of region i equals its housing services endowment. We define a regions's expenditure share α^i as the ratio of non-durable expenditures to non-durable plus housing services expenditures:

$$\alpha_t^i \equiv \frac{c_t^i}{c_t^i + \rho_t h_t^i} = \frac{1}{1 + \psi^{\varepsilon} (\rho_t^i)^{1-\varepsilon}}. \tag{7}$$

The last equality follows from equation (6) and shows the mapping between rental prices and expenditure shares.

The equilibrium consumption share follow a modified cutoff rule. The modified consumption weight is the product of the weight $\omega(s^t)$ and the non-durable expenditure share $\alpha(s^t)$ raised to the power $\frac{\gamma\varepsilon-1}{\varepsilon-1}$. Again, the growth rate g_t of the aggregate weight process determines the consumption growth of the unconstrained households. The modified aggregate consumption weight is

$$\tilde{\xi}^a_t(z^t) = \sum_{j=1}^{N} \widetilde{\omega}^j_t(\omega, s^t)\alpha^j_t(\omega, s^t)^{\frac{\gamma\varepsilon-1}{\varepsilon-1}} \tilde{\Phi}^j_t(\omega; z^t). \tag{8}$$

$\tilde{\Phi}_t(\cdot; z^t)$ is now the joint distribution over weights and expenditure shares at the start of period t. As before, households consumption share increases whenever it runs into a binding constraint. It now also increases when the nondurable expenditure share decreases and housing services and nondurables are complements ($\varepsilon < 1 < \gamma\varepsilon$).

Stochastic Discount Factor In this complete markets environment, there exists a unique and strictly positive stochastic discount factor (SDF) $\{m\}$ that satisfies the standard orthogonality condition (Harrison and Kreps (1979)):

$$E_t \left[m_{t+1} \left(s^{t+1}|s^t\right) R^j_{t+1} \left(s^{t+1}|s^t\right) \right] = 1, \tag{9}$$

for any gross return process R^j.[7]

The risk sharing rules determines any household's intertemporal marginal rate of substitution (IMRS). In each date and state, the payoffs are priced by the unconstrained household, who are the households with the highest IMRS. If not, there would be an arbitrage opportunity. When preferences are separable, the SDF consists of two elements:

$$m_{t+1} = \beta \left(\frac{c^a_{t+1}}{c^a_t} \right)^{-\gamma} (g_{t+1})^{\gamma}. \tag{10}$$

The first part is the representative agent pricing kernel under separability. The presence of collateral constraints contributes a second factor to the SDF:

$$g_{t+1} = \frac{\xi^a_{t+1}}{\xi^a_t}. \tag{11}$$

When none of the regions is constrained between t and $t+1$, the aggregate weight shock g_{t+1} equals one. Otherwise, the aggregate weight shock is strictly greater than one.

When preferences are non-separable, the SDF is again the marginal utility growth rate of the unconstrained households. The SDF takes a similar form as under separable preferences:

$$m_{t+1} = \beta \left(\frac{c^a_{t+1}}{c^a_t} \right)^{-\gamma} \left(\frac{\tilde{\xi}^a_{t+1}}{\tilde{\xi}^a_t} \right)^{\gamma}. \tag{12}$$

[7] In the model, financial assets are redundant securities that are priced using this (unique) SDF.

The weight shock in equation (12) is more complicated than the one in equation (11) because it also depends on the entire cross-sectional distribution of expenditure shares (see equation 8).[8]

3 From Model to Data

We use two approaches to derive testable implications from the model. The first approach links our model to the traditional risk-sharing tests based on linear consumption growth regressions (section 3.2). We refer to this approach as the *linear model*. In the second approach we stay closer to the model and use a simulated method of moments estimation to estimate the non-linear law of motion for consumption shares (section 3.3). We refer to this approach as the *non-linear model*. In both methods we explicitly take into account measurement error in consumption (section 3.1). Both approaches have advantages. The first approach is familiar from the risk-sharing literature. The second approach is closer to the model, but more complicated to implement than the first approach.

3.1 Measurement Error in Consumption

In both approaches we allow for measurement error in consumption. This is important because the model gives rise to a degenerate cross-sectional distribution for consumption shares: All unconstrained regions face the same rate of decline in their consumption shares while all constrained regions face the same sized jump in consumption shares. In the data, the cross-sectional distribution of consumption shares is non-degenerate. Allowing for measurement error in the estimation bridges the gap between model and data.[9]

We allow for multiplicative measurement error in consumption: $\left\{b^{i,c}\right\}$ is a random sequence of measurement error shocks. True non-durable consumption c_t^i equals observed consumption $\tilde{c}_t^i$ multiplied by measurement error:

$$c_t^i = e^{b_t^{i,c}} \tilde{c}_t^i; \tag{13}$$

The measurement error process b is i.i.d. over time, across goods, across regions (households) and normally distributed with standard deviation σ_b. In section 3.3 we experiment with different values for σ_b. We assume that income and rental prices are observed without error.

3.2 Linear Model

In this section we seek to connect our model to the linear consumption growth regressions that are standard in the Euler equation tests of full insurance. We show that under certain restrictions

[8] Alternatively, the SDF can again be decomposed into an aggregate component $m_{t+1}^a = \beta \left(\frac{c_{t+1}^a}{c_t^a}\right)^{-\gamma} \left(\frac{\alpha_{t+1}^a}{\alpha_t^a}\right)^{\frac{\gamma\varepsilon-1}{\varepsilon-1}}$ and an aggregate liquidity shock $\tilde{g}_{t+1}^{\gamma}$, where $\log \tilde{g}_{t+1} = -\Delta \log \hat{c}_{t+1}^{i^*} + \frac{\gamma\varepsilon-1}{\gamma(\varepsilon-1)} \Delta \log \hat{\alpha}_{t+1}^{i^*}$ and i^* denotes the unconstrained households. Hatted variables denote variables in deviation from the cross-sectional mean.

[9] This is in the spirit of Hansen and Sargent (1980), who write: 'Dynamic economic theory implies that agents' decision rules are exact (non-stochastic) functions of the information they possess about the relevant state variables governing the dynamic process they wish to control. The econometrician must resort to some device to convert the exact equations delivered by economic theory into exact stochastic equations susceptible to econometric analysis.'

on the regional consumption share processes, our model generates a linear relationship between regional consumption share growth and regional income share growth, very much like the restrictions estimated in the empirical risk-sharing literature. However, the correct right hand side variable arising from the model with separable preferences is not regional income share growth, but regional income share growth interacted with the housing collateral ratio. In the presence of non-separability in preferences, regional rental price growth and its interaction with the housing collateral ratio are additional right-hand side variables. To arrive at the linear consumption growth regressions, we specify a linear process for the regional consumption share growth (equation 15). Theory disciplines this approach in two ways. First, the weight process is known in the polar cases of autarky and perfect commitment. Second, the housing collateral ratio monotonically shifts the conditional distribution of household consumption growth between the polar cases. We restrict this shifting to be linear.

We start from the first order condition for nondurable consumption. Hatted variables denote variables in deviation from the cross-sectional mean. The Euler equation, expressed in growth rates in deviation from the cross-sectional average growth rate (growth rates of shares) is:

$$\Delta \log \hat{\xi}^i_{t+1} - \gamma \Delta \log \hat{c}^i_{t+1} + \left(\frac{\gamma\varepsilon - 1}{\varepsilon - 1} \right) \Delta \log \hat{\alpha}^i_{t+1} = 0. \tag{14}$$

The variable ξ^i is the consumption weight of region i, expressed in marginal utils: $\xi^i_t = (\omega^i_t)^\gamma$.

In the model the housing collateral ratio is always positive. Section 5 explains how we measure my in the data. By construction the empirical measure is negative half of the time. To bring the model and data on the same footing, we re-normalize the housing collateral ratio so that it is always positive: $\widetilde{my}_{t+1} = \frac{my^{max} - my_{t+1}}{my^{max} - my^{min}}$. The re-normalized housing collateral ratio $\widetilde{my}_{t+1}$ is a measure of collateral scarcity; it lies between zero and one.

We propose a linear specification for the region-specific consumption weight growth process:

$$\Delta \log \hat{\xi}^i_{t+1} = \gamma \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + \left(\gamma - \frac{\gamma\varepsilon - 1}{\varepsilon - 1} \right) \widetilde{my}_{t+1} \Delta \log \hat{\alpha}^i_{t+1}. \tag{15}$$

This specification arises from thinking about the $\Delta \log \hat{\xi}^i_{t+1}$ process in two limit cases of our model. In an autarkic economy, no risk-sharing is feasible and $\Delta \log \hat{c}^i_{t+1} = \Delta \log \hat{\eta}^i_{t+1} + \Delta \log \hat{\alpha}^i_{t+1}$. Substituting this into the Euler equation for nondurables, we get:

$$\Delta \log \hat{\xi}^{i,A}_{t+1} = \gamma \Delta \log \hat{\eta}^i_{t+1} + \left(\gamma - \frac{\gamma\varepsilon - 1}{\varepsilon - 1} \right) \Delta \log \hat{\alpha}^i_{t+1}.$$

In the polar opposite case of full commitment, perfect risk-sharing obtains and the consumption shares stay constant over time: $\Delta \log \hat{\xi}^{i,FC}_{t+1} = 0$. Our economy with limited commitment has the same equilibrium allocations as the autarky economy when $my_t = my^{min}\ \forall t$. Our economy has the same equilibrium allocation as the full commitment economy when $my_t = my^{max}\ \forall t$. The housing collateral ratio monotonically shifts the allocations in the limited commitment economy between those of an autarkic economy and an economy with full risk-sharing. Specification (15) encompasses both limit cases and assumes that the shifting is linear.

Substituting the expression (15) into (14) results in the Euler equation

$$\Delta \log \hat{c}^i_{t+1} = \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + \left(\frac{\gamma\varepsilon - 1}{\gamma(\varepsilon - 1)} \right) \Delta \log \hat{\alpha}^i_{t+1} + \left(1 - \frac{\gamma\varepsilon - 1}{\gamma(\varepsilon - 1)} \right) \widetilde{my}_{t+1} \Delta \log \hat{\alpha}^i_{t+1}.$$

Because we do not have regional data for expenditure share growth, but we do have rental price growth data, we use equation (7) to reformulate the consumption Euler equation.[10]

$$\Delta \log \hat{c}^i_{t+1} \approx \alpha_1 \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + (\alpha_2 + \alpha_3 \widetilde{my}_{t+1}) \Delta \log \hat{\rho}^i_{t+1} + (\alpha_4 + \alpha_5 \widetilde{my}_{t+1})(\hat{\rho}^i_t - 1)) \Delta \log \hat{\rho}^i_{t+1}.$$

To obtain a consumption growth regression that is linear in rental price growth, we used a Taylor expansion. The coefficients α are functions of the underlying structural parameters.[11] The parameters satisfy the following non-linear restrictions: $\frac{\alpha_3}{\alpha_2} = \frac{1-\gamma}{\gamma\varepsilon-1}$ and $\frac{\alpha_5}{\alpha_4} = \frac{1-\gamma}{\gamma(\gamma\varepsilon-1)}$. The coefficient of relative risk aversion is given by $\gamma = \frac{\alpha_3}{\alpha_2}\frac{\alpha_4}{\alpha_5}$.

Finally, we take into account measurement error in non-durable consumption. We express observed consumption shares with a tilde and assume that income shares and rental prices are measured without error. Equation (16) is the empirical specification we estimate in section 6:

$$\Delta \log \tilde{c}^i_{t+1} \approx \alpha_1 \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + (\alpha_2 + \alpha_3 \widetilde{my}_{t+1}) \Delta \log \hat{\rho}^i_{t+1} + (\alpha_4 + \alpha_5 \widetilde{my}_{t+1})(\hat{\rho}^i_t - 1)) \Delta \log \hat{\rho}^i_{t+1} + \nu^i_{t+1}, \tag{16}$$

where all measurement error terms are captured in ν_{t+1}.[12] In the empirical work, we set my^{max} and my^{min} equal to the sample maximum and minimum.

Discussion With fully-enforceable contracts and separable preferences, our economy collapses to the Lucas (1978) economy. In that world, idiosyncratic income shocks are fully insured. Only aggregate consumption shocks matter for individual consumption growth, capturing aggregate risk. This insight is the basis of the Euler equation tests of full insurance in Cochrane (1991) and Nelson (1994)'s comment on Mace (1991). In the language of our paper, households obtain full insurance when the housing collateral ratio is high in all periods: $my_t = my^{max}$ or $\widetilde{my}_t = 0 \; \forall t$. Consumption shares stay constant over time and are determined by the initial wealth distribution.

In contrast, limited enforceability leads to partial insurance. When housing collateral is scarce ($\widetilde{my}_t$ is high), more households run into binding constraints. This scarcity of collateral bounds the risk sharing capacity of the economy. The consumption share of constrained households depends

[10]We have $\Delta \log \alpha^i_{t+1} = -\Delta \log \left(1 + \psi^\varepsilon (\rho^i_{t+1})^{1-\varepsilon}\right)$. Using a linear expansion around $\rho^i_{t+1} = \rho^i_t$, $\Delta \log \left(1 + \psi^\varepsilon (\rho^i_{t+1})^{1-\varepsilon}\right) \approx (1-\varepsilon) \frac{1}{1+\psi^{-\varepsilon}(\rho^i_t)^{\varepsilon-1}} \Delta \log \rho^i_{t+1}$. To obtain a linear Euler equation we expand $\frac{1}{1+\psi^{-\varepsilon}(\rho^i_t)^{\varepsilon-1}}$ around $\rho^i_t = 1$: $\frac{1}{1+\psi^{-\varepsilon}(\rho^i_t)^{\varepsilon-1}} \approx \frac{1}{1+\psi^{-\varepsilon}} + (\varepsilon - 1) \frac{\psi^{-\varepsilon}}{(1+\psi^{-\varepsilon})^2} (\rho^i_t - 1)$.

[11]In particular: $\alpha_1 = 1$, $\alpha_2 = \frac{\gamma\varepsilon-1}{\gamma(1+\psi^{-\varepsilon})}$, $\alpha_3 = \frac{\varepsilon-1}{(1+\psi^{-\varepsilon})} - \frac{\gamma\varepsilon-1}{\gamma(1+\psi^{-\varepsilon})}$, $\alpha_4 = \frac{(1-\varepsilon)(\gamma\varepsilon-1)\psi^{-\varepsilon}}{\gamma(1+\psi^{-\varepsilon})^2}$, and $\alpha_5 = \left((\varepsilon - 1) - \frac{\gamma\varepsilon-1}{\gamma}\right)(1-\varepsilon)\frac{\psi^{-\varepsilon}}{(1+\psi^{-\varepsilon})^2}$.

[12]The measurement error term is $\nu^i_{t+1} = -\Delta \hat{b}^i_{t+1}$.

on their income shocks realization. As a result, the correlation between the consumption share and the income share increases in such periods.

With non-separable preferences and fully-enforceable contracts, the region-specific component of expenditure share growth affects region-specific consumption share growth. When preferences exhibit complementarity ($\varepsilon < 1$), a rental price increase decreases the non-durable consumption share $\left(\Delta \log \hat{\alpha}_t^i < 0\right)$. When the region's willingness to substitute over time is bigger than its willingness to substitute between goods ($\gamma\varepsilon < 1$), the region decreases its consumption share. Vice versa, when preferences exhibit substitutability ($\varepsilon > 1$), a rental price increase increases the non-durable consumption share $\left(\Delta \log \hat{\alpha}_t^i > 0\right)$. When the region's willingness to substitute over time is lower than its willingness to substitute between goods ($\gamma\varepsilon < 1$), the region increases its consumption share.

