Portfolio Demand and Housing Consumption Risk Hedging: Evidence from Geographic Variations in Housing Supply Elasticity

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Working paper
Jan., 2017
JEL No.: G11, R1

ABSTRACT

Using recent waves of PSID in the U.S., we show that households in metropolitan areas with less elastic housing supply invest a relatively larger fraction of their financial wealth in risky assets (stocks). We explain this stylized fact using a household portfolio choice model with both housing and nonhousing consumption, where the optimal holding of the risky assets is additionally motivated by households' hedging incentives against unfavorable housing price risk. We show that such motive is dependent on location and household lifecycle: it is stronger in places with less elastic housing supply and for young households on the rising path of lifecycle housing consumption profile. Our findings indicate that, besides adjusting homeownership choices, households also rely on financial asset as a means of hedging against housing consumption risk.

Key words: Housing Supply Elasticity; Housing Consumption Risk; Household Portfolio Composition; Cross-city Regression

Preliminary version not to be cited.

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1. Introduction

In developing the intertemporal capital asset pricing model (ICAPM) where investors hedge against changes in future investment opportunity, Merton (1973) points out that, in the presence of multiple consumption goods, "there would be systematic effects on the portfolio demands reflecting hedging behavior against unfavorable shifts in relative consumption goods prices". Since Merton (1973) focuses primarily on investment opportunity hedging and the equilibrium relationship among asset yields, he does not explore the hedging incentive against unfavorable shifts in relative consumption prices and its effect on investment portfolio choice. We formalize Merton's consumption hedging insight in a two-period-two-good model and examine its implications for heterogeneous portfolio choice across households in different cities. The model features a traded good and nontraded housing service, the shift in whose relative prices is correlated with the investment return on a risky asset.

We pay particular attention to housing because not only it is a major consumption good but also, more importantly, its market is local, so that the shift in its price relative to the traded good in relation to aggregate shocks may vary across regions. We take advantage of such variations to test the effect of consumption hedging incentives on households' portfolio compositions. We show that, as Merton (1973) argues, in contrast to the single consumption good model, the optimal risk-asset share in the two-period-two-good model contains an additional component reflecting households' incentive to hedge against unfavorable housing price shifts. Households are usually born in "short" position of housing service (Sinai and Souleles (2005)). Anticipating their future long position of housing, households seek to hedge housing consumption risk by investing in assets whose returns are positively correlated with housing price shifts. This is called "consumption hedge". Similar to the investment opportunity hedging components of risk-asset share in Merton (1973), which increase with the covariance between the asset return and the respective state variables, the consumption hedging component of the risk-asset share in our model increases with the covariance between the asset return and the housing price shifts. We empirically test the model implications using recent waves of the Panel

Study of Income Dynamics (PSID). We find that a 10 basis point increase in the covariance between regional housing price growth and S&P returns is typically associated with an increase of about 2 percentage points in the risk-asset share. Given that the households in the U.S. generally invest small share of their financial wealth in risky assets, the marginal effect of the consumption hedging incentive is not economically trivial.

The covariance between local housing price and the national stock market varies systematically across regions. We find it higher in cities with less elastic housing supply, where national economic shocks tend to be absorbed by growth in housing prices rather than quantities. The regional differences in housing supply elasticity due to geographic variations in land development conditions (Saiz (2010)) thus provide exogenous variations in the effectiveness of S&P asset as housing consumption risk hedge. We find that one unit decrease in the housing supply elasticity is associated with an increase of about 2.2 percentage points in the risk-asset share of household's financial portfolio.

The consumption hedging component of the risk-asset share in household financial portfolio would also vary across households depending on their lifecycle of housing consumption. Fang (2009), for instance, shows that U.S. households' lifecycle housing consumption rises with age until about age 60 when it flattens out. The effect of housing supply elasticity on risk-asset share would be more pronounced for younger households, who anticipate growing housing consumption. We further explore the lifecycle implications of consumption hedging demand and find, indeed, the risk-asset shares of young households affected more strongly by local housing supply conditions.

As a robustness check, we also construct an unbalanced short panel using 2001, 2005, and 2009 waves of the PSID and run pooled cross-section regressions with MSA × year dummies. The time variation of the housing supply elasticity in the panel overcomes the potential self-selection problem in the cross-section regressions caused by the possibility that less risk-averse households would self-select into big MSAs, which generally have low housing supply elasticities. In addition, since the MSA × year dummies control for any MSA and year effects, the endogeneity problem caused by omitted or unobservable

MSA characteristics is also absent in the pooled regressions. However, the MSA × year dummies render us unable to identify the effect of pure MSA level factors such as the housing supply elasticity. Therefore, with the panel data, we instead focus on lifecycle implications of the effect of housing supply elasticities on the risk-asset share and compare the portfolio choice of young households in elastic and inelastic MSAs. As expected, we find that, due to the housing consumption hedging incentive, young households living in less elastic MSAs are induced to hold relatively higher risk-asset shares. Moreover, the differences in risk-asset shares of young households in MSAs with elastic and inelastic housing supply decreases with the cut-off age that defines young households, suggesting that the youngest households whose housing consumption profiles are steepest have strongest hedging incentive against housing price risk.

The present paper makes several contributes to the literature. The findings about the heterogeneous financial portfolio composition across households due to lifecycle housing consumption differences and variations in local housing supply elasticity add to the literature on consumption-hedging demand for risky assets. By connecting the households' asset allocation choice to local housing supply elasticity, the present paper also add to a growing literature that brings finance and urban economics together (e.g., Ortalo-Magné and Prat (2016)). With increasing concentration of young and educated households in large metropolitan areas with relatively low housing supply elasticity (e.g., Moretti (2013); Gyourko *et al.* (2013); Hsieh and Moretti (2015)), the consumption-hedging demand would be growing. Our findings also suggest a growing demand for financial products to hedge housing consumption risk, such as futures contracts linked to regional housing price indexes (Case *et al.* (1993), which would provide more effective hedging against housing consumption risks.

The paper proceeds as follows. We first briefly review related papers in Section 2. Section 3 presents a simple two-period-two-goods model to motivate our empirical study. Section 4 contains discussion about data and variable construction, empirical model and results, and robustness checks. Finally, Section 5 concludes.

2. Related Literature

The paper first closely relates to the growing literature that aims to understand the households' hedging incentive against housing consumption risk and the subsequent consequences on homeownership, housing price, housing consumption, and the risk-return relationship for housing, etc. For example, Sinai *et al.* (2005) show that the incentive to hedge housing price risk by owning a house makes the probability to own and the price-to-rent ratio higher in markets with more volatile housing rent; Han (2008, 2010) find that stronger hedging incentives (e.g., steeper future housing consumption plans) induce larger housing demand (e.g., size of housing), *ceteris paribus*. In addition, Han (2013) shows that the hedging incentive to own helps to explain the negative risk-return relationship for housing observed in some MSAs in the U.S. In a spatial equilibrium setting, Ortalo-Magné *et al.* (2016) demonstrates that the hedge demand depends on the covariance between the agents' earnings and local equilibrium rents, and has consequences on location choice and investment in local real estate.

By taking particular focuses on households' asset allocation, the present paper complements the aforementioned studies by showing that households not only rely on owning more housing asset as a way to hedge against housing price risk, they are also trying to further eliminate housing price risk by investing in national stocks. They especially do so if the local housing supply is less elastic so that the housing price has higher correlation with risky stock returns, and if they are young households so that they expect larger long position of housing consumption in the future. In fact, because of high housing prices in a place with inelastic housing supply, consumption hedging with excess and lumpy housing investment would not be feasible for many households.