Finally, there is an interaction effect of limited enforceability and non-separability. When $\alpha_3 > 0$ and preferences exhibit substitutability ($\varepsilon > 1$), the correlation between the consumption share growth and rental price growth is higher when collateral is scarce (higher $\widetilde{my}_{t+1}$). Likewise, when $\alpha_3 < 0$ and preferences exhibit complementarity ($\varepsilon < 1$), there is less risk-sharing of rental price shocks when collateral is scarce.

3.3 Non-Linear Estimation

The equilibrium consumption share process follows a non-linear law of motion in the model. A region's consumption share increases to some cutoff level when its constraint is binding, and stays constant otherwise. The cutoff level itself crucially depends on the housing collateral ratio. We generate sample paths for the consumption share of each region according to this non-linear law of motion. The model dictates the specification of the cutoff level. Starting with an initial guess for the preference and cutoff parameters, we search for the parameter vector that minimizes the distance between the generated consumption data and the observed data. In addition we match asset pricing moments in model and data.

Because measurement error is unobservable, we use a simulated method of moments estimation that (1) searches over parameters Θ to match the correlation of consumption shares generated by simulation from the model with observed income shares with the correlation of consumption shares in the data with observed income shares and (2) that searches over parameters (γ, ε) to minimize pricing errors on an aggregate stock market return, a long bond return and a riskless rate.[13]

Evolution of Individual Consumption Shares The model provides a non-linear law of motion for the consumption share $\hat{c}_t^i \rightarrow \hat{c}_{t+1}^i$ for each region i, where $\hat{c}_t^i = \frac{c_t^i}{c_t^a}$.

Consumption shares follow a reservation weight policy, with threshold $\underline{\omega}_{t+1}$. If the time t consumption share of region i is below the threshold, it's time $t+1$ share is adjusted to the threshold. If its the time t consumption share is above the cutoff, it stays constant. The cutoff stipulates the consumption share when a region hits a binding constraint between t and $t+1$.

[13]We hold the time discount factor β fixed.

Consumption shares are normalized by the aggregate consumption weight process to ensure that they integrate to one:

$$\hat{c}^i_{t+1} = \begin{cases} \frac{\hat{c}^i_t}{\xi^a_{t+1}} & \text{if } \hat{c}^i_t > \underline{\omega}_{t+1}, \\ \frac{\underline{\omega}_{t+1}}{\xi^a_{t+1}} & \text{if } \hat{c}^i_t \leq \underline{\omega}_{t+1} \end{cases}$$

Cut-off rule with separable preferences The cut-off $\underline{\omega}_{t+1}$ is a function of the aggregate state of the economy: the aggregate consumption growth shock $\Delta \log c^a_{t+1}$, the aggregate housing collateral ratio $\widetilde{my}_{t+1}$ and the regional income share shock $\Delta \log \hat{\eta}^i_{t+1}$. We propose a parsimonious specification for the cut-off that captures the essence of the collateral effect. In particular, we specify the threshold as a *linear* function of the state variables:

$$\begin{aligned} \underline{\omega}_{t+1} = \quad & \theta_0 \bar{\eta} + \theta_1 \Delta \log c^a_{t+1} + \theta_2 \widetilde{my}_{t+1} \Delta \log c^a_{t+1} + \\ & \theta_3 \Delta \log \hat{\eta}_{t+1} + \theta_4 \widetilde{my}_{t+1} \Delta \log \hat{\eta}_{t+1} + \theta_5 \Delta \log c^a_t. \end{aligned} \tag{17}$$

The first term is the average income share of a region over the entire sample, it acts as a regional fixed effect. The interaction terms capture the essence of the collateral effect. First, for a given aggregate consumption growth state, the cutoff level is higher when housing collateral is scarcer ($\theta_2 > 0$). Second, a given income share shock raises the cutoff more when collateral is scarce ($\theta_4 > 0$). The true cut-off consumption share depends on the entire aggregate history of the economy $\Delta \log(c^a)^t$. The last term, associated with θ_5, captures a part of this history dependence.

When a region runs into a binding constraint, its individual history is erased. Its new consumption share is the consumption share for which the solvency constraint holds with equality. The latter only depends on the current income shock $\Delta \log \hat{\eta}_{t+1}$, the housing collateral ratio $\widetilde{my}_{t+1}$ and the aggregate history of the economy $\Delta \log(c^a)^t$. The cutoff rule does *not* depend on the history of region-specific income shocks $\Delta \log \hat{\eta}^t$. This is the *amnesia* property, shared by many limited commitment models (e.g. Albarran and Attanasio (2001) and Ljungqvist and Sargent (2004) for a general discussion).

In a companion paper (Lustig and VanNieuwerburgh (2004b)) we find that the linear specification for the cutoff rule with limited history dependence is a good approximation to the true risk-sharing rule, which is non-linear and has infinite aggregate history dependence. The R^2 of the regression (18) inside the model is 75 percent. The reason for this good fit is that much of the history dependence is encoded in the housing collateral ratio.

Cut-off rule with non-separable preferences Under non-separability, two things change. First, the cutoff additionally depends on expenditure share terms. The average region-specific expenditure share is part of the fixed effect (θ_6). The aggregate expenditure share growth ($\Delta \log \alpha^a_{t+1}$) and its interaction with the housing collateral ratio are the new aggregate state variables (θ_7 and θ_8). The cutoff also depends on the region-specific expenditure share growth ($\Delta \log \hat{\alpha}_{t+1}$) and its interaction with the housing collateral ratio (θ_9 and θ_10). To capture aggregate history dependence, we add last period's aggregate expenditure share growth ((θ_11). Finally, as is apparent from equations (12) and (8), the cutoff also depends on cross-regional distribution of individual expenditure share growth. We include the cross-sectional dispersion of expenditure share growth rates and its interaction with $\widetilde{my}$ as additional variables in the cutoff specification (θ_12 and θ_13).

Second, even in the absence of binding constraints, a region's consumption weight will change when its expenditure share changes. Therefore, prior to comparing last period's consumption share to the cutoff, we adjust last period's consumption share for the change in region-specific expenditure share growth. This adjustment imposes that:

$$\Delta \log \hat{c}^i_{t+1} = \frac{\gamma\varepsilon - 1}{\gamma(\varepsilon - 1)} \Delta \log \hat{\alpha}^i_{t+1}, \tag{18}$$

and guarantees that all unconstrained regions share the same marginal utility growth.

Because we don't have data for region-specific expenditure share growth, we exploit the mapping in equation (6) and use data on region-specific rental price growth instead.[14]

Simulation Algorithm

- For an initial guess for the parameter vector Θ, we evaluate the cutoff function $\{\underline{\omega}_t\}$ in equation (18) at the *observed* aggregate state variables (aggregate consumption growth, re-scaled housing collateral ratio and aggregate rental price growth in the case of non-separable preferences), labor income shares, and region-specific rental prices in the case of non-separability. This gives a $T-1$ by N matrix of cutoff realizations.

- For a fixed σ_b, we draw a panel of log-normally distributed random variables for measurement error: $\left\{b^{i,s}_t\right\}$ for $t = 1, 2, ..., T$ and $i = 1, 2, ..., N$. We draw S such panels, where $s = 1, 2, ..., S$ denotes the simulation index.[15]

- Because of the presence of measurement error, we distinguish between observed consumption shares (measured with error) and true consumption shares. We denote the observed consumption share by $\tilde{c}^{i,s}_1$. For each $s \in S$, we set the observed initial consumption share of region i equal to the first observation on the consumption share in the data. The true consumption share is obtained from $\hat{c}^{i,s}_1 = \tilde{c}^{i,s}_1 \exp(-\hat{b}^{is}_1)$.

- For each $s \in S$ we form a time series of length T of predicted consumption shares. Given $\hat{c}^{i,s}_t$, we find next period's consumption share $\{\hat{c}^{i,s}_{t+1}\}$ for every region by comparing last period's consumption share $\hat{c}^{i,s}_t$ to the current cutoff level (the (t, i) entry of the cutoff matrix). That is, we apply the non-linear law of motion for consumption shares predicted by the model. In the non-separable model, prior to comparing last period's consumption share to the cutoff,

[14]The adjustment in equation (18) becomes $\Delta \log \hat{c}^i_{t+1} = \frac{1-\gamma\varepsilon}{\gamma} \frac{1}{1+(\hat{\rho}^i_t)^{\varepsilon-1}} \Delta \log \hat{\rho}^i_{t+1}$.

[15]The measurement error variance σ^2_b is held fixed throughout the estimation. Below we report results for different values of σ_b.

we adjust last period's consumption share for the change in region-specific rental price growth that would occur if constraints did not bind. This adjustment is given in equation (18).

- We compute the aggregate weight shock g^s_{t+1} as the cross-sectional average in equation (11) for separable preferences or equation (12) for non-separable preferences. At the end of every period we re-normalize the consumption shares by the aggregate weight shock. This re-normalization guarantees that the population-weighted average of shares is one.

- Next period's *observed* consumption share is $\tilde{c}^{i,s}_{t+1} = \hat{c}^{i,s}_{t+1} \exp(\hat{b}^{is}_{t+1})$. We repeat this step S times to end up with S panels of size $T \times N$ model-predicted observed consumption shares.

- For each region, we form the model-predicted observed consumption share at time t by averaging over the S different measurement error realizations:

$$k^i_t(\Theta) = \frac{1}{S}\sum_{s=1}^{S} \tilde{c}^{i,s}_t,$$

  and the model-predicted aggregate weigh shock at time t

$$g_t(\Theta) = \frac{1}{S}\sum_{s=1}^{S} g^s_t.$$

  We do this for every period $t = 2, ..., T$.

- Given the initial guess for (γ, ε) and the fixed value for β, we construct the stochastic discount factor $\{m_t\}$, using the aggregate weight shock g_{t+1}, according to equation (10). We form the pricing error at time t

$$p^j_t(\Theta, \beta, \gamma) = m_t R^j_t - 1,$$

  where R^j is the gross return on asset $j \in J$.

We use a hill-climbing algorithm to find the parameters $(\Theta, \gamma, \varepsilon)$ that minimize the distance between the moments in the data and the moments simulated from the model. The algorithm matches three sets of moments: (1) the correlation between consumption and income share for each region (N moments), (2) the cross-sectional dispersion in consumption (3 moments), and (3) asset prices (J moments). More precisely, the objective is to minimize W:

$$W=\begin{bmatrix} \frac{1}{T-1}\sum_{t=1}^{T-1}(\tilde{c}_t^1-k_t^1(\Theta))\hat{y}_t^1 \\ \vdots \\ \frac{1}{T-1}\sum_{t=1}^{T-1}(\tilde{c}_t^N-k_t^N(\Theta))\hat{y}_t^N \\ \frac{1}{T-1}\sum_{t=1}^{T-1}(\sigma^i(\tilde{c}_t)-\sigma^i(k_t^N(\Theta))) \\ \frac{1}{T-1}\sum_{t=1}^{T-1}\left(\frac{\sigma^i(\tilde{c}_t)}{\sigma^i(\hat{y}_t)}-\frac{\sigma^i(k_t^N(\Theta))}{\sigma^i(\hat{y}_t)}\right) \\ \frac{1}{T-1}\sum_{t=1}^{T-1}\left(\frac{\sigma^i(\tilde{c}_t)}{\sigma^i(\hat{y}_t)}-\frac{\sigma^i(k_t^N(\Theta))}{\sigma^i(\hat{y}_t)}\right)my_t \\ \frac{1}{T-1}\sum_{t=1}^{T-1}p_t^1(\Theta,\beta,\gamma,\varepsilon) \\ \vdots \\ \frac{1}{T-1}\sum_{t=1}^{T-1}p_t^J(\Theta,\beta,\gamma,\varepsilon) \end{bmatrix}' \Omega \begin{bmatrix} \frac{1}{T-1}\sum_{t=1}^{T-1}(\tilde{c}_t^1-k_t^1(\Theta))\hat{y}_t^1 \\ \vdots \\ \frac{1}{T-1}\sum_{t=1}^{T-1}(\tilde{c}_t^N-k_t^N(\Theta))\hat{y}_t^N \\ \frac{1}{T-1}\sum_{t=1}^{T-1}(\sigma^i(\tilde{c}_t)-\sigma^i(k_t^N(\Theta))) \\ \frac{1}{T-1}\sum_{t=1}^{T-1}\left(\frac{\sigma^i(\tilde{c}_t)}{\sigma^i(\hat{y}_t)}-\frac{\sigma^i(k_t^N(\Theta))}{\sigma^i(\hat{y}_t)}\right) \\ \frac{1}{T-1}\sum_{t=1}^{T-1}\left(\frac{\sigma^i(\tilde{c}_t)}{\sigma^i(\hat{y}_t)}-\frac{\sigma^i(k_t^N(\Theta))}{\sigma^i(\hat{y}_t)}\right)my_t \\ \frac{1}{T-1}\sum_{t=1}^{T-1}p_t^1(\Theta,\beta,\gamma,\varepsilon) \\ \vdots \\ \frac{1}{T-1}\sum_{t=1}^{T-1}p_t^J(\Theta,\beta,\gamma,\varepsilon) \end{bmatrix}$$

where Ω is the weighting matrix and $\sigma^i(\cdot)$ stands for the cross-sectional standard deviation. In the estimation, Ω is the identity matrix.

We also estimate the model for a different set of moments. We replace the first N moments, matching the unconditional correlation between consumption shares and income shares in model and data for each region, by N moments which match the *conditional* mean consumption share in model and data for each region. The conditioning variable is $\widetilde{my}_{t-1}$, which indexes the risk-sharing capacity of the economy. I.e., the moment for the i^{th} region is $\frac{1}{T-1}\sum_{t=1}^{T-1}(\tilde{c}_t^i-k_t^i(\Theta))\widetilde{my}_{t-1}$. The other $3+J$ moments remain the same.

4 Data

In the empirical section (section 6) we use a new data set of US metropolitan area level macroeconomic variables, as well as standard aggregate macroeconomic variables. All series are annual and for the United States.

4.1 Aggregate Macroeconomic Data

We use two distinct measures of the nominal housing collateral stock HV: the market value of residential real estate wealth (HV^{rw}) and the net stock current cost value of owner-occupied and tenant occupied residential fixed assets (HV^{fa}). The first time series is from the Flow of Funds (Federal Board of Governors) for 1945-2002 and from the Bureau of the Census (Historical Statistics for the US) prior to 1945. The last series is from the Fixed Asset Tables (Bureau of Economic Analysis) for 1925-2001. Appendix A provides detailed sources. We use both HV^{rw}, which is a measure of the value of housing owned by households, and HV^{fa} which is a measure of the value of housing households live in, to be robust to changes in the home-ownership rate over time. Real per household variables are denoted by lower case letters. The real, per household housing collateral series hv^{rw}, hv^{fa} are constructed using the all items consumer price index from the Bureau of Labor Statistics, p^a, and the total number of households, N, from the Bureau of the Census. Aggregate nondurable and housing services consumption, and labor income plus transfers data are from the National Income and Product Accounts (NIPA). Real per household labor income plus transfers is denoted by y.

4.2 Regional Macroeconomic Data

We construct a panel data set for the 30 largest metropolitan areas in the US. The regions combine for 47 percent of the US population. The metropolitan data are annual for 1951-2002. Thirteen of the regions are metropolitan statistical areas (MSA). The other seventeen are consolidated metropolitan statistical areas (CMSA), comprised of adjacent and integrated MSA's. Most CMSA's did not exist at the beginning of the sample. For consistency we keep track of all constituent MSA's and construct a population weighted average for the years prior to formation of the CMSA (see appendix A).

Price Indices Data are for urban consumers from the Bureau of Labor Statistics. The Consumer Price all items Index $p_t^{i,a}$, its rent component $p_t^{i,h}$ and the food component $p_t^{i,c}$ are available at the metropolitan level (Bureau of Labor Statistics). The price of rent is a proxy for the price of shelter and the price of food is a proxy for the price of non-durables. We use the rent and food components because the shelter and non-durables components are only available from 1967 onwards. Two-thirds of consumer expenditures on shelter consists of owner-occupied housing. The Bureau of Labor Statistics uses a rental equivalence approach to impute the price of owner-occupied housing. Because ρ_t^i is a relative *rental* price, our theory is conceptually consistent with the Bureau of Labor Statistics approach. All indices are normalized to 100 for the period 1982-84.

Consumption and Income Inter-regional risk-sharing studies use retail sales data as a proxy for non-durable consumption (DelNegro (1998) and references therein). Such data for metropolitan areas have not been used before. We collect retail sales data from the annual Survey of Buying Power published by Sales & Marketing Management (S&MM). Nominal non-durable consumption for region i, C_t^i, is total retail sales minus hardware and furniture sales and vehicle sales. From the same source we obtain the number of households in each region, N_t^i. Real per household consumption c^i is nominal non-durable consumption deflated by $p_t^{i,c}$ and divided by the number of households N_t^i.

Disposable personal income Y_t^i is also from S&MM. Disposable personal income consists of labor income, financial market income and net transfers. The latter two contain a potentially important insurance component. Therefore we also use labor income plus net transfers from the Regional Economic Information System (REIS). The latter are only available for 1970-2000. Real per household disposable income η^i is nominal disposable income deflated by $p_t^{i,a}$ and divided by the number of households N_t^i.

Appendix A compares non-durable retail sales and disposable income data with aggregate consumption and income data, with metropolitan non-durable consumption data from the Consumption Expenditure Survey (1986-2000 from Bureau of Labor Statistics), and with metropolitan labor income data plus transfers (1969-2000 from REIS). The correlation between the growth rates of aggregate real non-durable consumption per household and the metropolitan average of real non-durable retail sales per household is 0.77. Also, our metropolitan data are highly correlated with the metropolitan data from the Bureau of Labor Statistics and the REIS.

There are no complete consumer price index data for Baltimore, Buffalo, Phoenix, Tampa and Washington. There are no complete consumption and income data for Anchorage. Elimination of these regions leaves us with annual data for 23 metropolitan regions from 1951 until 2002. This is the regional data set we use in section 6.

5 Measuring the Housing Collateral Ratio

This section measures the aggregate housing collateral ratio my. my is defined as the ratio of collateralizable housing wealth to non-collateralizable human wealth. Human wealth, the present discounted value of labor income, is unobserved. We assume that the non-stationary component of human wealth H is well approximated by the non-stationary component of labor income Y. In particular, $\log(H_t) = \log(Y_t) + \epsilon_t$, where ϵ_t is a stationary random process. The assumption is valid in a model in which the expected return on human capital is stationary (see Jagannathan and Wang (1996) and Campbell (1996)).

Log, real, per household real estate wealth ($\log hv$) and labor income plus transfers ($\log y$) are non-stationary. According to an augmented Dickey-Fuller test (ADF), the null hypothesis of a unit root cannot be rejected at the 1 percent level. This is true for both hv^{rw} and hv^{fa}.

We compute $myhv = \log hv - \log y$ and remove a constant and a trend. The resulting time series $myrw$ and $myfa$ are mean zero and stationary, according to an ADF test. Formal justification for this approach comes from a likelihood-ratio test for cointegration between $\log hv$ and $\log y$ (Johansen and Juselius (1990)). If a linear combination of $\log hv$ and $\log y$, $\log(hv_t) + \varpi \log(y_t) + \chi$, is trend stationary, the components $\log hv$ and $\log y$ are said to be stochastically cointegrated with cointegrating vector $[1, \varpi, \chi]$. We additionally impose the restriction that the cointegrating vector eliminates the deterministic trends, so that $\log(hv_t) + \varpi \log(y_t) + \vartheta t + \chi$ is stationary. The test shows that the null hypothesis of no cointegration relationship can be rejected, whereas the null hypothesis of one cointegration relationship cannot. This is evidence for one cointegration relationship between housing collateral and labor income plus transfers (see Lustig and VanNieuwerburgh (2004a) for the estimates).

For the common sample period 1925-2001, the correlation between $myrw$ and $myfa$ is 0.86 . Figure 1 displays my between 1925 and 2002. The series exhibit large persistent swings. They reach a maximum deviation in 1932-33. Residential wealth and residential fixed assets are 30 and 34 percent above their respective joint trends with human wealth. The series reach a minimum in 1944-45, when $myrw$ is $-.57$ and $myfa$ is $-.38$.

6 Empirical Evidence of the Collateral Effect

In our metropolitan data, income growth is more strongly correlated across regions than consumption growth. The time average of the cross-sectional correlation of consumption growth is 0.27, lower than the cross-correlation of labor income growth of 0.48. From the perspective of the complete markets model this is a puzzle, known as the "quantity anomaly."

Figure 2 shows that, when collateral is scarce, US regions accomplish less risk-sharing. On the left axis is the collateral scarcity measure $\widetilde{myrw}$ (solid blue line). On the right axis is the ratio of the cross-sectional consumption share dispersion to the income share dispersion (dashed red line) in our 1952-2002 data set. The latter ratio is often used as a measure of the degree of risk sharing (e.g. Albarran and Attanasio (2001)). The denominator takes into account that it is more difficult to share income risk when income shares are more dispersed. When the ratio is high, regions are unable to share income risk with each other. We see that this is the case for US regions when housing collateral is scarce. The elasticity of the degree of risk-sharing with respect to the housing collateral ratio is 0.16. We find that the ratio of consumption share dispersion to income share dispersion is twice as high when my is at its lowest value in the sample as when my is at its highest value in the sample (1.79 versus .83).

In this section, we provide empirical evidence that consumption growth is imperfectly correlated across US metropolitan areas. We estimate our model and find evidence that US metropolitan regions share a larger proportion of idiosyncratic shocks when the housing collateral ratio is high. Time-variation in the degree of risk-sharing due to changes in the value of housing collateral sheds new light on the consumption correlation puzzle.

In section 6.1 we estimate the linear model of section 3.2. In section 6.2 we estimate the non-linear model described in section 3.3.

6.1 Linear Model

Identification and Econometric Issues We make one assumption: $E\left[\nu_t^i \widetilde{my}_{t-k}\right] = 0,\ \forall k \geq 0$. Since only aggregate variables affect the aggregate housing collateral ratio my and only region-specific preference shifts enter in ν^i, the assumption follows from the theory.

Correlation between residuals and regressors renders least squares estimators of the parameters in equation (16) inconsistent. Therefore, it is important to understand when such correlation arises. When $\Delta \log \hat{\eta}_t^i$ and $\Delta \log \hat{\rho}_t^i$ are cross-sectionally independent of ν_t^i, the regressors and residuals are orthogonal. This assumption is clearly violated for household-level data. For example, a family expansion changes preferences for consumption $\Delta \hat{b}_t^i$ and affects labor supply, and therefore labor income $\Delta \log\left(\hat{\eta}_t^i\right)$. It is less obvious that such correlation arises at the metropolitan level. Demographic shocks average out when aggregated over households. Indeed, the metropolitan data show that household-level characteristics such as average household size, age of head, and female labor supply are very similar across the 23 metropolitan areas. An adverse shock to an industry predominantly located in one region, a large population influx in a region, or a change in the demographical composition are other candidate shocks. Such shocks certainly affect regional rental price growth and per household income growth, but it is less obvious that they affect preference changes or measurement error in a systematic way. Only when they do, income and rental price changes need to be instrumented to obtain consistent estimates. In that case, and because of the autoregressive nature of $\widetilde{my}$, an instrumental variables estimator that uses two, three and four-period leads of dependent and independent variables as instruments is appropriate (Arellano and Bond (1991)).

The linear model under separability Under separability, the linear model collapses to the following equation:

$$\Delta \log\left(\hat{c}_{t+1}^{i}\right) = \alpha_0^i + \alpha_1 \widetilde{my}_{t+1} \Delta \log\left(\hat{\eta}_{t+1}^{i}\right) + \nu_{t+1}^{i},$$

where α_0^i are region-specific fixed effects. The reports for the estimation are in panel A of table 1.

To ensure that the collateral effect, picked up in α_1, is not entirely due to income changes, we estimate the same equation, but written so that it contains a separate income term:

$$\Delta \log\left(\hat{c}_{t+1}^{i}\right) = \beta_0^i + \beta_1 \Delta \log\left(\hat{\eta}_{t+1}^{i}\right) + \beta_2 my_{t+1} \Delta \log\left(\hat{\eta}_{t}^{i}\right) + \nu_{t+1}^{i}.$$

Note that this equation contains the collateral ratio my_{t+1} rather than the re-scaled ratio $\widetilde{my}_{t+1}$, which measures collateral scarcity. The parameter β_1 in the second specification corresponds to $\alpha_1 \frac{my^{max}}{my^{max}-my^{min}}$ in the first specification and the coefficient β_2 corresponds to $-\alpha_1 \frac{1}{my^{max}-my^{min}}$. The results are in panel B of the same table.

We start with a test for full consumption insurance. The null hypothesis of full insurance is $H_0 : \alpha_1 = 0$ in panel A and $H_0 : \beta_1 = \beta_2 = 0$ in panel B. The null hypothesis of complete consumption insurance is strongly rejected. The p-value for a Wald test is 0.00 for all rows in table 1. This is consistent with the findings of the regional risk-sharing literature for US states (Hess and Shin (1998)). In all rows of panel A, α_1 is positive and measured precisely. The point estimate for α_1 has a simple interpretation when the support of my is symmetric around zero and the current period $my_{t+1} = 0$. Then $\frac{\alpha_1}{2}$ measures the fraction of income growth shocks that the regions cannot insure away in an average period. Over the entire sample, between 33 percent (row 1) and 37 percent of disposable income growth shocks end up in consumption growth. Two-thirds of shocks are insured away on average.

More importantly, the correlation of region-specific consumption growth and region-specific income growth is higher when housing collateral is scarce. The histogram for my allows us to gauge the extent of time variation in the degree of risk sharing. The fifth percentile value for $myrw$ and the coefficient on α_1 in row 1 imply a degree of risk-sharing of 34.6 percent. The 95th percentile implies a degree of risk-sharing of 91.5 percent. Likewise, for $myfa$ the risk-sharing intervals is $[35.9, 92.4]$. The coefficient estimates for the period 1970-2000 are only slightly higher (rows 3-4, panel A). The point estimates for α_1 are higher when we use labor income growth instead of disposable income growth (rows 5-6). They are statistically indistinguishable from 1.00, the number predicted for α_1 by the theory.[16] The risk-sharing intervals are $[5, 88]$ for row 5 and $[8, 89]$ for row 6. All point estimates imply a large extent of time-variation in the degree of risk-sharing.

The estimates in panel B confirm that the correlation of region-specific consumption growth and region-specific income growth is lower when housing collateral is abundant: $\beta_2 < 0$ is negative in all rows. The coefficient β_2 is estimated precisely. The coefficients β_1 and β_2 imply that two-thirds of income shocks are insured away on average, but that there is substantial time variation in the degree of risk sharing.

Rows 10-12 of table 2 report instrumental variable (3SLS) estimates where income changes are instrumented by 2 and 3-period leads of independent and dependent variables. The instrumental variables estimates reject full insurance. The coefficient estimates are close to the ones obtained by Generalized Least Squares. Again, they imply a substantial degree of time-variation in risk-sharing.

In summary, the degree of risk sharing between metropolitan areas is higher in periods in which there is a relative abundance of collateral.

The linear model under non-separability Tables 2 shows the estimation results for the consumption Euler equation under non-separability:[17]

$$\Delta \log \tilde{c}^i_{t+1} \approx \alpha_1 \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + (\alpha_2 + \alpha_3 \widetilde{my}_{t+1}) \Delta \log \hat{\rho}^i_{t+1} + (\alpha_4 + \alpha_5 \widetilde{my}_{t+1})(\hat{\rho}^i_t - 1) \Delta \log \hat{\rho}^i_{t+1} + \nu^i_{t+1}.$$

The estimation results for this regression are in table 2.

As in the separable model, we also estimate a specification with a separate income term. By using my rather than $\widetilde{my}$, we obtain point estimates for the six parameters β, reported in table 3.

Four points about tables 2 and 3 are worth noting. First, the point estimates for α_1 and (β_1, β_2) are very similar to the ones in table 1. The conclusions with respect to the time-variation in the degree of income risk-sharing are robust to the inclusion of rental price growth terms which arise from non-separability.

Second, a fraction $\alpha_2 + \frac{\alpha_3}{2}$ of rental price shocks end up in consumption growth, when $my_{t+1} = 0$ and $\hat{\rho}_t = 1$. In row 1 (2), 72 (70) percent of rental price shocks are insured away. Note that this corresponds closely to the value of $1 - \beta_3$, evaluated at the point estimates in table 3.

Third, the point estimates for α_2 through α_5 allow us to identify the structural parameters (γ,ε). As we pointed out, $\frac{\alpha_3}{\alpha_2} = \frac{1-\gamma}{\gamma\varepsilon - 1}$ and $\frac{\alpha_5}{\alpha_4} = \frac{1-\gamma}{\gamma(\gamma\varepsilon-1)}$. The coefficient of relative risk aversion γ is identified by the ratio of $\frac{\alpha_3}{\alpha_2}$ to $\frac{\alpha_5}{\alpha_4}$. The intratemporal elasticity of substitution ε then follows from the expression for $\frac{\alpha_3}{\alpha_2}$. For row 1, the point estimates for α imply (γ,ε)=(.82 [.17], 1.06 [.06]) and for row 2 we (γ,ε)=(.42 [.30], .77 [1.35]). Standard errors in brackets are computed using the delta method. The estimates obtained using labor income data are similar in magnitude, but more precise. For row 5 (row 6) we find an implied γ of 1.05 [.73] (.58 [.34]) and an implied ε of .99 [.12] (.98 [.25]). The estimated coefficient of relative risk aversion over the joint consumption bundle

[16] The interpretation is that the sample minimum and maximum for my correspond to its theoretical autarky and perfect commitment values.

[17] We recall that the term $(\hat{\rho}^i_t - 1)\Delta \log \hat{\rho}^i_{t+1}$ is defined as $(\rho^i_t - 1)\Delta \log \rho^i_{t+1} - \frac{1}{N}\sum_{i=1}^N (\rho^i_t - 1)\Delta \log \rho^i_{t+1}$.

is low relative to the standard values above one (log preferences). The intratemporal elasticity of substitution is close to one.

Fourth, rows 7-8 of table 2 report instrumental variable (3SLS) estimates where income and rental price changes are instrumented by two, three and four-period leads of independent and dependent variables. The instrumental variables estimates reject full insurance. The coefficient estimates are close to the ones obtained by Generalized Least Squares.