To some extent, this research also has similarities with papers studying the role of nontradable goods in an open economy in explaining the "home bias", which documents that investors concentrate on domestic assets in their portfolios despite the apparent diversification gains to be had from holding foreign asset. Several papers show that the bias arise as households try to hedge the fluctuations in their consumption of nontraded goods (Baxter *et al.* (1998), Eldor *et al.* (1988), Hnatkovska (2010), and Tesar (1993)). Although this research investigates geographic variation of household's portfolio across regions within a country, it is clear that the local housing service that play crucial role in the current study is comparable to the nontraded goods in an open economy. We show that consumption hedging incentive depends importantly on the supply elasticity of the nontraded good.

The viewpoint of allocating investment in assets that have returns correlated with housing price as a means of hedging housing risk is not new in the portfolio choice model with housing. In constructing the consumption-based capital asset pricing model with housing and housing transaction cost, Flavin and Nakagawa (2008) has pointed out that if the covariance matrix of risky asset and housing prices is not block diagonal, risky financial assets would be used to hedge the risk associated with current and future housing price. However, the same as Merton (1973), Flavin *et al.* (2008) focus not on portfolio choice but on the Euler equation of the housing CCAPM and they assume zero covariance between housing price and stocks. Englund *et al.* (2002), Iacoviello and Ortalo-Magné (2003), and Quigley (2006) examine hedging housing risk in a mean-variance framework by allowing positions in real estate stocks and housing price derivative instruments, but because they treat housing risk purely from the investment perspective and ignores future housing consumption needs, the consumption hedge incentive is absent in their model. We differ from this line of research by treating housing as a consumption good, and exploring the effect of geographic variation in the covariance matrix between regional housing prices and national stock returns on household portfolio composition. By focusing on cross-sectional variations in asset allocation, the present study also differs from the literature that examines the lifecycle portfolio compositions with housing (e.g., Cocco (2004), Fischer and Stamos (2013), Hu (2005), and Yao and Zhang (2005)).

Finally, it is widely recognized that the housing supply elasticity varies substantially across regions that are due to either differences in either physical and geographical constraints or regulatory practices (Glaeser *et al.* (2008), Green *et al.* (2005), Ortalo-Magné and Prat (2011), Quigley and Raphael (2005), and Saiz (2010)), and that the price elasticity of housing supply plays important role in affecting housing price level, volatility, persistence of housing market cycles, and urban form (Ferreira and Gyourko (2011) , Fu *et al.* (2010), Glaeser *et al.* (2006), Glaeser *et al.* (2008), Huang and Tang

(2012), and Paciorek (2013)). As the volatility and boom-bust cycles of housing market crucially depend on the local housing supply elasticity (Ferreira *et al.* (2011), Glaeser *et al.* (2008), Huang *et al.* (2012), and Paciorek (2013)), the covariance between housing price and national stock market returns, and hence the households' portfolio composition, also depend on housing supply elasticity. However, little research has been undertaken to understand the implications of local housing supply elasticity for household's asset allocation. The present study fills the gap by establishing the link between geographic variation in the housing supply elasticity and households' asset allocation.

3. Conceptual Framework

This section presents a conceptual framework to motivate our empirical study. We construct a simple two-period-two-goods model to show how the housing supply elasticity affects the optimal holding of risky assets. It is shown that unlike the single consumption good model, the optimal holding of risky assets is additionally motivated by households' consumption hedging incentives against unfavorable housing price shocks.

Consider a representative household living for two periods[2]. Assume the household has saving S after consumption at time t. At time $t+1$, the household consumes all its wealth comprising gross return on investment and its labor income. In order to maximize the consumption utility at time $t+1$, the household optimally allocates its saving S to two available financial securities: a risky asset (stocks) with gross return R_{t+1}^{s} and a risk-free asset (Treasury bills) with constant gross return R_f. The return on the stocks follows a log-normal distribution with mean r^s and variance σ_s^2:

$$r_{t+1}^{s} = \ln\left(R_{t+1}^{s}\right) \sim N(r^s, \sigma_s^2) \tag{1}$$

[2] A two-period model is simple to handle, and importantly, sufficient for our purpose. Fama (1970) has noted that as long as the preference and the investment opportunity sets are invariant with state and time, the intertemporal portfolio choice problem of infinite horizon or multiple periods can be treated as if the households have single period utility function. Our model settings satisfy the conditions stated in Fama (1970).

Because we are interest in households' hedging incentives against the risk of relative consumption goods prices, we assume households consume both nonhousing (numeraire) good C_{t+1} and housing service H_{t+1} at time $t+1$ and have CRRA preferences:

$$U\left(C_{t+1}, H_{t+1}\right)=\frac{\left(\left(C_{t+1}\right)^{\omega}\left(H_{t+1}\right)^{1-\omega}\right)^{1-\gamma}}{1-\gamma} \tag{2}$$

where $0<\omega<1$ and $\gamma>0$ represent the consumption share of nonhousing goods and relative risk aversion, respectively. The household obtains housing service from a rental market at a rental price P_{t+1}^{h}, which also follows a log-normal distribution:[3]

$$p_{t+1}^{h}=\ln\left(P_{t+1}^{h}\right) \sim N(p^{h}, \sigma_{h}^{2}) \tag{3}$$

where p^{s} and σ_{h}^{2} are the mean and variance of housing rent. The housing rent p_{t+1}^{h} and the risky return r_{t+1}^{s} are not independent of each other, but have contemporaneous covariance σ_{sh}. As we will show below, the covariance between the housing rent and the risky return is critical for understanding the regional difference in households' asset allocations.

Let α be the proportion of saving invest in stocks over stocks plus bills, and $R_{t+1}^{p}=\alpha\left(R_{t+1}^{s}-R^{f}\right)+R^{f}$ the return on investment portfolio at time $t+1$. Following Deaton (1991) and Carroll (1997), we denote the sum of gross return on investment R_{t+1}^{p} and labor income Y_{t+1} by *cash-on-hand* at time $t+1$: $R_{t+1}^{p}S+Y_{t+1}$. Therefore, the household's optimization problem could be summarized as:

[3] Because housing price is the capitalization of housing rent, assuming households own housing rather than renting will not alter the theoretical results of the paper but render the model less tractable. For simplicity, we assume households in the model are housing renters. In addition, the distributional assumption of P_{t}^{h} is not critical. We assume log-normal distribution because it allows us to obtain analytical solution of optimal risk-asset share later. When analytical solutions are not practical, we will assume the price of housing service (housing rent) follows gamma distribution, as suggested by empirical evidences.

$$\begin{aligned} &\max_{\alpha,\, C_{t+1},\, H_{t+1}} \; E_t\left(U(C_{t+1}, H_{t+1})\right) \\ &s.t.:\; C_{t+1} + P^h_{t+1} H_{t+1} = R^p_{t+1} S + Y_{t+1} \end{aligned} \tag{4}$$

According to (2) and (4) , we can have the household's indirect utility function:

$$\begin{aligned} &E_t\left(V(P^h_{t+1}, R^p_{t+1}; \mathrm{Y}_{t+1})\right) \\ &= (1-\gamma)^{-1}\, \omega^{\omega(1-\gamma)}\, (1-\omega)^{(1-\omega)(1-\gamma)}\, S^{1-\gamma} E_t\left(\left(R^p_{t+1} + \frac{\mathrm{Y}_{t+1}}{S}\right)^{1-\gamma} \left(P^h_{t+1}\right)^{(\omega-1)(1-\gamma)}\right) \end{aligned} \tag{5}$$

Equation (5) clearly shows that the optimal risk-asset share α^* depends on the joint distribution of risky return R^s_{t+1}, the income to saving ratio Y_{t+1}/S, and the housing rent P^h_{t+1}. Because of the power of summation in the conditional expectation, we are not able to obtain analytical solution for α^* with the distributional assumptions given above. To obtain analytical solution for a better understanding, we first ignore labor income and assume $Y_{t+1} = 0$ for certain. We will later relax the assumption of zero labor income, and solve for α^* numerically to examine how our results are sensitive to assumptions about labor income risk.