Robustness We also estimate the linear model with the housing collateral ratio estimated on the postwar sample. my^{max} and my^{min} are defined as the largest and smallest observation on the housing collateral ratio in the period 1951-2002. We find that the conclusions with respect to the time variation in the degree of risk sharing remain unchanged.[18]

6.2 Non-Linear Model

Next, we report the results for the simulated method of moments estimation, described in section 3.3. The estimation recovers the structural parameters: the degree of relative risk aversion γ (separable preferences), the intratemporal elasticity of substitution between non-durables and housing services ε (non-separable preferences) and the parameters in the parametric cutoff specification Θ in equation (18).

Non-linear model under separability Table 4 reports the estimates of the collateral model under separable preferences. In specification 1 in the first column, the history dependence is shut off in the cutoff rule; θ_5 in equation (18) is set to zero. The coefficients in the cutoff specification have the expected sign: in a recession the cutoff goes up ($\theta_1 < 0$). This effect is stronger in a period with scarce housing collateral ($\theta_2 > 0$). More importantly, households with positive income innovations are more likely to run into binding constraints. This effect is stronger when collateral is scarce. Indeed, we find that an income share increase increases the cutoff when housing collateral is scarce ($\theta_4 > 0$). In an average period, $\widetilde{my} = .5$ and an income share increase raises the cutoff level ($\theta_3 + \frac{\theta_4}{2} > 0$). θ_4 is positive as predicted by the collateral mechanism, and measured precisely.

Figure 3 illustrates the risk-sharing dynamics and how they relate to the evolution of the housing collateral ratio. It plots our measure of collateral scarcity $\widetilde{myrw}$ on the left axis (solid blue line) against actual cross-regional consumption share dispersion (dashed green line) and estimated consumption share dispersion (dotted red line). The collateral scarcity measure and the consumption share dispersion in the data show a strong positive co-movement over time. The estimated cross-sectional consumption share dispersion tracks the actual dispersion very well (with the exception of the 1990s), because the estimation takes into account how the availability of housing collateral affects the risk-sharing capacity of the economy. The correlation between the predicted cross-regional consumption share dispersion and our measure of collateral scarcity is 0.51.

[18]Detailed results available upon request.

A time-varying degree of risk sharing across regions should also manifest itself in a time-varying correlation between regional and aggregate consumption growth. For rolling 20 year windows, we compute the correlation between each region's consumption growth and aggregate consumption growth. We average these correlations across regions. The resulting average correlation with aggregate consumption growth is high when housing collateral is scarce. This is shown in figure 4, which plots the observed and predicted correlation of regional consumption growth with aggregate consumption growth. As collateral became relatively more abundant between 1977 and 1988, regions' consumption growth became more correlated with aggregate consumption growth.

Table 4 also shows that the correlation between the rescaled housing collateral ratio and the aggregate weight shock is positive (.36). This is predicted by the theory: When collateral is scarce, the aggregate weight shock g is higher. The rate at which unconstrained households' consumption share drifts down and constrained households' consumption share jumps up is positively correlated with the scarcity of housing collateral. Figure 5 illustrates this. It plots the estimated aggregate weight shock (for specification 2), observed aggregate consumption growth (dashed green line) and the estimated consumption share dispersion (dotted red line). Aggregate weight shocks happen usually in recession. When there is a positive aggregate weight shock, the consumption share dispersion jumps up. In the absence of such shock it slowly drifts down.

The behavior of the aggregate weight shock also helps to explain asset prices. The collateral effect increases the volatility in the stochastic discount factor. The aggregate weight shock g is 1.37 at its maximum. Recall that g would is one if constraints are never binding. In the estimation, the multiplicative component of the stochastic discount factor due to the presence of housing collateral constraints accounts for three quarters of the volatility in the stochastic discount factor (SDF). As a result, the estimated Sharpe ratio for the collateral model is 3 times as volatile as the one in the standard consumption asset pricing model. The coefficient estimate for the degree of risk aversion is much smaller than the traditional estimates from the complete markets consumption-based asset pricing model. Because of the importance of the component in the SDF associated with the collateral effect, the coefficient of relative risk aversion does not need to be so high to reconcile volatile asset prices with smooth aggregate consumption.

Cutoff specification 2 in the second column of table 4 adds limited history dependence. The estimate for θ_4 is still positive and measured precisely. The new term, lagged consumption growth enters negatively ($\theta_5 < 0$). The objective function W is the lower for the specification with limited history dependence.

We estimate the same model for different magnitudes of measurement error volatility. The last column of Table 5 replicates the last column of table 4. The other columns estimate the same model but for $\sigma_b = .005, .010, .015$. The value of the objective function is non-monotonic in the standard deviation of measurement error. It is lowest for $\sigma_b = .02$. More importantly, all parameter estimates have the same sign, similar magnitudes, and are similarly precisely estimated.

Finally, if the cutoff specification does not depend on the housing collateral ratio ($\theta_2 = 0 = \theta_4$ in specification 2), the model performs significantly worse. Not only is the Simulated Method of Moments objective function higher (.074), but the predicted consumption shares don't line up with the observed consumption shares. Figure 6 is an illustration of this failure. Just as in figure 3, it plots actual cross-regional consumption share dispersion (dashed green line) and estimated consumption share dispersion (dotted red line). The actual and estimated (predicted) consumption share dispersion are quite different.

Non-linear model under non-separability Under non-separability, both the pricing kernel and the law of motion for individual consumption shares are different. The *representative agent* pricing kernel additionally depends on aggregate rental price growth. The cutoff consumption share, which reflects the risk of binding collateral constraints, also depends on rental price changes. Table 6 reports four different specifications for the cutoff level.

The new terms in specification 3 are the average region-specific rental price level (fixed effect), the aggregate rental price growth rate and the latter interacted with the housing collateral ratio. In specification 4, we add region specific rental price changes and their interaction term with the housing collateral ratio. In the third column, we add limited history dependence by including one lag of aggregate consumption growth and aggregate rental price growth. Finally, specification 6 includes the cross-regional dispersion of rental prices and its interaction with the housing collateral ratio. These terms capture the dependence of the cutoff weight on the distribution of rental prices. For parsimony we omit the lagged aggregate consumption growth and aggregate rental price growth variables in this specification.

The parameter ε is the intratemporal elasticity of substitution between non-durable and housing services consumption. This estimate ranges from -.4 to .9 and has mostly a large standard error. The non-separable model has a hard time pinning down this parameter. The coefficients on the new rental price growth terms in the cutoff specification coming from the non-separability ($\theta_6 - \theta_{13}$) are measured less precisely than the coefficients on the terms from the separable specification. However, the parameter estimates for θ_3 and θ_4 (columns 2-5) have the right sign and are still precisely estimated. When regions witness a positive relative income shock, the cutoff level increases more when housing collateral is relatively scarce ($\theta_4 > 0$). This indicate the presence of the collateral effect under non-separable preferences, just as in the model with separable preferences. The correlation between the aggregate weight shock is the measure of collateral scarcity is large and positive (.3-.5).

In sum, even when preferences are non-separable, the main collateral effect is strongly present. In addition the non-separable model matches simulated and observed consumption paths more closely: The objective function W is lowest in specification 4.

Robustness The parameter estimates are very similar when we replace the first N moments, which match the unconditional correlation between consumption shares and income shares in model and data for each region, by N moments which match the conditional mean consumption share in model and data. The conditioning variable is $\widetilde{my}_{t-1}$, which indexes the risk-sharing capacity, or equivalently, the investment opportunity set. The last 6 moments are unchanged. Table 7 shows the parameter estimates for specification 1 and 2, corresponding to columns 1 and 2 of table 4 and for specification 4 and 5, corresponding to columns 2 and 3 of table 6.

Again, the parameter θ_4 is positive, and measured precisely. The parameter estimates imply that consumption is relatively more dispersed than income in times when collateral is scarce.

7 Regional Housing Collateral

So far we have used aggregate collateral measures only. This is consistent with our theoretical setup, in which households are allowed to own a fraction of the housing stock in different regions. In equilibrium, housing collateral is efficiently distributed over the regions. If households were instead restricted to be the full owner of the housing stock in their region, regional collateral measures would affect risk-sharing. In the decentralized setup, no markets for home-ownership in other regions would exist. Houses would be priced off the region-specific intertemporal marginal rate of substitution, rather than off the IMRS of the unconstrained agents. This would modify the collateral constraints. Here we briefly discuss the *empirical* relationship between the degree of risk-sharing and two regional measures of collateral. We use the framework of the *linear* model. We also investigate the role of regional variation in homestead exemptions.

Linear Model with Regional Collateral Measures We find that the regional collateral variables lend additional support to the collateral effect. In particular, regions with a higher home ownership rate and regions with a higher value of housing wealth are better able to smooth regional income shocks. Table 8 summarizes the findings and appendix A describes the regional collateral data, available for 1975-2000.

First, regions with a higher *home-ownership rate* can sustain a higher degree of risk sharing. The interaction term of the home-ownership rate with the region-specific income growth rate is positive and measured precisely (row 1). The coefficient α_1 implies that a region with a 50 percent home-ownership rate shares 63 percent and a region with a 75 percent home-ownership shares 82 percent of income risk. Second, a higher regional housing collateral value increases the degree of risk-sharing. The log deviation of the collateral value in region i from the cross-sectional median, $\hat{hv}_{it}$, is the measure of regional collateral abundance used in row 2. The estimate α_1 is statistically unambiguously positive. Time variation in the regional collateral variable implies variation in risk-sharing. The sensitivity of consumption growth to region-specific income growth is twice as high (.39) for the region whose housing collateral stock is half as valuable relative to the median region than for the region whose collateral stock is twice the value of the collateral stock of the median region (.17). Third, rows 3 and 4 show that, when both the interaction term with my and the interaction term with $\hat{hv}_{it}$ are included, the aggregate collateral effects drives out the regional one. This is consistent with the fact that their is a large common component in regional collateral movements. The first principal component of hv_{it} is 74 percent.

Homestead Exemption In our model, households face bankruptcy under Chapter 7 of US bankruptcy legislation. Upon default, they give up collateral assets but their future labor income is protected. Some US states have homestead exemptions, which allow households to keep their primary residence out of a bankruptcy foreclosure. There is considerable regional variation in exemption levels. Here we evaluate the impact of the homestead exemption on the housing collateral effect.

We construct a dummy variable that is one for metropolitan areas located in states with exemption levels above \$20,000 and zero elsewhere.[19] We also construct a variable which measures the exemption level itself. We fail to find an effect that is significant from zero. In a regression

$$\Delta \log\left(\hat{c}^i_{t+1}\right) = \alpha^i_0 + \alpha_1 \Delta \log\left(\hat{\eta}^i_{t+1}\right) + \alpha_2 hstd_{t+1} \Delta \log\left(\hat{\eta}^i_{t+1}\right) + \alpha_3 \Delta \log\left(\hat{\rho}^i_{t+1}\right) + \alpha_4 hstd_{t+1} \Delta \log\left(\hat{\rho}^i_{t+1}\right) + \nu^i_{t+1},$$

the coefficient estimate for α_2 is -.07 with standard error .06 when $hstd$ is the exemption dummy, and -.02 with standard error .02 when $hstd$ is the exemption level expressed in \$100,000. The interaction terms have the wrong sign, and are insignificant. In regressions with the homestead exemption interaction terms and the housing collateral interaction terms, the former fail to be significant, whereas the latter remain virtually unchanged from previously reported estimates.

In our sample, homestead exemptions do not seem to affect the role of housing collateral as a risk-sharing device. For the majority of states, these exemptions are rather small (less than \$20,000). Also, even in those states with unlimited exemptions, mortgage lenders always retain seniority over the collateral assets.

[19] Homestead exemption levels by state can be found at: http://www.successdna.com/documents/HomesteadChart.pdf

8 Conclusion

This paper presents empirical evidence for partial risk-sharing among US metropolitan areas. We find evidence that the amount of insurance the regions obtain against region-specific income shocks and rental price shocks varies over time. The source of this incomplete and time-varying degree of risk sharing is variation in the ratio of collateralizeable housing wealth relative to non-collateralizeable human wealth.

We develop a general equilibrium model with housing collateral in which households have to back up their state-contingent promises with the value of their house. Time variation in the price of housing induces time variation in the economy's ability to share labor income risk. When the housing collateral value is low, there is an increase in idiosyncratic risk. Households run more frequently into binding collateral constraints and are less able to share labor income risk with each other. Our theory predicts low cross-correlation of consumption growth in such periods. However, when collateral is abundant, region-specific income growth and consumption growth correlations are lower and cross-correlations of consumption growth are higher.

The data seem to support this qualification; conditioning on the housing collateral ratio weakens the consumption growth puzzle for US regions. Conversely, in times when housing collateral is scarce, the dispersion of consumption growth relative to income growth is twice as high as when collateral is abundant. We estimate the model using panel data of metropolitan area consumption, income and rental prices. A structural estimation of the model's consumption dynamics implies a time path for consumption growth dispersion that matches the one in the data. The housing collateral effect is the key element that enables this match. In a linear Euler equation estimation, we find similar time-variation in the degree of risk-sharing. Regions can insure 34 percent of income growth shocks when collateral is scarce and 92 percent when housing collateral is abundant. Similar findings for region-specific housing collateral measures strengthen the evidence for the collateral effect.

Two aspects of financial markets are often studied separately. One is their role in allocating risk, the other is the asset returns. In Lustig and VanNieuwerburgh (2004b), we numerically solve for a calibrated version of the model described here and study its asset pricing implications. We find that the collateral mechanism is important to quantitatively match unconditional and conditional asset pricing moments, as well as to generate meaningful variation in returns across assets. In Lustig and VanNieuwerburgh (2004a), we test the model's asset pricing predictions and confirm their empirical plausibility. In this paper, we presented evidence that supports the main mechanism underlying these asset pricing results: time variation in the extent of risk-sharing.

The insights in this paper on the role of collateral wealth in sustaining risk-sharing may have broader implications. DeSoto (2000) argues that many of the problems of poor countries stem from the absence of legal and financial institutions that allow people to borrow against property. Lacking clear property rights and an active mortgage market, they are unable to share income risk and finance growing business.

References

Albarran, Pedro and Orazio Attanasio, "Empirical Implications of Limited Commitment," 2001. Working Paper UCL.

Alvarez, Fernando and Urban Jermann, "Efficiency, Equilibrium, and Asset Pricing with Risk of Default.," *Econometrica*, 2000, *68* (4), 775–798.

Arellano, Manuel and Stephen Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 1991, *58*, 277–297.

Attanasio, Orazio P. and Guglielmo Weber, "Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey," *The Journal of Political Economy*, December 1995, *103* (6), 1121–1157.

—— **and Steven J. Davis**, "Relative Wage Movements and the Distribution of Consumption," *The Journal of Political Economy*, December 1996, *104* (6), 1127–1262.

Backus, David, Patrick Kehoe, and Finn Kydland, "International Real Business Cycles," *Journal of Political Economy*, 1992, *100* (4), 745–75.

Blundell, Richard, Luigi Pistaferri, and Ian Preston, "Partial Insurance, Information and Consumption Dynamics," July 2002. Mimeo.

Campbell, John Y., "Understanding Risk and Return," *The Journal of Political Economy*, April 1996, *104* (2), 298–345.

Case, Karl E. and Robert J. Shiller, "Prices of Single-Family Homes Since 1970: New Indexes for Four Cities," *New England Economic Review*, September/October 1987, pp. 46–56.

—— **, John M. Quigley, and Robert J. Shiller**, "Comparing Wealth Effects: The Stock Market versus The Housing Market," October 2001. UC Berkeley Working Papers.

Cochrane, John H., "A Simple Test of Consumption Insurance," *The Journal of Political Economy*, October 1991, *99* (5), 957–976.