3.1. Assume No Labor Income ($E_t[Y_{t+1}] = 0, Var_t[Y_{t+1}] = 0$)

If $Y_{t+1} = 0$ for certain, the indirect utility function can be simplified as:

$$\begin{aligned} &E_t\left(V(p^h_{t+1}, r^p_{t+1}; 0)\right) \\ &= (1-\gamma)^{-1}\, \omega^{\omega(1-\gamma)}\, (1-\omega)^{(1-\omega)(1-\gamma)}\, S^{1-\gamma} E_t\left(\exp\left((1-\gamma) r^p_{t+1} + (\omega-1)(1-\gamma)\, p^h_{t+1}\right)\right) \end{aligned} \tag{6}$$

where r^p_{t+1} is the log of the portfolio return: $r^p_{t+1} = \ln\left(R^p_{t+1}\right)$. According to the approximation method in Campbell and Viceira (2001), the log of portfolio return r^p_{t+1} can be approximated as $r^p_{t+1} \approx \alpha(r^s_{t+1} - r^f) + r^f + \frac{1}{2}\left(\alpha - \alpha^2\right)\sigma^2_s$, where $r^f = \ln\left(R^f\right)$. Plug the approximation into (6), we can solve for the optimal risk-asset share:

$$\alpha^* = \frac{r^s - r^f + \frac{1}{2}\sigma_s^2}{\gamma\sigma_s^2} + \frac{(1-\omega)(\gamma-1)\sigma_{sh}}{\gamma\sigma_s^2} \tag{7}$$

Equation (7) gives us a clear understanding about the determinants of optimal risk-asset share in a model with two consumption goods. The first term in is the risk-asset share in a model without housing consumption. As expected, it increases with the risk premium $r^s - r^f + \frac{1}{2}\sigma_s^2$ but decrease with risk aversion γ and variance of stock returns σ_s^2. The second term is of our primary interest. It shows that as long as the elasticity of intertemporal substitution (EIS) is not too high ($\gamma > 1$), the optimal risk-asset share increases with the covariance between the housing rent p_{t+1}^h and the risky return r_{t+1}^s:

$$\frac{\partial\alpha^*}{\partial\sigma_{sh}} = \frac{(1-\omega)(\gamma-1)}{\gamma\sigma_s^2} > 0 \tag{8}$$

As the sign of $\frac{\partial\alpha^*}{\partial\sigma_{sh}}$ critically hinges on the magnitude of risk aversion γ, it is worth mentioning that the existing studies on the elasticity of intertemporal substitution generally support that EIS<1, implying γ>1. For instance, Havránek *et al.* (2013) collect 2,735 estimates of the elasticity of intertemporal substitution in consumption from 169 published studies that cover 104 countries, and find the mean reported estimates of EIS is 0.5. Among the six countries that they have more than 50 estimates, Havránek *et al.* (2013) find the second largest EIS (0.6) for the US, following the largest EIS (0.9) for Japan. The mean reported estimate of EIS for the US is also close to the baseline calibration of 2/3 used by Smets and Wouters (2007). Therefore, we take γ>1 so that $\frac{\partial\alpha^*}{\partial\sigma_{sh}} > 0$. A simple calibration with $\omega = 0.8$, $\gamma = 5$ and $\sigma_S^2 = 0.16^2$ suggests that the marginal effect of 10 basis points increase in σ_{sh} on the optimal risk-asset share is 0.625 percentage point. As we will discuss in Section 4, the mean risk-asset share of the U.S. households' portfolio is relatively low (0.17) and the standard deviation of σ_{sh} during

1992-2012 across MSAs is 27.12 basis points, so the marginal effect is not economically unimportant.

If we denote η as the housing supply elasticity, we are mainly interested in the sign of $\frac{\partial \alpha^*}{\partial \eta}$. Because demand shocks will mostly translate into price effects rather than quantity effect in less elastic areas, the covariance between housing price and stock returns should be higher in these areas, implying $\frac{\partial \sigma_{sh}}{\partial \eta} < 0$. Note that although the covariance between housing price and stock returns needs to be positive for effective hedging, we do not put restrictions on the sign of σ_{sh}. The actual covariance between local house price and national stock returns, albeit most likely being positive, can be negative in the data. We only maintain that housing prices in areas with less elastic housing supply are more sensitive to aggregate shocks so that the covariance between house price and national stock returns moves opposite to the local housing supply elasticity. This is consistent with findings in the literature. For instance, Leung and Teo (2011) constructs a multi-region general equilibrium model and show numerically that the correlation between the regional house price and the contemporary stock price is singnificantly higher in region with higher housing stock adjustment costs. Yoshida (2015) also construct a general equilibrium model and demonstrate that the covariation of stock and housing prices is positive where land supply is inelastic but could be negative for a sufficiently large value of supply elasticity, a prediction supported by data from the U.S. metropolitan areas and OECD countries. It is important that the negative correlation between housing supply elasticity and the covariance between housing price growth and stock returns has empirical support, as we will also see in the next section where we discuss our data[4]. Therefore, we have:

$$\frac{\partial \alpha^*}{\partial \eta} = \frac{\partial \alpha^*}{\partial \sigma_{sh}} \frac{\partial \sigma_{sh}}{\partial \eta} = \frac{(1-\omega)(\gamma-1)}{\gamma \sigma_s^2} \frac{\partial \sigma_{sh}}{\partial \eta} < 0 \tag{9}$$

[4] There readers will be referred to Table 2 to look for the negative correlation between the housing supply elasticities and the covariance between the housing price growth and S&P returns revealed by the data.

$\frac{\partial \alpha^*}{\partial \sigma_{sh}} > 0$ in (8) and $\frac{\partial \alpha^*}{\partial \eta} < 0$ in (9) provide the bases for the main tests in the paper.

An implicit assumption behind (8) and (9) is that, for $\frac{\partial \alpha^*}{\partial \sigma_{sh}} > 0$ to hold, the agent is expecting a "long" position of housing service in the next period. Therefore, as long as households have incremental demand for housing, the hedge demand for correlated asset (e.g., stocks) will operate regardless whether the households are housing owners or renters. Since young households are more likely to trade up to a bigger home and hence have stronger hedge incentives, the negative effect of the housing supply elasticity on risk-asset share due to hedge demand should be arguably more pronounced for them. By contrast, since older households would possibly downsize their housing consumption in the future, or even they maintain a flatten housing consumption profile, they are more likely to have multiple real estate assets and hence will possibly "short" housing in the future, we expect the effect of the housing supply elasticity on risk-asset share is weak or even opposite for them. These arguments are similar to those presented in Han (2010), which shows that homeownership serves as hedge against future housing costs, especially for households with strong hedging incentives. This paper replaces homeownership with correlated risky stocks as a hedging vehicle, and will also test these lifecycle implications in our empirical analyses[5].

We abstract from labor income in the above discussion. If the labor income is riskless, and is high in less elastic areas as suggested by spatial equilibrium model, households will have a higher risk-asset share because of the substitutability of labor income for bills (Bodie *et al.* (1992)). This is still the case even the labor income has idiosyncratic risk (Viceira (2001)). Therefore, the effect of housing supply elasticity on risk-asset share through the consumption hedging incentives will be confounded by the substitution effect. However, because the real labor income normalized by housing price is not necessarily

[5] The assumed "long" position of housing also implies that households are mostly afraid of upside risk, a concern of the majority of households. Therefore, although there is evidence that the housing supply function is kinked in that it is elastic with respect to positive shocks but inelastic with respect to downward shocks (Glaeser and Gyourko (2005); Han (2009)), the asymmetry of housing supply should have limit implication in the current context.

higher in less elastic areas, omitting the substitution effect may not seriously bias the estimation of hedging effect. Nonetheless, we control for household family incomes in our empirical models in order to control for the possible substitution effect.

Abstracting from labor income will be more problematic if the labor income shocks contain region-specific components so that the covariance between the labor income shock and unexpected stock returns are systematically different across regions. For example, it is likely that regions may respond differently to nationwide forces, such as monetary and fiscal policies, changes in relative price of energy, and technological innovations. Difference in industrial mixes may also contribute to regional labor income cycles. As shown in Viceira (2001), whenever the return on risky asset is positively (negatively) correlated with labor income, the optimal risk-asset share contains a nonzero component representing negative (positive) hedging demand for stocks. Therefore, if the regional labor income shock has specific covariance with the national stock returns, it systematically affects households' asset allocation in that region.

However, there is little empirical evidence on whether and to what extent the labor income differs across regions, let alone how the differences are correlated with the housing supply elasticity. To examine the sensitiveness of the model prediction to the abstraction of labor income risk, we next assume risky nonzero income and experiment with various assumptions on the joint distribution of risky return R_{t+1}^{s}, the income to saving ratio Y_{t+1}/S, and the housing rent P_{t+1}^{h}. In our empirical analyses, we will use the standard deviation of real per capita income by MSAs to control for reginal income risk.

3.2. Assume Risky Nonzero Labor Income ($E_t[Y_{t+1}] \neq 0, Var_t[Y_{t+1}] \neq 0$)

The housing supply elasticity η could not only affect the covariance between housing rent and stock return σ_{sh}, but also have impact on the covariance between labor income and stock return σ_{sy}, and the covariance between labor income and housing rent σ_{yh}. Without clear theoretical and empirical guidance on the calibrations of the changes of σ_{sy} and σ_{yh} with respect to η relative to changes of σ_{sh}, we assume both σ_{sy} and σ_{yh}

increase in pace with σ_{sh} when η deceases, that is, $\frac{\partial \sigma_{sy}}{\partial \eta} = \frac{\partial \sigma_{yh}}{\partial \eta} = \frac{\partial \sigma_{sh}}{\partial \eta} < 0$. This is an extreme assumption about how the joint distribution of risky return, labor income, and housing rent are affected by η.

With the above assumption, we can solve for the optimal risk-asset share numerically. As before, we set $\omega = 0.8$, $\gamma = 5$ and $\sigma_s^2 = 0.16^2$. The expected risky return r^s and return on risk-free asset are set to be $r^s = 0.08$, $r^f = 0.03$, respectively. In addition, we assume the housing rent P_{t+1}^h and the labor income normalized by saving Y_{t+1}/S follow gamma distributions. To obtain the shape and scale parameters of these gamma distributions, we first set mean and variance of P_{t+1}^h and Y_{t+1}/S. Using the 2011 wave of PSID, we find the cross-sectional mean and variance of housing rent P_{t+1}^h and income to total wealth ratio Y_{t+1}/S are $P^h = 39.05$, $\sigma_{P^h}^2 = 701.74$, $YS = 8.36$, and $\sigma_{YS}^2 = 6608.90$, respectively[6]. These imply the shape and scale parameters of the gamma distributions being $\kappa_{P^h} = 2.13$, $\theta_{P^h} = 17.97$, $\kappa_{YS} = 0.01$, and $\theta_{YS} = 709.54$. With these parameters at hand, we then increase the Spearman's rank correlation between the housing rent and stock returns $\rho\left(R_{t+1}^s, P_{t+1}^h\right)$ from 0 to 1 that can be considered as being caused by the decreases in the housing supply elasticity, and at the same time set the Spearman's rank correlation between the housing rent and the normalized labor income $\rho\left(P_{t+1}^h, Y_{t+1}/S\right)$ and the Spearman's rank correlation between the stock return and the normalized labor income $\rho\left(R_{t+1}^s, Y_{t+1}/S\right)$ being the same as $\rho\left(R_{t+1}^s, P_{t+1}^h\right)$ so that all of them increase in the same pace[7]. For a given set of the Spearman's rank correlations, we first translate them into Pearson's correlation, and then simulate correlated multivariate normal random variables

[6] The housing rent is deflated by CPI-U 2010 average (1982-84=100), and the income to total wealth ratio are restricted to samples with positive income and total wealth. Although the cross-sectional distribution may be poor estimate of the distribution of time series data, which are our interest here, the exact shape and scale parameters of the distributions are not critical in our numerical exercise because what matter are the correlations among the time series, which we set exogenously in order to examine the sensitiveness of the results to the changes in correlations.

[7] Because we fix the variance of the variables, the covariances are determined by the correlations.

10^6 times. These random variables are transformed to follow log normal distribution (R^s_{t+1}) and gamma distributions (P^h_{t+1} and Y_{t+1}/S) before calculating the expectation in equation (5). We finally solve the optimal risk-asset share that maximizes the expectation using the golden search method[8].

Figure 1 depicts how the optimal risk-asset share α^* changes as $\rho\left(R^s_{t+1}, P^h_{t+1}\right)$ increases from 0 to 1. Note that in this figure, $\rho\left(R^s_{t+1}, Y_{t+1}/S\right)$ and $\rho\left(P^h_{t+1}, Y_{t+1}/S\right)$ increase in the same pace as $\rho\left(R^s_{t+1}, P^h_{t+1}\right)$ increases. As can be seen, the optimal risk-asset share α^* still increases with the $\rho\left(R^s_{t+1}, P^h_{t+1}\right)$ even under the extreme assumption that $\rho\left(P^h_{t+1}, Y_{t+1}/S\right)$ and $\rho\left(R^s_{t+1}, P^h_{t+1}\right)$ increase simultaneously. This is consistent with the prediction of the simple model without labor income or with riskless labor income.

[Figure 1]

Overall, the simple two-period-two-goods model in this section suggests that, for the purpose of hedging housing price risk, the positive covariance between housing price growth and risky returns induce households to have higher demand for risky assets. Because the covariance depends on local housing supply elasticity, the model predicts households living in areas with less elastic housing supply should invest a relatively larger fraction of their financial wealth in risky assets. In addition, because housing consumption demand depends on lifecycle, the effect of housing supply elasticity on risk-asset share should be more pronounced for young households. We proceed to empirically test the model predictions in the next section.