DelNegro, Marco, "Aggregate Risk Sharing Across US States and Across European Countries," January 1998. Yale University mimeo.

DeSoto, Hernando, *The Mystery of Capital: Why Capitalism Triumphs in the West and Fails Everywhere Else*, New York, NY: Basic Books; First edition, 2000.

Eichenbaum, Martin and Lars Peter Hansen, "Estimating Models with Intertemporal Substitution Using Aggregate Time Series Data," *Journal of Business and Economic Statistics*, 1990, *8* (1), 53–69.

Gertler, Paul and Jonathan Gruber, "Insuring Consumption Against Illness," *American Economic Review*, 2002, *92*, 51–70.

Hansen, Lars Peter and Thomas J. Sargent, "Formulating and Estimating Dynamic Linear Rational Expectations Models," *Journal of Economic Dynamics and Control*, 1980, *2*, 7–46.

Harrison, Michael J. and David M. Kreps, "Martingales and Arbitrage in Multiperiod Securities Markets," *Journal of Economic Theory*, 1979, *20*, 381–408.

Hess, Gregory D. and Kwanho Shin, "Intranational Business Cycles in the United States," *Journal of International Economics*, April 1998, *44* (2), 289–313.

Jagannathan, Ravi and Zhenyu Wang, "The Conditional CAPM and the Cross-Section of Expected Returns," *The Journal of Finance*, March 1996, *51* (1), 3–53.

Johansen, Soren and Katarina Juselius, "Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, May 1990, *52*, 169–210.

Kehoe, Patrick J. and Fabrizio Perri, "International Business Cycles with Endogenous Incomplete Markets," *Econometrica*, May 2002, *70* (3), 907–928.

Kehoe, Timothy and David Levine, "Debt-Constrained Asset Markets.," *Review of Economic Studies*, 1993, *60*, 865–888.

Krueger, Dirk, "Risk Sharing in Economies with Incomplete Markets," June 2000. mimeo.

—— **and Fabrizio Perri**, "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory.," November 2003. Mimeo.

Levine, Ross, "Financial Development and Economic Growth: Views and Agenda," *Journal of Economic Literature*, 1997, *35*, 688–726.

Ljungqvist, Lars and Thomas J. Sargent, *Recursive Macroeconomic Theory, Second Edition*, Cambridge, Mass.: MIT Press, 2004.

Lucas, Robert, "Asset Prices in an Exchange Economy," *Econometrica*, 1978, *46* (6), 1429–54.

Lustig, Hanno, "The Wealth Distribution and Aggregate Risk," 2003. Mimeo University of Chicago.

—— **and Stijn VanNieuwerburgh**, "Housing Collateral, Consumption Insurance and Risk Premia: An Empirical Perspective," 2004. Forthcoming Journal of Finance.

—— **and** —— , "A Theory of Housing Collateral, Consumption Insurance and Risk Premia," April 2004. Working Paper NYU Stern and University of Chicago.

Mace, Barbara J., "Full Insurance in the Presence of Aggregate Unicertainty," *The Journal of Political Economy*, October 1991, *99* (5), 928–956.

Nelson, Julie A., "On Testing for Full Insurance using Consumer Expenditure Survey Data," *The Journal of Political Economy*, April 1994, *102* (2), 384–394.

Pollakowski, Henry O., "Data Sources for Measuring House Price Changes," *Journal of Housing Research*, 1995, *6* (3), 377–389.

9 Figures and Tables

Figure 1: Housing Collateral Ratio 1925-2001.
Ratio of housing wealth, measured by non-farm residential wealth ($myrw$) and residential fixed asset wealth ($myfa$) to human wealth.

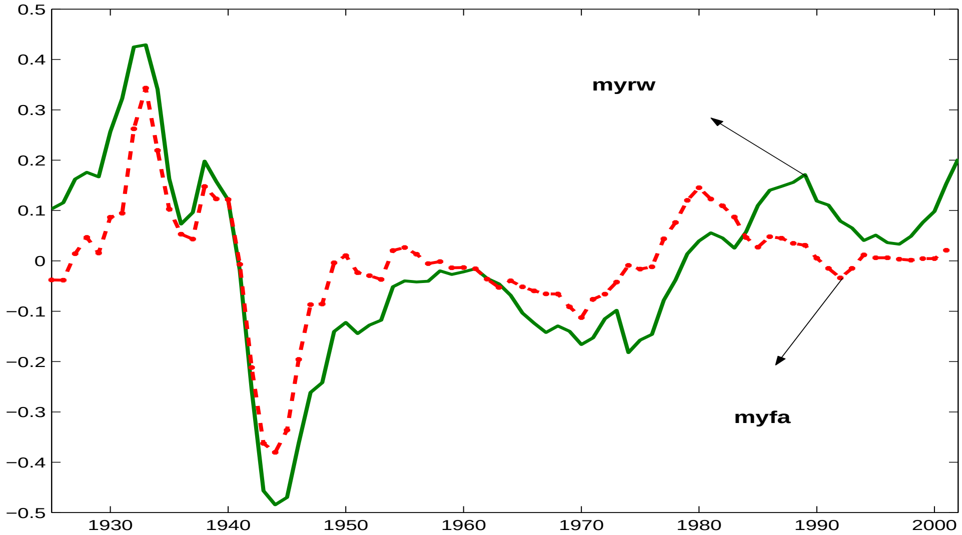

Figure 2: Housing Collateral Scarcity and Degree of Risk Sharing.
On the left axis is the collateral scarcity measure $\widetilde{myrw}$ (solid blue line). On the right axis is the ratio of observed cross-sectional consumption share dispersion to income share dispersion (dashed red line). When collateral is scarce, US regions accomplish less risk-sharing

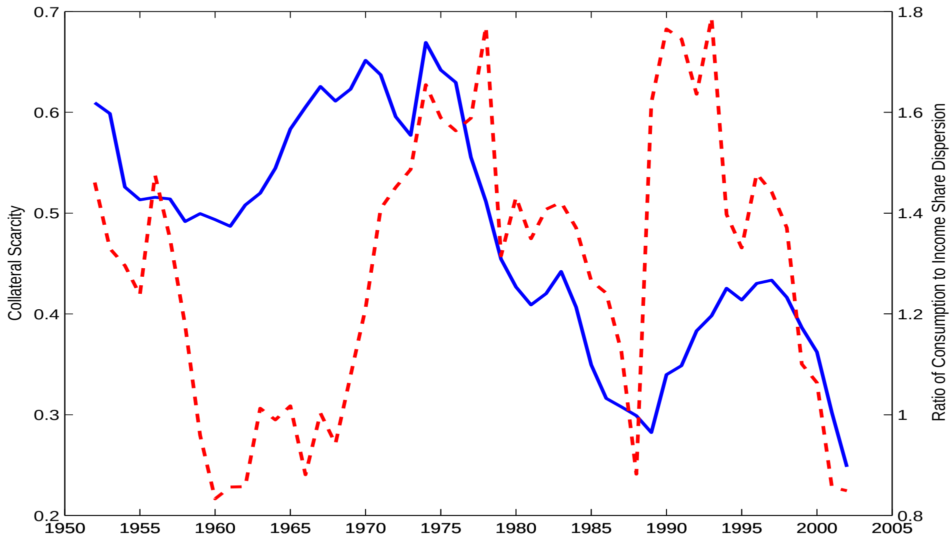

Figure 3: Housing Collateral Ratio and Cross-Regional Consumption Share Dispersion.
On the left axis is the collateral scarcity measure $\widetilde{myrw}$ (solid blue line). On the right axis is the observed (dashed green line) and predicted (dotted red line) cross-sectional consumption share dispersion. The predicted dispersion is the one that corresponds to the model under separability (specification 2).

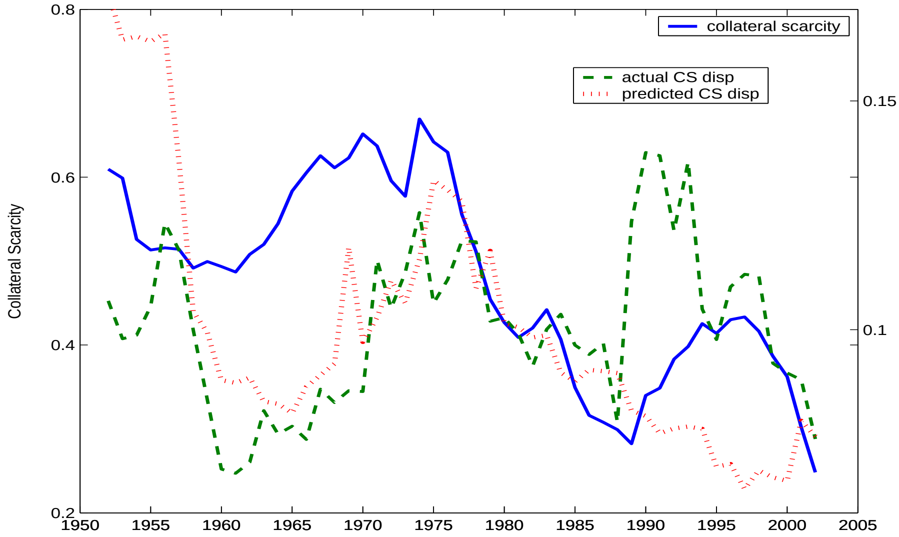

Figure 4: Housing Collateral Ratio and Correlation between Regional and Aggregate Consumption Growth.
On the left axis is the collateral scarcity measure $\widetilde{myrw}$ (solid blue line). On the right axis is the observed (dashed green line) and predicted (dotted red line) average correlation between the past 20 years over regional consumption growth and aggregate consumption growth. The average is taken across regions. The predicted dispersion is the one that corresponds to the model under separability (specification 2).

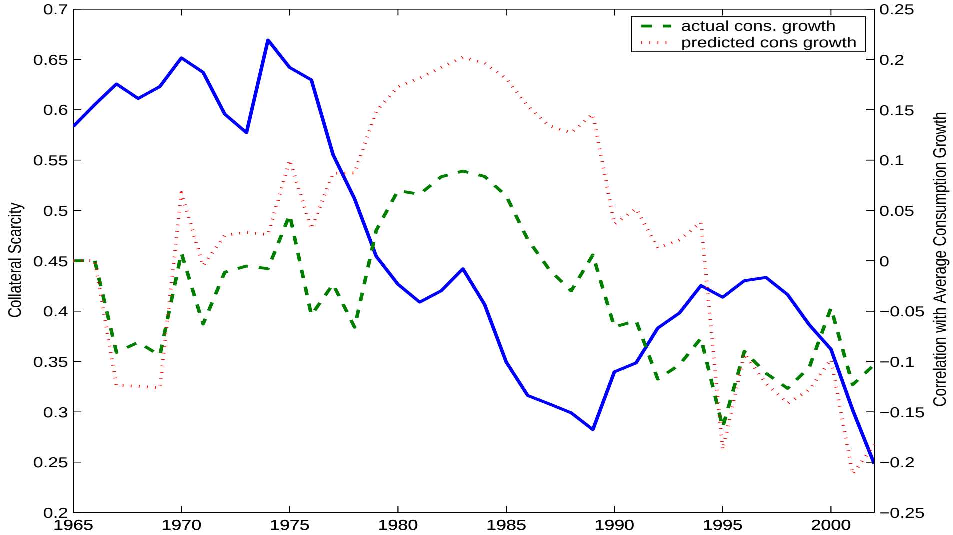

Figure 5: Estimated Aggregate Weight Shock and Consumption Share Dispersion, and Observed Aggregate Consumption Growth
On the left axis is the estimation-implied aggregate weight shock g (solid blue line) and observed aggregate consumption growth (dashed green line). On the right axis is the predicted cross-sectional consumption share dispersion (dotted red line). The predicted dispersion is the one that corresponds to the model under separability (specification 2).

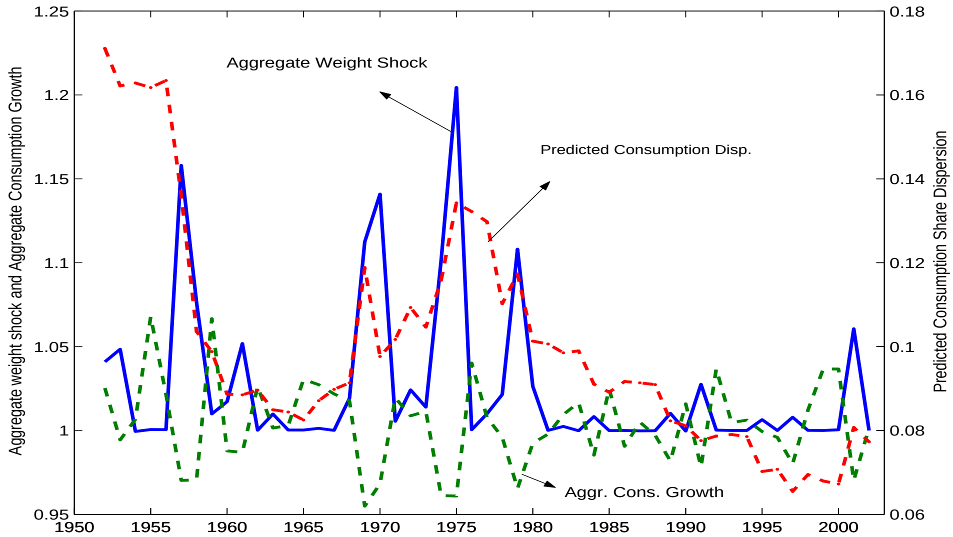

Figure 6: Housing Collateral Ratio and Cross-Regional Consumption Share Dispersion: No Collateral Effect.
On the left axis is the collateral scarcity measure $\widetilde{myrw}$ (solid blue line). On the right axis is the observed (dashed green line) and predicted (dotted red line) cross-sectional consumption share dispersion. The predicted dispersion is the one that corresponds to the model under separability (specification 2) but with $\theta_2 = 0 = \theta_4$ in the cutoff specification.

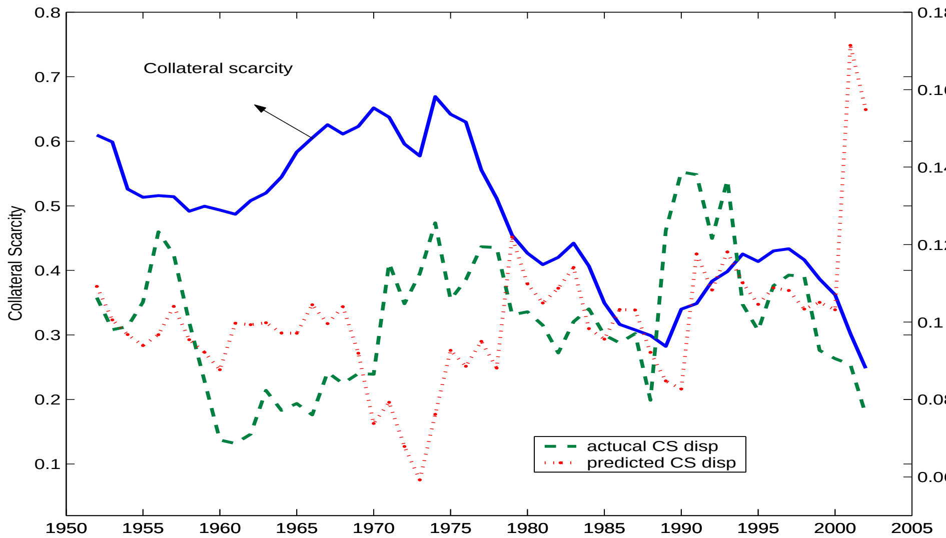

Table 1: Linear Estimation, Separable Preferences.