4. Empirical Evidence

4.1. Data and Variable Construction

To test the implications of the model, we use various sources of data on both household and MSA levels. We extract household level risk-asset shares from recent waves of the

[8] Matlab code for numerically solving the optimal risk-asset share is available upon request.

Panel Study of Income Dynamics (PSID)[9]. They are the dependent variable in our empirical analyses. We construct the covariance between housing price growth and S&P returns in MSAs, and test directly its effect on risk-asset shares in accordance to equation (8). To test equation (9), we use the housing supply elasticities in MSAs estimated by Saiz (2010) as explanatory variable[10]. Saiz (2010) also provides the undevelopable land shares in MSAs. Because of its exogeneity, the undevelopable land shares have advantage of being less likely correlated with omitted regional factors. Therefore, we also use them as a proxy for housing supply elasticities. We discuss in details the definition of variables and the data sources below.

Risk-asset share and other household characteristics: Starting at the household level, the risk-asset share and other household characteristics are obtained from the PSID. The PSID contains rich household level information about asset holdings and many other household characteristics including age, gender, education, family income, and so on. Following the common practice in empirical literature, we define risk free savings as the sum of cash, checking and savings, bond and insurance, and refer the risky assets as the sum of holdings of stocks and mutual funds. We extract the risk-asset share from the PSID as the ratio of risky assets to financial assets, which is the sum of the risky assets and risk free savings.

Although the PSID is a longitudinal study that tracks households and their descendants over time, we focus on the recent wave of the PSID for the year of 2011 in our empirical analysis. This is not only because our primary focuses are on the cross-sectional variation of households' risk-asset shares, but also because we lack reliable time-series measure of housing supply elasticities. Saiz (2010)'s measure of housing supply elasticities are widely used in the literature (see e.g., Huang *et al.* (2012), Mian and Sufi (2011) , and Paciorek (2013)), and they are cross-sectional. As a result, we choose the 2011 wave of

[9] PSID data are public available at http://psidonline.isr.umich.edu/. However, "PSID-Geocode Match Files" that identify the location (e.g., MSAs) where respondents live are restricted. Some of the data used in this analysis are derived from Restricted Data Files of the Panel Study of Income Dynamics, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are not available from the authors. Persons interested in obtaining PSID Restricted Data Files should contact through the Internet at PSIDHelp@isr.umich.edu.

[10] We thank Albert Saiz for sharing his data with us.

PSID because the year of survey is closer to the year in which Saiz (2010) estimate the MSA housing supply elasticities.

As a robustness check of the results from the 2011 wave of PSID, we also use the 2001, 2005 and 2009 waves of PSID to construct alternative samples of unbalanced short panel and run pooled cross-section regressions[11]. The data structure of unbalanced short panel has the advantage of allowing us to add MSA × year dummies in the empirical model. These dummies help to control for unobservable MSA characteristics and year effects at the expense of not identifying pure MSA level factors such as housing supply elasticity. Therefore, we will focus the lifecycle implications of the model in our pooled cross-section regressions by comparing young households' portfolio composition across MSAs. We will discuss more about the robustness check with alternative waves of the PSID in section 4.3.

Housing supply elasticity and undevelopable land share: At the MSA level, we rely on the housing supply elasticities in MSAs estimated by Saiz (2010). Using the satellite-generated data, Saiz (2010) computes the undevelopable land shares in MSAs, which are the percentage of land within a 50-km radius from the metropolitan central cities that are unsuitable for housing development because of water bodies, wetlands, and steep slopes. Saiz (2010) then provides estimates of housing supply elasticity measure as functions of both physical and regulatory constraints for 269 major metropolitan areas in the U.S. It ranges from 0.60 to 12.15, with smaller value indicating lower housing supply elasticity.

Because the housing supply elasticities are considered to be endogenous to population growth and other MSA economic factors, the empirical results can be biased if there are omitted and unobservable MSA characteristics that are correlated with both of housing supply elasticity and households' investment behavior. In contrast, the undevelopable land share, as an argument of the housing supply elasticity function, is generally regarded as purely exogenous to most regional economic factors. The exogeneity of the

[11] Again, we do not use all the consecutive biennial waves of PSID from 2001 to 2009 in constructing the panel because we are more interested in cross-sectional variation. In addition, because there is little time-variation in the housing supply elasticity within short periods, using all consecutive waves of the PSID adds little value for testing cross-sectional differences.

undevelopable land share is useful for dealing with the potential endogeneity problem caused by omitted and unobservable MSA characteristics. Therefore, we also use the undevelopable land shares as a proxy for housing supply elasticities in our cross-section regressions. Clearly, the undevelopable land shares in MSAs are negatively correlated with the housing supply elasticity, as argued by Saiz (2010).

Covariance between housing price growth and risky returns: We construct the covariances between housing price growth in MSAs and the S&P 500 returns so that we can examine their correlation with the housing supply elasticities and undevelopable land shares, and directly test their effect on households' risk-asset shares. As we show in the conceptual framework, it is the negative correlation with the covariance between housing price growth and risky returns through which the housing supply elasticity affects risk-asset share. We want to see whether the negative correlation exists in the data. To construct the covariances, the quarterly Federal Housing Finance Agency Purchase-Only Indexes in 100 largest MSAs spanning 1991Q1-2014Q2 (hereafter the FHFA indexes) are used. We define the yearly housing price growth in MSAs as the log difference of the 4th quarter FHFA indexes. Data on S&P composition price and dividend from Rober Shiller's website are used to measure stock returns. For each MSA, we use the yearly housing price growth and stock returns from 1992 to 2013 to calculate the covariance between housing price growth and S&P 500 returns.

Other MSA economic variables: To control for other regional factors, we obtain local unemployment rates by MSA from Bureau of Labor Statistics, population by MSA from U.S. Census Bureau, and GDP by MSA from Bureau of Economic Analysis. We will use the average unemployment rate, the average population growth, and the average GDP growth in MSAs from 2007 to 2011 as controls for regional factors. Using the 2011 PSID, we also calculate mean of risk free savings to wealth ratio for households whose family income is below the 5% percentile of the empirical family income distribution in each MSA, and use it to control for the potential regional difference in the social security network.

As discussed in the conceptual framework section, regional-specific income risks may correlate with housing supply elasticities and affect households' portfolio choice. However, it is difficult to find appropriate measures of income risk in empirical analysis[12]. In our cross-section regressions, we follow Carlino and Sill (2001) and use the standard deviation of real per capita income from 2008 to 2012 by MSA as control for potential regional difference in labor income risk[13]. In the robustness check with alternative samples, the MSA × year dummies in the pooled cross-section regressions are able to control for MSA characteristics including regional labor income risks.

With the aforementioned datasets at hand, we then merge the MSA level data with the PSID using location identifier in PSID-Geocode Match Files. Because the risk-asset share is not defined for households with zero financial assets, we restrict our sample to households with positive financial asset. We also transform some household control variables to minimize the effect of outliers. For example, we divide household yearly income and total wealth by the sample mean in order to reduce their magnitude, and we take the log of household mortgage payment after adding a small number (0.01). In addition, we multiply the covariance by 10,000 so that its unit is basis point. Other household controls such as education, gender, marital status, occupation, race, health status, and family composition change are dummy or category variables and are left as they are. After steps of merging and cleaning the data, the final usable cross-sectional sample based on 2011 wave of PSID consists of 3,906 households from 211 MSAs[14].

Table 1 presents summary statistics of the combined data. In the table, we define MSAs with inelastic housing supply as those with housing supply elasticities lower than 25% percentile of the cross-sectional distribution, and otherwise elastic MSAs. As can be seen, households on average hold 17% of financial wealth in risky asset. While the mean of risk-asset share of households in MSAs with elastic housing supply is 0.15, its value is

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[12] Most studies about the effect of labor income risk on portfolio choice are theoretical and rely on numerical simulation (see e.g., Bodie *et al.* (1992), Viceira (2001), and Polkovnichenko (2007)). Some empirical analyses rely on self-reported indicators of income risk (e.g., Guiso *et al.* (1996)).

[13] Although nominal per capita income by MSA is available since 1969, the real per capita income by MSA that is adjusted by regional price parities (RPP) is only recently available from 2008 to 2012 at www.bea.gov/regional/index.htm

[14] However, the exact sample size will vary with the specifications of empirical model.

relative higher for households in MSAs with inelastic housing supply (0.20). In the lower panel of Table 1, we observe that the means of the covariances between housing price growth and S&P stock returns are all positive, regardless the elasticities of housing supply. This suggests the national stock could serve as an effective tool to hedge housing consumption risk for households who are expecting to be in a "long" position of housing in the future. We can also observe from Table 1 that the undevelopable land share and the covariance between housing price growth and S&P stock returns are negatively correlated with the housing supply elasticity: In MSAs with inelastic housing supply, the means of the undevelopable land share and the covariance are both much higher. This relation is more evident in Table 2, which presents the correlation matrix of these three variables. It suggests that the housing price growths in less elstic MSAs indeed have higher covariance with the national stock returns, consistent with the implications of the general equilibrium model in Leung *et al.* (2011) and Yoshida (2015). Importantly, this lends support to our conjecture in the conceptual framework because the negative correlation between the housing supply elasticity and the covariance between housing price growth and risky returns are critical for the effect of housing supply elasticity on the hedging demand for stocks to operate.

[Table 1 here]

[Table 2 here]

4.2. Empirical Methodology and Results

This section presents our empirical specifications and results of testing the cross-sectional difference in households' portfolio composition caused by households' hedging demand for stocks, which in turn depends on housing supply elasticities and households' lifecycles. We first examine the model implications on cross-sectional difference in risk-asset share, and then proceed to subsample regressions by age group in order to investigate the lifecycle implications.

4.2.1. The effect of housing supply elasticities on portfolio demand

In accordance to equation (9) and equation (8), our baseline specification are cross-section regressions with the risk-asset share of a household i in MSA k $\left(\alpha_{i,k}\right)$ as dependent variable and the MSA level variables of interest (x_k) as explanatory variable. Specifically, we estimate the linear model of the following form:

$$\alpha_{i,k} = \beta_0 + \beta_1 x_k + \Theta \mathrm{X}_i + \Phi \mathrm{Z}_k + \varepsilon_{i,k} \tag{10}$$

where x_k is either the housing supply elasticity, the undevelopable land share, or the covariance between housing price growth and S&P returns. X_i is a vector of household level controls including household head's age, family size, log of mortgage payment, income relative to sample mean, total wealth relative to sample mean, dummy or category variables for housing status, household head's education, gender, marital status, occupation, race, health status, and family composition change. Z_k is a vector of MSA level controls including average unemployment rate, average population growth, and average GDP growth from 2007 to 2011, the standard deviation of real per capita income from 2008 to 2012, and the mean risk free saving to financial asset ratio of low income households.

The conceptual framework in Section 3 predicts that households live in less elastic MSAs should invest relative more in stocks, indicating a negative sign on β_1 when the explanatory variable is the housing supply elasticity. Because the undevelopable land share is negative correlated with the housing supply elasticity, the sign on β_1 should be positive when x_k is the undevelopable land share. Finally, according to equation (8), the sign on the covariance between housing price growth and S&P returns should be positive.

Table 3 reports the estimation results by OLS, with column (1) to (3) representing results from using either housing supply elasticities, undevelopable land shares, or the covariance between housing price growth and S&P returns as explanatory variable, respectively. Column (1) of Table 3 shows that, as expected, the sign on the housing supply elasticity is significantly negative at 5% level: One unit decrease in the housing supply elasticity is associated with about an increase of 2.2 percentage points in the risk-asset share. Given the mean risk-asset share across households in the sample is 17%, the marginal effect of the housing supply elasticity on the risk-asset share is economically substantial.

[Table 3]

To address the potential endogeneity problem caused by omitted and unobservable MSA characteristics that are correlated with both the housing supply elasticity and households' investment behavior, we replace the housing supply elasticity with the undevelopable land share and repeats the analysis. Because the undevelopable land share is negatively correlated with the housing supply elasticity, and other mechanisms affecting the risk-asset share are unlikely to be systematically different in MSAs with high and low undevelopable land share, the measurement of land constraint is a valid proxy of the housing supply elasticity and should have positive effect on risk-asset shares. Column (2) of Table 3 reports the regression results of using the undevelopable land share as explanatory variable. Consistent with the theory, the sign on the undevelopable land share is significantly positive. The coefficient suggests that an increase of 10 percentage points of the undevelopable land share will result in an increase of 0.82 percentage point in the risk-asset share. This lends further support to model predictions.

The third column of Table 3 report the estimation results using the covariance between housing price growth and S&P return as explanatory variable. This is a direct test of model implications expressed in equation (8). Consistent with the model prediction, the covariance has significantly positive effect on risk-asset share. An increase of 10 basis points in the covariance between housing price growth and S&P returns corresponds to an increase of 2 percentage points in risk-asset share of households' portfolio, a number not too far away from model prediction in Section 3.1[15].

The effects of other control variables on risk-asset share are generally in line with existing findings. For example, the risk-asset shares increase with age, homeownership,

[15] Recall that our simple calibration in Section 3.1 suggests 10 basis point increases in the covariance will cause risk-asset share increases by 0.625 percentage point.

education, family income, and total wealth, and decrease with family size and if household head is female. Other regional variables generally have expected sign but are not statistically significant. For instance, the sign on mean risk free saving to financial asset ratio of low income households is negative, suggesting the worse the social security the lower the risk-asset share; high unemployment rate is associated with low risk-asset share, while high population and GDP growth are related to high risk-asset shares. Although the coefficients are not significant, the regional labor income risk seems to have negative effect on risk-asset share.

4.2.2. Test on lifecycle implications

The channel through which the housing supply elasticity has impact on the risk-asset share depends on not only the negative effect of the housing supply elasticity on the covariance between housing price growth and S&P returns, but also the housing consumption plan of the households. If households currently own housing and have little demand for upsizing housing consumption, their hedging demands for stocks are weak. Therefore, the effect of housing supply elasticity on risk-asset share, if any, should be moderate for old households, who are likely to downsizing their housing consumption in the future. Actually, the effect of the housing supply elasticity on risk-asset share could be opposite to the model prediction for old households because they are expecting a "short" position of housing in the future[16]. In contrast, young households have steepest lifecycle housing consumption profile. Expecting upcoming increases in housing consumptions, they should have strongest hedging demand for stocks. The dependence of hedging motive on the households' lifecycle housing consumption plan suggests that the effect of housing supplies on risk-asset shares should be more pronounced for young households.