In panel A we estimate: $\Delta \log\left(\hat{c}^i_{t+1}\right) = \alpha^i_0 + \alpha_1 \widetilde{my}_{t+1} \Delta \log\left(\hat{\eta}^i_{t+1}\right) + \nu^i_{t+1}$. In panel B we estimate: $\Delta \log\left(\hat{c}^i_{t+1}\right) = \beta^i_0 + \beta_1 \Delta \log\left(\hat{\eta}^i_{t+1}\right) + \beta_2 my_{t+1} \Delta \log\left(\hat{\eta}^i_{t+1}\right) + \nu^i_{t+1}$. Rows 1-2 are for the period 1952-2002 (1166 observations). The measure of idiosyncratic income is disposable personal income. Rows 3-4 are identical to rows 1-2 but are for the period 1970-2000 (713 observations) in panel A and 1970-2002 (759 observations) in panel B. Regressions 5-6 use labor income plus transfers, available only for 1970-2000. In each block, the rows use the variables $myrw$ and $myfa$, estimated for the period 1925-2002. my^{max} (my^{min}) is the sample maximum (minimum) in 1925-2002. The coefficients on the fixed effect, α^i_0, are not reported. Estimation is by feasible Generalized Least Squares, allowing for both cross-section heteroscedasticity and contemporaneous correlation. Rows 7-8 are the results for the instrumental variable estimation by 3SLS. Instruments are a constant, $\log(\hat{y}^i_{t+2})$, $\log(\hat{y}^i_{t+3})$, $\log(\hat{y}^i_{t+4})$, $\Delta\hat{\rho}^i_{t+2}$, $\Delta\hat{\rho}^i_{t+3}$, $\Delta\hat{\rho}^i_{t+4}$, $\log(\hat{c}^i_{t+2})$, $\log(\hat{c}^i_{t+3})$, $\log(\hat{c}^i_{t+4})$, and my_{t+2}, my_{t+3}, my_{t+4}. The period is 1952-1998 (1051 observations). All results are for 23 US metropolitan areas.

		Panel A			Panel B				
Coll.	Measure	α_1	σ_{α_1}	R^2	β_1	σ_{β_1}	β_2	σ_{β_2}	R^2
1	$myrw$	.70	(.05)	*6.4*	.35	(.03)	-.30	(.26)	*6.5*
2	$myfa$	.75	(.06)	*6.9*	.36	(.03)	-1.74	(.50)	*6.8*
3	$myrw$	.70	(.03)	*4.7*	.33	(.02)	-.64	(.17)	*4.7*
4	$myfa$	.78	(.03)	*5.0*	.37	(.02)	-2.12	(.31)	*5.0*
5	$myrw$	1.02	(.05)	*10.5*	.48	(.02)	-1.03	(.23)	*10.5*
6	$myfa$	1.08	(.05)	*10.3*	.51	(.03)	-1.13	(.30)	*10.4*
7	$myrw$	.63	(.07)		.31	(.04)	-.32	(.38)	
8	$myfa$	.69	(.08)		.32	(.04)	-1.75	(.64)	

Table 2: Linear Estimation, Non-Separable Preferences (A).

We estimate: $\Delta \log \tilde{c}^i_{t+1} = \alpha_1 \widetilde{my}_{t+1} \Delta \log \hat{\eta}^i_{t+1} + (\alpha_2 + \alpha_3 \widetilde{my}_{t+1}) \Delta \log \hat{\rho}^i_{t+1} + (\alpha_4 + \alpha_5 \widetilde{my}_{t+1})(\hat{\rho}^i_t - 1) \Delta \log \hat{\rho}^i_{t+1} + \nu^i_{t+1}$. Rows 1-2 are for the period 1952-2001 (1166 observations). The measure of idiosyncratic income is disposable personal income. Rows 3-4 are identical to rows 1-2 but are for the period 1970-2000 (713 observations). Regressions 5-6 use labor income plus transfers, available only for 1970-2000 (704 observations). All rows use the rescaled $myrw$ and $myfa$, estimated for the period 1925-2002. my^{max} (my^{min}) is the sample maximum (minimum) in 1925-2002. The coefficients on the fixed effect, α^i_0, are not reported. Estimation is by feasible Generalized Least Squares, allowing for both cross-section heteroscedasticity and contemporaneous correlation. Rows 7-8 are the results for the instrumental variable estimation by 3SLS. Instruments are a constant, $\log(\hat{y}^i_{t+2})$, $\log(\hat{y}^i_{t+3})$, $\log(\hat{y}^i_{t+4})$, $\Delta\hat{\rho}^i_{t+2}$, $\Delta\hat{\rho}^i_{t+3}$, $\Delta\hat{\rho}^i_{t+4}$, $\log(\hat{c}^i_{t+2})$, $\log(\hat{c}^i_{t+3})$, $\log(\hat{c}^i_{t+4})$, and my_{t+2}, my_{t+3}, my_{t+4}. The period is 1952-1998 (1074 observations).All results are for 23 US metropolitan areas.

Coll.	Measure	α_1	σ_{α_1}	α_2	σ_{α_2}	α_3	σ_{α_3}	α_4	σ_{α_4}	α_5	σ_{α_5}	R^2
1	$myrw$	.68	(.05)	.98	(.18)	-1.40	(.39)	1.13	(.96)	-1.95	(1.74)	*9.3*
2	$myfa$	.74	(.06)	.53	(.21)	-.46	(.48)	1.72	(1.41)	-3.48	(2.81)	*9.5*
3	$myrw$	.75	(.04)	.64	(.05)	-.57	(.11)	1.90	(.49)	-2.69	(.92)	*9.0*
4	$myfa$	.81	(.04)	.53	(.07)	-.40	(.15)	.34	(.82)	.35	(1.66)	*9.0*
5	$myrw$	1.01	(.04)	.80	(.09)	-.97	(.22)	.66	(.67)	-.77	(1.23)	*14.3*
6	$myfa$	1.09	(.05)	.62	(.14)	-.60	(.32)	.61	(1.18)	-1.03	(2.40)	*13.8*
7	$myrw$	.55	(.07)	.87	(.24)	-1.31	(.53)	.30	(1.69)	-.84	(2.96)	
8	$myfa$	.62	(.08)	1.09	(.31)	-1.66	(.71)	2.18	(1.83)	-4.23	(3.67)	

Table 3: Linear Estimation, Non-Separable Preferences (B).

We estimate: $\Delta \log \left(\hat{c}^i_{t+1}\right) = \beta^i_0 + \beta_1 \Delta \log \left(\hat{\eta}^i_{t+1}\right) + \beta_2 my_{t+1} \Delta \log \left(\hat{\eta}^i_t\right) + \beta_3 \Delta \log \left(\hat{\rho}^i_{t+1}\right) + \beta_4 my_{t+1} \Delta \log \left(\hat{\rho}^i_t\right) + \beta_5 (\hat{\rho}^i_t - 1) \Delta \log \left(\hat{\rho}^i_{t+1}\right) + \beta_6 my_{t+1} (\hat{\rho}^i_t - 1) \Delta \log \left(\hat{\rho}^i_{t+1}\right) + \nu^i_{t+1}$. Rows 1-2 are for the period 1952-2001 (1166 observations). The measure of idiosyncratic income is disposable personal income. Rows 3-4 are identical to rows 1-2 but are for the period 1970-2000 (703 observations). Regressions 5-6 use labor income plus transfers, available only for 1970-2000. All rows use $myrw$ and $myfa$, estimated for the period 1925-2002. The coefficients on the fixed effect, β^i_0, are not reported. Estimation is by feasible Generalized Least Squares, allowing for both cross-section heteroscedasticity and contemporaneous correlation. Rows 7-8 are the results for the instrumental variable estimation by 3SLS. Instruments are a constant, $\log(\hat{y}^i_{t+2})$, $\log(\hat{y}^i_{t+3})$, $\log(\hat{y}^i_{t+4})$, $\Delta\hat{\rho}^i_{t+2}$, $\Delta\hat{\rho}^i_{t+3}$, $\Delta\hat{\rho}^i_{t+4}$, $\log(\hat{c}^i_{t+2})$, $\log(\hat{c}^i_{t+3})$, $\log(\hat{c}^i_{t+4})$, and my_{t+2}, my_{t+3}, my_{t+4}. The period is 1952-1998 (1074 observations). All results are for 23 US metropolitan areas.

Coll.	Measure	β_1	σ_{β_1}	β_2	σ_{β_2}	β_3	σ_{β_3}	β_4	σ_{β_4}	β_5	σ_{β_5}	β_6	σ_{β_6}	R^2
1	$myrw$	.32	(.03)	-.58	(.26)	.33	(.04)	1.47	(.43)	.21	(.20)	2.28	(1.92)	*9.3*
2	$myfa$	.35	(.03)	-1.76	(.50)	.32	(.05)	.96	(.68)	.10	(.17)	4.56	(3.83)	*9.4*
3	$myrw$	.35	(.02)	-.57	(.17)	.37	(.01)	.58	(.12)	.63	(.13)	3.18	(1.03)	*9.0*
4	$myfa$	.39	(.02)	-1.19	(.27)	.34	(.01)	.54	(.21)	.51	(.13)	-.25	(2.37)	*9.0*
5	$myrw$	.47	(.02)	-1.04	(.18)	.34	(.02)	1.04	(.24)	.30	(.17)	.88	(1.37)	*14.3*
6	$myfa$	.51	(.02)	-.78	(.31)	.34	(.03)	.92	(.44)	.14	(.17)	.66	(3.31)	*14.0*
7	$myrw$	.25	(.04)	-.68	(.39)	.26	(.05)	1.44	(.60)	-.08	(.34)	.96	(3.23)	
8	$myfa$	.28	(.04)	-2.06	(.64)	.31	(.06)	1.61	(.95)	.06	(.22)	7.97	(5.08)	

Table 4: Non-Linear Estimation, Separable Preferences.

The estimation is by simulated method of moments (S=20), using the N+6 moments described in the text. The measurement error volatility is fixed at $\sigma_b = .02$. The discount factor is fixed at $\beta = .95$. The weighting matrix is the identity matrix in 3 iterations and the Newey-West HAC matrix for the computation of standard errors. The housing collateral ratio is $myrw$. The parameter γ is a preference parameter; the parameters in the consumption weight cutoff specification parameter are Θ. The two columns correspond to two different specifications of the cutoff process, discussed in the text. The last three rows report the aggregate weight shock and collateral scarcity, the highest realization of the aggregate weight shock, and the Simulated Method of Moments function value W. Data are for 1951-2002 for 23 US metropolitan areas.

Parameter	Specif. 1	Specif. 2
γ	.51 (.34)	.27 (.17)
θ_0	.69 (.07)	.53 (.12)
θ_1	-14.24 (5.17)	-8.85 (21.60)
θ_2	.05 (8.62)	28.53 (50.23)
θ_3	-7.36 (4.31)	-29.53 (2.79)
θ_4	25.72 (9.87)	60.10 (5.54)
θ_5		-23.61 (5.48)
$corr(g, \widetilde{my})$	.36	.16
$max(g)$	1.37	1.81
W	0.054	.0313

Table 5: Non-Linear Estimation, Separable Preferences - Size of Measurement Error

Same as table 4, for four different values of the volatility of the measurement error σ_b. The cutoff specification corresponds to the second column of table 4 (specif. 2).

Parameter	$\sigma_b = .005$	$\sigma_b = .010$	$\sigma_b = .015$	$\sigma_b = .020$
γ	.71 (.42)	.45 (.29)	.60 (.38)	.27 (.17)
θ_0	.85 (.02)	.70 (.09)	.79 (.05)	.53 (.12)
θ_1	-5.82 (11.76)	-13.33 (9.79)	-9.59 (4.01)	-8.85 (21.60)
θ_2	.49 (22.02)	-2.72 (16.97)	.13 (9.45)	28.53 (50.23)
θ_3	-8.75 (2.86)	-5.48 (3.69)	-7.85 (4.72)	-29.53 (2.79)
θ_4	27.54 (6.98)	21.96 (8.47)	26.30 (10.63)	60.10 (5.54)
θ_5	1.95 (1.42)	1.66 (.53)	.90 (1.09)	-23.61 (5.48)
$corr(g, \tilde{my})$	.41	.33	.37	.16
$max(g)$	1.20	1.39	1.27	1.81
W	.0548	.0511	0.0546	.0313

Table 6: Non-Linear Estimation, Non-Separable Preferences

The estimation is by simulated method of moments (S=20), using the N+6 moments described in the text. The measurement error volatility is fixed at $\sigma_b = .02$. The discount factor is fixed at $\beta = .95$. The weighting matrix is the identity matrix in 3 iterations and the Newey-West HAC matrix for the computation of standard errors. The housing collateral ratio is $myrw$. The parameters γ and ε are preference parameters, the parameters in the consumption weight cutoff specification parameter are Θ. The last three rows report the aggregate weight shock and collateral scarcity, the highest realization of the aggregate weight shock, and the Simulated Method of Moments function value W. The four columns denote different specifications for the cutoff rule discussed in the text. Data are for 1951-2002 for 23 US metropolitan areas.

Parameter	Specif. 3	Specif. 4	Specif. 5	Specif. 6
γ	.40 (.57)	1.09 (.54)	.51 (.34)	.94 (.51)
ε	.90 (3.47)	-.38 (.43)	.16 (1.76)	.02 (.91)
θ_0	.48 (.15)	.36 (.25)	.59 (.14)	.48 (.23)
θ_1	-3.70 (8.00)	-10.56 (9.25)	-1.70 (5.37)	-4.72 (8.85)
θ_2	2.19 (15.34)	16.44 (17.73)	-.36 (11.25)	-.18 (17.03)
θ_3	-12.73 (3.17)	.47 (2.33)	-9.41 (4.57)	-5.24 (4.88)
θ_4	35.44 (7.96)	10.01 (3.97)	27.91 (9.92)	20.61 (11.89)
θ_5			-2.90 (1.77)	
θ_6	.43 (.14)	.35 (.23)	.35 (.14)	.23 (.14)
θ_7	3.83 (12.84)	-15.66 (22.07)	3.00 (17.12)	-6.33 (25.99)
θ_8	.75 (31.01)	.81 (45.87)	-6.90 (33.09)	.16 (51.34)
θ_9		-2.99 (8.86)	-1.34 (13.55)	-2.51 (9.60)
θ_{10}		5.19 (20.83)	1.48 (32.70)	.30 (29.86)
θ_{11}			1.00 (5.43)	
θ_{12}				1.28 (1.82)
θ_{13}				.14 (4.31)
$corr(g, \widetilde{my})$	.49	.33	.46	.46
$max(g)$	1.21	1.34	1.25	1.25
W	.0546	.0245	.0550	.0363

Table 7: Non-Linear Estimation - Different Moments.

Same as in table 4 columns 1 and 2 and table 6 columns 2 and 3, expect that the first N moments in the estimation match the conditional mean consumption share in model and data for each region, conditional on the lagged housing collateral ratio $\tilde{my}_{t-1}$. the last 6 moments are unchanged.

	Separable Prefs.		Non-Separable Prefs.	
Parameter	Specif. 1	Specif. 2	Specif. 4	Specif. 5
γ	.62 (.33)	.68 (.45)	.93 (.48)	.89 (.51)
ε			-.50 (.52)	-.15 (.74)
θ_0	.72 (.07)	.83 (.03)	.47 (.18)	.47 (.13)
θ_1	-10.84 (5.83)	-6.44 (9.00)	-6.15 (17.72)	-3.57 (16.44)
θ_2	-2.07 (11.63)	.37 (17.41)	7.98 (31.62)	.47 (29.63)
θ_3	-4.86 (3.18)	-5.17 (2.31)	-4.27 (2.98)	-4.88 (3.30)
θ_4	20.34 (6.21)	20.57 (4.54)	17.69 (4.71)	20.69 (6.91)
θ_5		1.94 (.57)		1.66 (1.85)
θ_6			.29 (.19)	.32 (.10)
θ_7			-13.33 (34.69)	-9.00 (30.91)
θ_8			-.59 (61.38)	-4.11 (53.54)
θ_9			-3.54 (11.60)	-1.16 (4.24)
θ_{10}			1.29 (23.58)	-.18 (9.73)
θ_{11}				4.34 (4.59)
$corr(g, \widetilde{my})$	.38	.36	.38	.46
$max(g)$	1.31	1.18	1.38	1.26
W	.0138	.0135	.0073	.0079

Table 8: Risk-Sharing Tests with Regional Collateral Measures.

The table reports estimation results for $\Delta \log\left(\hat{c}_{t+1}^i\right) = \alpha_0^i + \alpha_1 X_{t+1}^i \Delta \log\left(\hat{\eta}_{t+1}^i\right) + \alpha_2 \Delta \log\left(\hat{\rho}_{t+1}^i\right) + \alpha_3 X_{t+1}^i \Delta \log\left(\hat{\rho}_{t+1}^i\right) + \nu_{t+1}^i$. In row 1, X^i is one minus the region-specific home-ownership rate (594 observations). In row 2, X^i is (2.5-$\widehat{hv}_{it}$), where the hat denotes the log ratio of $hv_t^i = HV_t^i / p_t^{i,a}$ to the cross-sectional median hv_t^{med} (574 observations). In rows 3 and 4, X^i includes both the interaction term of regression 2 and the interaction term between income share growth and the aggregate housing collateral ratio. The coefficient on the interaction term with my is reported in the columns α_1 and α_3 in the second line. In all regressions η is labor income plus transfers. The coefficients on the fixed effect, α_0^i, are not reported. Estimation is by feasible Generalized Least Squares allowing for both cross-section heteroscedasticity and contemporaneous correlation. All regressions are for the period 1975-2000 for 23 US metropolitan areas, the longest period with metropolitan housing data.

	Coll. Measure	α_1	σ_{α_1}	α_2	σ_{α_2}	α_3	σ_{α_3}	R^2
1	$(1 - HO^i)$	.74	(.04)	1.67	(.27)	-1.51	(.68)	10.6
2	$(\hat{hv}_{max} - \hat{hv}_i)$	.11	(.01)	1.55	(.42)	.25	(.17)	9.0
3	$(\hat{hv}_{max} - \hat{hv}_i)$	-.01	(.02)	2.52	(.65)	.43	(.18)	9.5
	$\widetilde{myrw}_t$	.76	(.13)			-3.45	(1.31)	
4	$(\hat{hv}_{max} - \hat{hv}_i)$	-.03	(.02)	-.88	(.69)	.37	(.17)	9.4
	$\widetilde{myfa}_t$	.84	(.12)			4.95	(1.34)	

A Data Appendix

This appendix describes the metropolitan data set in detail. First we define aggregate collateral measures (section A.1). Then, we define metropolitan areas and describe the sample (section A.2). In section A.3, we describe consumption and income data and compare them to national aggregates. Lastly, we describe regional housing collateral measures (section A.4).

A.1 Aggregate Collateral Measures

Residential Wealth 1890-1970: Historical Statistics of the United States, Colonial Times to 1970, series N197, "Non-farm Residential Wealth". Original source: Grebler, Blanck and Winnick, The Capital Formation in Residential Real Estate: Trends and Prospects, Princeton University press, 1956 (Tables 15 and A1). Excluded are clubs, motels, dormitories, hotels and the like. The series measures the current value of structures and land. Structures are reported in current dollars by transforming the value in constant dollars by the construction cost index (series N121 and 139). Structures in constant dollars are obtained from an initial value of residential wealth in 1890 (based on 1890 Census report 'Real Estate Mortgages') and estimates of net capital formation in constant dollars. Land values are based on an estimation of the share of land value to total value using federal Housing Administration data. These estimates are in Winnick, Wealth Estimates for Residential Real Estate, 1890-1950, doctoral dissertation, Columbia University, 1953.

1945-2001: Flow of Funds, Federal Reserve Board, Balance sheet of households and non-profit organizations (B.100, row 4). Line 4: Market value of (owner-occupied) household real estate (code FL155035015). The market value of real estate wealth includes land and structures, inclusive vacant land, vacant homes for sale, second homes and mobile homes.

Fixed Assets 1925-2001: Bureau of Economic Analysis, Fixed Asset Tables, Current cost of net stock of owner-occupied and tenant-occupied residential fixed assets for non-farm persons. This includes 1-4 units and 5+ units and is the sum of new units, additions and alterations, major replacements and mobile homes.

A.2 Metropolitan Areas

Definition The concept of a metropolitan areas is that of a core area containing a large population nucleus, together with adjacent communities having a high degree of economic and social integration with that core. They include metropolitan statistical areas (MSA's), consolidated metropolitan statistical areas (CMSA's), and primary metropolitan statistical areas (PMSA's). An area that qualifies as an MSA and has a population of one million or more may be recognized as a CMSA if separate component areas that demonstrate strong internal, social, and economic ties can be identified within the entire area and local opinion supports the component areas. Component areas, if recognized, are designated PMSA's. If no PMSA's are designated within the area, then the area remains an MSA.

The S&MM survey uses the definitions of MSA throughout the survey and of CMSA when CMSA's are created. We use the 30 metropolitan areas described in table 9. Before the creation of the CMSA's, we keep track of all separate MSA's that later form the CMSA in order to obtain a consistent time series. For example, the Dallas-Forth Worth CMSA consists of the population-weighted sum of the separate Dallas MSA and Forth Worth MSA until 1973 and of the combined area thereafter.

Households The total number of households in the 30 metropolitan areas is 47 percent of the US total in 2000 compared to 40 percent in 1951. The total number of households are from the Bureau of the Census. Most of the increase occurs before 1965. Likewise, the 30 metropolitan areas we consider contain exactly 47 percent of the population in 1999 (see tables 9 and 10, first column).

Table 9: Population and Composition of Metropolitan Areas.
Total population numbers (in thousands) are displayed next to the metropolitan areas. For the Consolidated Metropolitan areas (CMSA), the constituent MSA's are listed and the fraction of their population in the total of the CMSA is shown next to their name. All numbers are from the Regional Economic Information System of the Bureau of Economic Analysis for the year 2000.

Anchorage (AK), MSA	**261**	**Miami CMSA**	**3,897**
Atlanta (GA), MSA	**4,145**	Miami, FL	58.1%
Baltimore (MD), MSA	**2,557**	Fort Lauderdale, FL	41.9%
Boston CMSA	**6,068**	**Milwaukee CMSA**	**1,691**
Boston, MA-NH	58.6%	Milwaukee-Waukesha, WI	88.8%
Worcester, MA-CT	8.7%	Racine, WI	11.2%
Lawrence, MA-NH	6.7%	**Minneapolis (MN-WI) MSA**	**2,797**
Lowell, MA-NH	5.1%	**New York CMSA**	**21,134**
Brockton, MA	4.3%	New York, NY	45.5%
Portsmouth-Rochester, NH-ME	4.2%	Bergen-Passaic, NJ	6.6%
Manchester, NH	3.4%	Bridgeport, CT	0.5%
Nashua, NH	3.3%	Dutchess County, NY	1.2%
New Bedford, MA	3.2%	Danbury, CT	0.4%
Fitchburg-Leominster, MA	2.5%	Jersey City, NJ	3.0%
Buffalo (NY), MSA	**1,169**	Middlesex-Somerset-Hunterdon, NJ	5.6%
Chicago CMSA	**9,176**	Monmouth-Ocean, NJ	5.4%
Chicago, IL	90.3%	Nassau-Suffolk, NY	13.5%
Gary, IN	6.9%	Newburgh, NY-PA	1.8%
Kenosha, WI	1.6%	Newark, NJ	9.9%
Kankakee, IL	1.1%	New Haven-Meriden, CT	6.2%
Cincinnati CMSA	**1,983**	Stamford-Norwalk, CT	0.6%
Cincinnati, OH-KY-IN	92.6%	Trenton, NJ	1.7%
Hamilton-Middletown, OH	7.4%	Waterbury, CT	0.5%
Cleveland CMSA	**2,946**	**Philadelphia CMSA**	**6,194**
Cleveland-Lorain-Elyria, OH	76.4%	Philadelphia, PA-NJ	82.4%
Akron, OH	23.6%	Wilmington, NC	9.5%
Dallas CMSA	**5,254**	Atlantic-Cape May, NJ	5.7%
Dallas, TX	67.4%	Vineland-Millville-Bridgeton, NJ	2.3%
Fort Worth-Arlington, TX	32.6%	**Phoenix - Mesa MSA**	**3,276**
Denver CMSA	**2,597**	**Pittsburgh (PA), MSA**	**2,356**
Denver, CO	81.7%	**Portland CMSA**	2,273
Boulder-Longmont, CO	11.3%	Portland-Vancouver, OR-WA	84.7%
Greeley, CO	7.0%	Salem, OR	15.3%
Detroit CMSA	**5,463**	**Saint Louis (MO-IL), MSA**	**2,606**
Detroit, MI	81.4%	**San Diego (CA), MSA**	**2,825**
Ann Arbor, MI	10.6%	**San Francisco CMSA**	**7,056**
Flint, MI	8.0%	San Francisco, CA	24.6%
Honolulu (HI), MSA	**876**	San Jose, CA	23.9%
Houston CMSA	**4,694**	Oakland, CA	34.1%
Houston, TX	89.5%	Vallejo-Fairfield-Napa, CA	7.4%
Galveston-Texas City, TX	5.3%	Santa Cruz-Watsonville, CA	3.6%
Brazoria, TX	5.2%	Santa Rosa, CA	6.5%
Kansas City (MO-KS), MSA	**1,782**	**Seattle CMSA**	**3,562**
Los Angeles CMSA	**16,440**	Seattle-Bellevue-Everett, WA	67.9%
Los Angeles-Long Beach, CA	58.1%	Tacoma, WA	19.8%
Orange County, CA	17.4%	Bremerton, WA	6.5%
Riverside-San Bernardino, CA	20.0%	Olympia, WA	5.8%
Ventura, CA	4.6%	**Tampa (FL), MSA**	**2,404**
		Washington,DC-MD-VA-WV, PMSA	**4,948**

A.3 Metropolitan Consumption and Income Data

Appendix A.3 compares non-durable retail sales and disposable income with aggregate consumption and income data (Table 10), with metropolitan non-durable consumption data from the Consumption Expenditure Survey (Bureau of Labor Statistics, 1986-2000, Table 11) and with metropolitan labor income data plus transfers from the REIS for 1969-2000 (Table 12). The correlation between the growth rates of aggregate real non-durable consumption per household and the metropolitan average of real non-durable retail sales per household is 0.77. Also, our metropolitan data are highly correlated with the metropolitan data from the Bureau of Labor Statistics and the REIS.

Source and Definitions We collect data from the Survey of Buying Power (and Media Markets), a special September issue of the magazine Sales and Marketing Management. The data are proprietary and we thank S&MM for permission to use them. We use five series and reproduce the S&MM definitions below.

Total retail sales measures sales from five major store groups considered to be the primary channels of distribution for consumer goods in local markets. Store group sales represent the cumulative sales of all products and or services handled by a particular store type, not just the product lines associated with the name of the store group. The five store groups are: food stores, automotive dealers, eating and drinking places, furniture, home furnishings and appliance stores, and general merchandize stores. Total retail sales reflect net sales. Receipts from repairs and other services by retailers are also included, but retail sales by wholesalers and service establishments are not.

Automotive dealer sales are sales by retail establishments primarily engaged in selling new and used vehicles for personal use and in parts and accessories for these vehicles. This includes boat and aircraft dealers and excludes gasoline service stations.

Furniture, home furnishings and appliance store sales measures sales by retail stores selling goods used for the home, other than antiques. It includes dealers in electronics (radios, TV's, computers and software), musical instruments and sheet music, and recordings.

Households measures the number of households, defined by the Census which includes all persons occupying a housing unit. A single person living alone in a housing unit is also considered to be a household. The members of a household need not be related.

Effective Buying Income is an income measure of income developed by S&MM. It is equivalent to disposable personal income, as produced by the Bureau of Economic Analysis in the NIPA tables. It is defined as the sum of labor market income, financial income and net transfers minus taxes. *Labor income* is wages and salaries, other labor income (such as employer contributions to private pension funds), and proprietor's income (net farm and non-farm self-employment income). *Financial income* is interests (from all sources), dividends (paid by corporations), rental income (including imputed rental income of owner-occupants of non-farm dwellings) and royalty income. *Net transfers* is Social Security and railroad retirement, other retirement and disability income, public assistance income, unemployment compensation, Veterans Administration payments, alimony payments, alimony and child support, military family allotments, net winnings from gambling, and other periodic income minus social security contributions. *Taxes* is personal tax (federal, state and local), non-tax payments (fines, fees, penalties, ...) and taxes on owner-occupied nonbusiness real estate. Not included is money received from the sale of property, the value of income in kind (food stamps, public housing subsidy, medical care, employer contributions for persons), withdrawal of bank deposits, money borrowed, tax refunds, exchange of money between family members living in the same household, gifts and inheritances, insurance payments and other types of lump-sum receipts. Income is benchmarked to the decennial Census data.

We create a *durable retail sales* series by adding automotive dealer sales and furniture, home furnishings and appliance store sales. *Non-durable retail* sales is total retail sales minus durable retail sales.

Comparison with Aggregate Data We construct aggregate non-durable retail sales per households and compare it to aggregate non-durable consumption per household. The aggregate consumption data are from the National Income and Product Accounts (NIPA). The two nominal time series are very similar. Non-durable metropolitan retail sales per household are on average 17 percent higher than national non-durable consumption per household. Their correlation between their growth rates is 0.75. The one exception is 1999 when retail sales grow at a rate of 19.6 percent compared to 5.6 percent for non-durable consumption. We believe this is an anomaly in the data and deflate the 1999 retail sales so that the metropolitan average growth rate equals the national one. This correction is identical across areas. The volatility of NIPA consumption growth is 2.57 percent whereas the volatility of aggregated S&MM non-durable retail sales is 2.89 percent. For comparison, the volatility of non-durable retail sales growth at the regional level varies between 3.8 percent (Washington-Baltimore CMSA) and 8.3 percent (Dallas-Forth Worth CMSA).

We compare the sum of motor vehicles and parts and furniture and household equipment for the US. to the metropolitan data on automotive dealer sales and furniture, home furnishings and appliance store sales. Nationwide, these two categories of consumption make up 84 percent of all durable purchases. Sales are higher by an average of 30 percent. The pattern of the two series mimic each other closely. The correlation between national durable consumption growth and the average metropolitan durable retail sale growth is 0.80. For 1999 the sales data show a much bigger increase than the durable consumption data (27 percent versus 8.6 percent). As for non-durables, we correct the 1999 metropolitan retail sales for this discrepancy. We refer to the two series as *metropolitan* non-durable and durable *consumption*per household.