To test the lifecycle implications of the model, we divide our samples into two different age groups: young households and old households. According to Fang (2009)'s estimates,

[16] Empirical evidence on the downsizing of housing at the old age is mixed. Chiuri and Jappelli (2010) use 60 microeconomic surveys on about 300,000 individuals residing in 15 OECD countries to explore the pattern of elderly homeownership and find that ownership rates decline considerably after age 60 in all countries. Using U.S. data, Venti and Wise (2004) find that old households are unlikely to discontinue homeownership and liquidate home equity to support general nonhousing consumption needs.

the consumption profile for housing of the U.S. households starts to flattens out at about age 60 (see Figure 3 and Figure 4 therein). Therefore, we first define young households as those of which the head's age is not greater than 60, otherwise old households, and then repeat the analyses of model (10) using the subsamples of either young or old households. Table 4 shows the regression results, with the first three columns for subsamples of young households and the last three columns for subsamples of old households. Again, we use either the housing supply elasticity, the undevelopable land share, or the covariance between housing price growth and S&P returns as explanatory variable. The estimates for these variables have expected signs and are all significant for young household subsamples. In contrast, they are all insignificant for the old age group.

[Table 4]

Although we have shown that households living in MSAs with less elastic housing supply invest more in risk-asset, the demand for risk-asset can increase in these MSAs not only because of the housing consumption hedging mechanism, but also because of other unobserved factors that are correlated with housing supply elasticity. For instance, big MSAs tend to have less elastic housing supply and at the same time provide people with job opportunities with better prospect; it is possible that more educated and risk-taking households may self-select into these places because of their capability of bearing risk or unobserved attitudes towards risk. To avoid such factors and further explore the heterogeneity in the demand for stocks caused by hedging incentive against housing price risk, we restrict samples to young households (the head's age $<$ 60) and define an indicator representing the strength of their hedging incentive based on both households' housing consumption profiles and housing status. Particularly, in accordance to Fang (2009) which shows that the housing consumption plans of both renter and home owners have steepest slop before the age of about 35, we define "strong hedger" as those households that (1) head's age is less than 36, (2) do not own housing, and (3) do not own other real estate asset, and then add an interaction term between "strong hedger" and the explanatory variables x_k above into model (10). Note that the interaction term will isolate the effect of hedging mechanism from other unobserved factors that are correlated with both demand for risk-asset and characteristics of either hedgers or MSAs[17].

The regression results with interaction term between the strength of hedging incentive and x_k are reported in Table 5. As before, the coefficients on x_k have expected sign and are statistically significant except when x_k is the housing supply elasticity. Although not all of the coefficients on "Strong hedger" are statistically significant, the positive signs suggest that "Strong hedger" invest more in risk-asset. While unobserved MSA-level and household-level characteristics could potential bias the coefficients on x_k and "Strong hedger" separately, the coefficients on the interaction term between x_k and "strong hedger" should still be consistent since it depends only on the interaction of household-level characteristics with the MSA-level housing supply conditions. It is compelling to see that the coefficients on the interaction term in each column of Table 5 are all significant and have expected signs, suggesting that "strong hedger" in MSAs with less elastic housing supply holds relatively more in risk-asset than their counterparts in the same places. These findings lend further support to the hypothesis that the young housing renters have stronger hedging incentive and hence hold higher fraction of their financial wealth in risky stocks for the purpose of hedging against housing consumption risk.

[Table 5]

4.3. Robustness Check with Alternative Waves of the PSID

We use earlier waves of the PSID to provide a robustness check of results from 2011 wave of the PSID. Specifically, we use the 2001, 2005 and 2009 waves of the PSID to construct an unbalanced short panel, and run pooled cross-section regressions using this alternative samples. Due to lack of time-series measure of housing supply elasticity, we combine information on MSA population and undevelopable land shares to create a time-varying dummy variable ($inelasticMSA_{k,t}$) to indicate whether a MSA has inelastic

[17] This identification strategy follows that in Sinai *et al.* (2005), which shows that the probability of home owning increases with local rent volatility and a household's expected horizon in its home. To isolate the role of rent risk from other unobserved factors (e.g., housing transaction cost) that affect both ownership demand and either horizon or rent volatility separately, Sinai *et al.* (2005) add an interaction term between local rent volatility and expected horizon and focus the sign on this term.

housing supply: The dummy equals to one if both the undevelopable land share and the population in the MSA is above the 75% percentile of their empirical distributions, and zero otherwise. As discusses in Saiz (2010), the undevelopable land share is more likely to play role in affecting housing supply elasticity in MSAs with large population. Although it is basically time-invariant, the populations in MSAs would have significant relative changes in the last decade [18]. Therefore, the inelasticity dummy variable $inelasticMSA_{k,t}$ should be able to at least partially capture variations in the housing supply elasticity across MSAs and over time.

Due to data availability, we do not collect regional economic factors in our pooled cross-section regressions. Instead, we run pooled cross-section regression with MSA × year dummies. This allows us to control for MSA and year effects at the expense of not identifying pure MSA level factors such as housing supply elasticity. However, we can explore the lifecycle implications of housing supply elasticity on risk-asset shares, following the identification strategy in Sinai *et al.* (2005). Explicitly, we specify our econometric model as follow:

$$\alpha_{i,k,t} = \beta_0 + \beta_1 Young_{i,t} + \beta_2 Young_{i,t} \times inelasticMSA_{k,t} + \Theta X_{i,t} + \Phi MSA_k \times Year_t + \varepsilon_{i,k,t} \quad (11)$$

where is $\alpha_{i,k,t}$ the risk-asset share of household i living in MSA k at time t. The $Young_{i,t}$ is a dummy variable that equal one if the household head's age is blow a cut-off age that defines young and zero if the household head's age is above 40 [19]. The $inelasticMSA_{k,t}$, as discussed above, indicates whether a MSA k at time t belongs to the

[18] For instance, 2010 census special reports on "Patterns of Metropolitan and Micropolitan Population Change" suggests that there are substantial geographic variation in population growth in the U.S. between 2000 and 2010, with rapid growth in some areas of the country and sizable declines in others. According to the report, the fastest-growing metro areas were located in either the South or the West, with fastest population gainers led by Palm Coast, FL, and followed by St. George, UT; Las Vegas-Paradise, NV; Raleigh-Cary, NC; and Cape Coral-Fort Myers, FL. Two metro areas in the southern states of Louisiana and Arkansas (New Orleans and Pine Bluff, respectively) and three areas located partially or entirely in the states of Ohio, Pennsylvania, and West Virginia (Youngstown-Warren-Boardman, OH-PA; Johnstown, PA; and Steubenville-Weirton, OH-WV) are the fastest-declining metro areas. The report is available at https://www.census.gov/prod/cen2010/reports/c2010sr-01.pdf.

[19] Note that we will experiment with different cut-off ages in order to examining how β_2 is sensitive to the cut-off age defining young households. For the purpose of comparability, we exclude observations with household heads' age in-between the cut-off age and 40, but keep households with age above 40 as the base group.

inelastic MSA group. It equals $landshareHigh_k \times populationHigh_{k,t}$, with $landshareHigh_k$ or $populationHigh_{k,t}$ being indicator that equals one if the corresponding variable in the MSA (undevelopable land share or the population) is above the 75% percentile of its empirical distribution. $X_{i,t}$ includes the same household level controls as before, and $MSA_k \times Year_t$ is a set of MSA × year dummies.