Effective buying income (EBI) per household corresponds to the Bureau of Economic Analysis's disposable income (personal income minus personal tax and non-tax payments). The S&MM income data are tracking disposable income closely. There are a two discrete jumps in the EBI time-series (1988 and 1995), but the concept remains disposable, personal income. The S&MM is not precise as to which income categories were excluded between 1987 and 1988 and between 1994 and 1995. From comparing the definition of EBI before and after the changes, it seems to us that the most important changes are the exclusion of other labor income (such as employer contributions to pension plans, ...) and income in kind (such as food stamps, housing subsidies, medial care,...). To obtain a consistent time-series, we correct the S&MM income data by the ratio of average EBI to disposable income from the NIPA. This correction is identical across areas. We refer to this series as *metropolitan disposable income* per household. Table 10 summarizes.

Table 10: Comparison With Aggregate US data.

The first column gives the number of households in the metropolitan data set. The second column gives the fraction of US households that are in the metropolitan data set. The third column gives the nondurable retail sales per household (in $) in the metropolitan data set (NDS). The fourth column gives the ratio of non-durable retail sales per household to non-durable consumption per household in the NIPA data (NDC). The fifth and sixth column do the same for durable sales and consumption (DS and DC). The seventh and eight column give the effective buying income per household in the metropolitan data set (EBI) and the ratio of the latter to disposable income per household from NIPA (DI).

Year	HH (000)	metr. HH (%)	NDS ($)	NDS to NDC	DS ($)	DS to DC	EBI ($)	EBI to DI
1951	17,623	39.4	3,008	1.23	799	1.36	5,959	1.15
1960	23,080	43.7	3,519	1.22	899	1.26	7,711	1.11
1970	28,332	44.7	4,688	1.09	1,180	1.05	11,936	1.03
1980	36,144	44.7	9,683	1.12	2,660	1.24	24,975	1.00
1990	41,784	44.8	15,418	1.15	5,531	1.37	43,698	0.95
2000	49,379	47.2	24,741	1.30	11,888	1.90	56,566	0.83

Comparison with CEX Data We compare the SM&M data to the non-durable and durable consumption data from the Consumer Expenditure Survey (CEX). Based on household data, the Bureau of Labor Statistics (Bureau of Labor Statistics) provides metropolitan averages for 13 overlapping two-year periods (1986-87 until 1994-95 and 1996-97 until 1999-2000). The two data sources have 25 regions with full data in common. Buffalo is in the CEX sample until 1994-95 and is replaced by Tampa, Denver and Phoenix from 1996-97 onwards.

Consumption expenditures on non-durables are defined as in Attanasio and Weber (1995): It includes food at home, food away from home, alcohol, tobacco, utilities, fuels and public services (natural gas, heating fuel electricity, water, telephone and other personal services), transportation (gasoline and motor oil, public transportation), apparel and services (clothes, shoes, other apparel products and services), entertainment, personal care products and services, reading, and miscellaneous items. Durable consumption includes vehicle purchases and household furnishings and equipment. Consumption expenditures on housing services measure the cost of shelter. $p_t^{ih}h_t^i$ is comprised of owned dwellings, rented dwellings and other lodging. The CEX imputes the cost for owner-occupied dwellings by adding up mortgage interest rates, property taxes and maintenance, improvements, repairs, property insurance and other expenditures. The average expenditure share on housing was 31.5 percent in 2000.

Non-durable and housing services consumption add up to 55-60 percent of total annual consumption expenditures. Excluded consumption items are consumer durables (furniture, household supplies), vehicle purchases, insurance (vehicle, life, social security), health care and education.

For each area, we construct bi-annual averages from the S&MM consumption data. The correlation between all data cells is 0.77 for non-durables and 0.66 for durables. The average correlation across regions is 0.88 for non-durables and 0.73 for durables. We conclude that the metropolitan sales data give an accurate measure of consumption on non-durables and durables at the metropolitan level.

We also compare the bi-annual averages of before-tax income from the CEX with the metropolitan disposable income. The correlation is high for each region. The average correlation across regions is 0.94 and is 0.91 for all data cells jointly. Table 11 summarizes the correlations by region for the 25 areas with all 13 periods.

Table 11: Comparison With Household Data.

Correlation of household non-durable consumption, durable consumption and income data, aggregated by the CEX for metropolitan areas and the metropolitan area non-durable and durable retail sales and disposable income data from S&MM.

MSA	Nond.Cons	Dur.Cons	Income
Washington, DC (PMSA)	0.926	0.660	0.973
Baltimore, MD (PMSA)	0.973	0.791	0.956
Atlanta, GA (MSA)	0.740	0.522	0.944
Miami, FL (CMSA)	0.533	0.399	0.922
Dallas, TX (CMSA)	0.939	0.839	0.917
Houston, TX (CMSA)	0.936	0.955	0.932
Los Angeles, CA (CMSA)	0.836	0.845	0.944
San Francisco, CA (CMSA)	0.921	0.797	0.981
San Diego, CA (MSA)	0.838	0.511	0.961
Portland, OR (CMSA)	0.989	0.932	0.973
Seattle, WA (CMSA)	0.928	0.841	0.935
Honolulu, HI (MSA)	0.858	0.409	0.956
Anchorage, AK (MSA)	0.931	0.601	0.847
New York, NY (CMSA)	0.952	0.727	0.957
Philadelphia, PA (CMSA)	0.812	0.698	0.932
Boston, MA (CMSA)	0.876	0.515	0.799
Pittsburgh, PA (MSA)	0.921	0.759	0.846
Chicago, IL (CMSA)	0.803	0.601	0.953
Detroit, MI (CMSA)	0.960	0.534	0.956
Milwaukee, WI (CMSA)	0.792	0.636	0.949
Minneapolis-St, Paul, MN (MSA)	0.940	0.863	0.972
Cleveland, OH (CMSA)	0.881	0.878	0.956
Cincinnati, OH (CMSA)	0.898	0.864	0.974
St. Louis, MO (MSA)	0.881	0.815	0.945
Kansas City, MO-KS (MSA)	0.958	0.708	0.961
Average	0.881	0.708	0.938

Comparison with REIS Data Disposable income contains two important channels of insurance. It includes income from financial markets and the net income from government transfers and taxes. For consumption to fully capture income smoothing, the income concept should exclude smoothing that takes place through financial markets, credit markets and through the federal tax and transfer system. The Regional Economic Information System (REIS) of the Bureau of Economic Analysis allows us to construct separate series for labor market income, financial market income and net transfers for each metropolitan area.

For the overlapping period 1969-2000, we compute the correlation between the idiosyncratic component of log disposable income, $\log\left(\hat{y}_t^{i,d}\right)$, from the S&MM and labor income plus transfers $\log\left(\hat{y}_t^{i,lt}\right)$ from the REIS. Table 12 shows that the correlation is generally high, but with a few exceptions (Miami, Cincinnati, Milwaukee). The average correlation is 0.64. This imperfect correlation is due to a combination of measurement error in income and insurance through financial markets. The discrepancy warrants use of both income measures in the empirical analysis.

Table 12: Comparison With Regional Income Data

Correlation of regional disposable income from S&MM and labor income plus Transfers from REIS.

South and West	Coeff.	Northeast and Midwest	Corr.
Washington, DC (PMSA)	0.79	New York, NY (CMSA)	0.84
Baltimore, MD (PMSA)	0.42	Philadelphia, PA (CMSA)	0.82
Atlanta, GA (MSA)	0.73	Boston, MA (CMSA)	0.73
Miami, FL (CMSA)	-0.18	Pittsburgh, PA (MSA)	0.57
Dallas, TX (CMSA)	0.63	Buffalo, NY (MSA)	0.77
Houston, TX (CMSA)	0.86	Chicago, IL (CMSA)	0.76
Los Angeles, CA (CMSA)	0.85	Detroit, MI (CMSA)	0.74
San Francisco, CA (CMSA)	0.65	Milwaukee, WI (CMSA)	0.12
San Diego, CA (MSA)	0.75	Minneapolis-St, Paul, MN (MSA)	0.70
Portland, OR (CMSA)	0.57	Cleveland, OH (CMSA)	0.90
Seattle, WA (CMSA)	0.60	Cincinnati, OH (CMSA)	-0.23
Honolulu, HI (MSA)	0.84	St. Louis, MO (MSA)	0.54
Anchorage, AK (MSA)	0.80	Kansas City, MO-KS (MSA)	0.57
Phoenix, AZ (MSA)	0.83		
Denver, CO (CMSA)	0.67	**Average**	**0.64**

A.4 Regional Housing Collateral

Following Case, Quigley and Shiller (2001), we construct the market value of the housing stock in region i as the product of four components:

$$HV_t^i = N_t^i \; HO_t^i \; HP_t^i \; V_0^i$$

V_0^i is the median house price for detached single family housing from the US Bureau of the Census for 2000. For the CMSA's, it is constructed as a population weighted average of the median home value for the constituent MSA's. Population data are from the REIS.

Home Ownership Home ownership rates HO_t^i are from the US Bureau of the Census. We combine home ownership rates for 1980, 1990 and 2000 from the Decennial Census with annual home ownership data for the largest 75 cities for 1986-2001, also from the Bureau of the Census. We project a home ownership rate for 1986 using the 1980 and 1990 number and the annual changes in the national home ownership rate. We use the changes in the major cities to infer MSA-level changes between 1986 and 1990. Between 1981 and 1986 and 1975 and 1979 we apply national changes to the MSA's. This procedure captures most of the regional and time series behavior of home-ownership rates. Figure 7 shows a gradual increase in the US home-ownership starting in 1965, only interrupted by a decline in the period 1980-95. Table 13 illustrates the large regional differences in the median home value and home ownership rate in 1980 and 2000.

House Price Index HP_t^i is the housing price index from the Office of Federal Housing Enterprize Oversight, based on the weighted repeat sales method of Case and Shiller (1987). It measures house price increases in detached single family homes between successive sales or mortgage refinancing of the identical housing unit. The index is available from 1975 onwards for all MSA's. We construct an index for the CMSA's as a population weighted average of the MSA's. The OFHEO database contains 17 million transactions over the last 27 years. There is a literature on quality-controlled house price indices. They broadly fall into two categories. Hedonic methods capture the contribution of narrowly defined dwelling unit and location characteristics to the price of a house in a certain region (number of bedrooms, garage, neighborhood safety, school district, etc.). Out of sample, houses are priced as a bundle of such characteristics. Repeat sales indices are based on houses that have been sold or appraised twice. Because they pertain to the same property, they control for a number of hedonic characteristics (bedrooms, neighborhood safety, etc.). See Pollakowski (1995) for a literature review and a description of data availability.

Regional collateral values contain a large common component. A principal component analysis on the real variable $hv_t^i = HV_t^i / p_t^{i,a}$ shows that the first principal component explains 74% of the total variation in regional housing values. The largest three principal components explain 95% of the variation. We define the **region-specific**

housing collateral value: $\widehat{hv}_t^i = \log\left(\frac{hv_t^i}{hv_t^m}\right)$, where hv_t^m is the cross-sectional median of hv_t^i. The first principal component of $\widehat{hv}_t^i$ is still 55 percent and the first 3 principal components account for 92 percent of the variation in the idiosyncratic collateral value.

Table 13: Median Home Value and Home-Ownership Rate.

The table shows median home values for 1980 and 2000 (in thousands of nominal dollars) and the home ownership rate for 1980 and 2000 (in percent). All data are from the US Bureau of the Census, Decennial Survey 1980 and 2000

MSA	V_{80}	V_{00}	HO_{80}	HO_{00}
Washington, DC (PMSA)	79.9	178.9	54.3	64.0
Baltimore, MD (PMSA)	51.4	134.9	60.0	66.9
Atlanta, GA (MSA)	47.7	135.3	61.4	66.4
Miami, FL (CMSA)	57.0	126.1	61.5	63.2
Dallas-Fort Worth, TX (CMSA)	45.6	100.0	64.7	60.4
Houston, TX (CMSA)	52.8	89.7	59.1	60.7
Tampa, FL (MSA)	39.9	93.8	71.7	70.8
San Francisco, CA (CMSA)	98.4	353.5	55.8	57.8
Los Angeles, CA (CMSA)	87.6	203.3	53.8	54.8
San Diego, CA (MSA)	90.0	227.2	55.1	55.4
Portland, OR (CMSA)	60.8	165.4	63.2	63.0
Seattle, WA (CMSA)	66.0	195.4	63.8	62.9
Honolulu, HI (MSA)	129.5	309.0	49.9	54.6
Anchorage, AK (MSA)	89.2	160.7	56.6	60.1
Denver, CO (CMSA)	69.1	179.5	63.0	66.4
Phoenix, AZ (MSA)	59.2	127.9	68.7	68.0
New York, NY (CMSA)	62.5	203.1	44.2	53.0
Philadelphia, PA (CMSA)	42.2	122.3	67.7	69.9
Boston, MA (CMSA)	52.0	203.0	54.8	60.6
Pittsburgh, PA (MSA)	42.7	68.1	69.0	71.3
Buffalo, NY (MSA)	39.7	89.1	63.7	66.2
Chicago, IL (CMSA)	62.8	159.0	58.5	65.2
Detroit, MI (CMSA)	43.5	132.6	70.2	72.2
Milwaukee, WI (CMSA)	59.2	131.9	61.1	62.1
Minneapolis-St, Paul, MN (MSA)	62.3	141.2	67.2	72.4
Cleveland, OH (CMSA)	52.1	117.9	66.6	68.8
Cincinnati, OH (CMSA)	47.9	116.5	63.8	67.1
St. Louis, MO (MSA)	41.8	99.4	68.2	71.4
Kansas City, MO-KS (MSA)	43.5	104.7	66.4	67.9
Tampa, FL (MSA)	59.9	85.2	73.0	71.0

Figure 8 shows the evolution of the relative rental price $\rho_t^i = p_t^{i,h}/p_t^{i,c}$ for the Bay Area, St.-Louis and the US average. The Bay Area and St.-Louis have the most divergent rental prices among all regions in our sample. The plot reveals a large and slow-moving *common* component in relative rental prices.

Figure 7: Home-Ownership rate in the U.S.

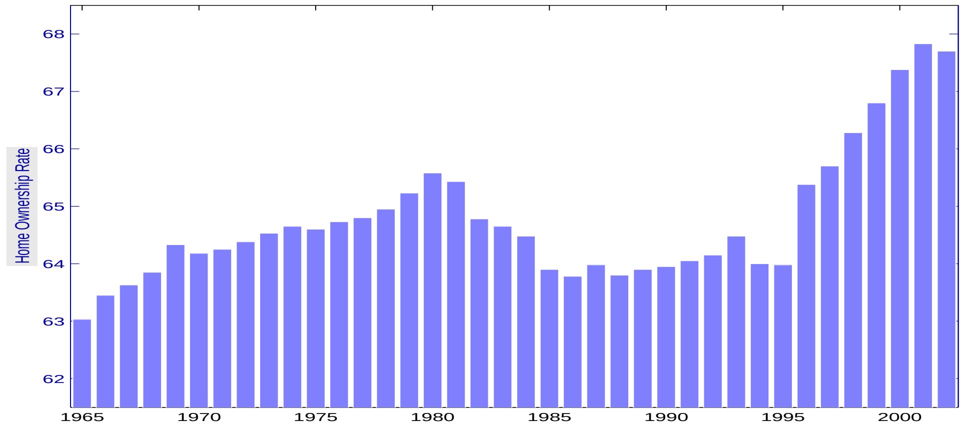

Figure 8: Regional variation in ratio of rent to food component of consumer price index.