The specification (11) compares the portfolio composition of young households and old households. Because the base group is the old households ($Young_{i,t} = 0$), β_1 tells the difference in risk-asset shares between these two demographic groups, *ceteris paribus*. More importantly, as the $MSA_k \times Year_t$ controls for any cross-sectional variation of MSA characteristics in each year, the specification (11) use the within-MSA variation in the elasticity of housing supply over time to identify the hedging demand for risk-asset, that is, it compares the difference in risk-asset shares of young households within the same MSAs. Note that by using within-MSA variation in the elasticity of housing supply over time, this specification helps to mitigate the self-selection problem aforementioned that young and risk-taking households self-select into big MSAs with better job opportunities and less elastic housing supply. The coefficient β_2 on the interaction term would suggest additional difference in risk-asset shares of young households if the MSAs they live become less elastic in housing supply. A positive β_2 suggests they hold a higher risk-asset share in comparison with times with elastic housing supply.

As before, we first set the cut-off age at 36 and report estimation results in Table 6. The significant and negative β_1 shows that young households hold a smaller fraction of their financial portfolio in risky assets than old households. However, the significant and positive β_2 suggests that the gap is narrower if the MSAs they live become less elastic in housing supply. All else equal, young households have risk-asset share about 3.4 percentage points higher at times when the MSAs have less elastic housing supply, a figure that is about a fifth of the sample mean of the share of risky asset in households' financial portfolio. This result provides significant evidence on the effect of consumption risk hedging on households' portfolio choices.

[Table 6]

If the difference in risk-asset shares of young households presented in Table 6 is not sharp enough, we could expect the coefficients on β_2 should increase if we set a lower value for the cut-off age, as younger households have stronger hedging demand due to their steeply rising housing consumption profile. Therefore, we further experiment with the cut-off age from 26 to 41 to examine how the coefficient β_2 changes with the cut-off age. Figure 2 depicts the results by showing β_2 and the 95% confidence interval as a function of the cut-off age. Being consistent with the theory, we find that both the value and significance of β_2 are greatest when the cut-off age is 26. In other words, for the youngest households (households' age < 26), because they have steepest housing consumption plan and the strongest incentive to hedging housing consumption risk, the relative difference in risk-asset shares at times when MSAs have elastic and inelastic housing supply are and significantly different from zero sharpest for those young households. When the cut-off age increases, both the magnitude and significance level of the difference decrease.

[Figure 2]

5. Conclusion

Households on a rising housing consumption path face housing price risks in places where housing supply is inelastic. In a simple two-period-two-good model we show that holding risky assets, whose returns are correlated with housing price shocks, provides consumption hedging benefits. In particular, this consumption benefit is greater in places where housing supply elasticity is lower. Using recent waves of PSID, we show that households living in MSAs with inelastic housing supply indeed hold relatively higher fraction of their financial portfolio in stocks. Consistent with the household lifecycle consumption theory, we further show that the effect of housing supply elasticity on risk-asset share is more pronounced for young households as they are on the rising path of housing consumption profile.

The present study contributes to a growing literature on households' housing consumption hedging behavior. In addition to its effects on homeownership (Sinai *et al.* (2005)), timing and size of housing consumption (Han (2008, 2010)), and the price-rent ratio in the housing market (Sinai *et al.* (2005) and Han (2013)), the housing consumption hedging incentive also significantly affect households' investment choices, especially for young households. Our findings suggest that financial innovations, such as housing futures and option contracts that are tied to regional housing price indices (Case *et al.* (1993)), have a promising demand. As population continues to concentrate in larger and denser metropolitan areas, where housing supply elasticity tends to be lower, such demand is likely to increase. However, improving the attractiveness of a financial product to households is always challenging and would be a promising area for future research.

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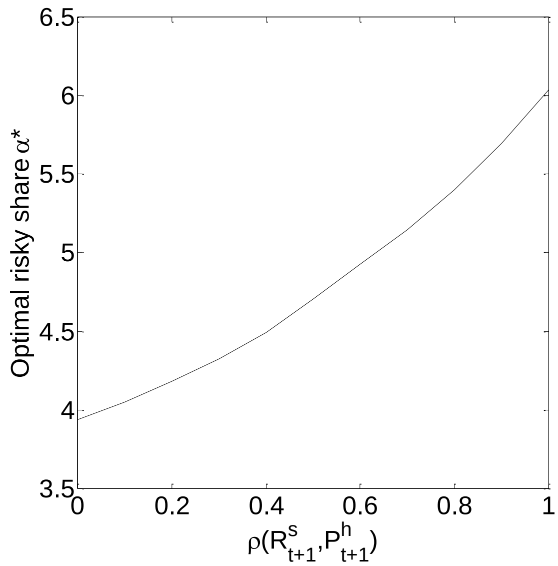
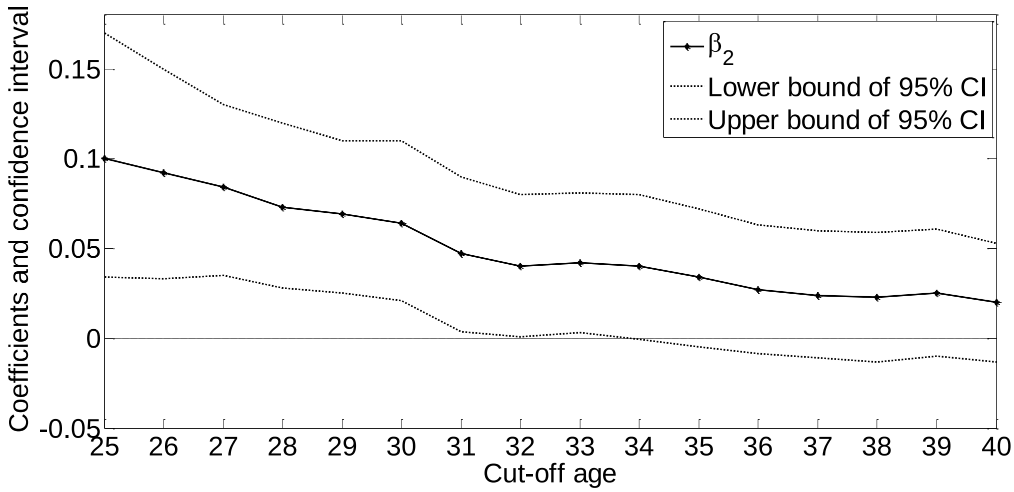
Figure 1: Optimal risk-asset share when labor income is risky



Notes: The figure shows how the optimal risk-asset share moves with the correlation between the housing price changes and risky returns when labor income is risky. We solve for the optimal risk-asset share $\boldsymbol{\alpha}^*$ in equation for $\boldsymbol{\rho}(\boldsymbol{R}^s_{t+1}, \boldsymbol{P}^h_{t+1})$ increasing from 0 to 1, with $\boldsymbol{\rho}(\boldsymbol{P}^h_{t+1}, \boldsymbol{Y}_{t+1}/\boldsymbol{S})$ and $\boldsymbol{\rho}(\boldsymbol{R}^s_{t+1}, \boldsymbol{Y}_{t+1}/\boldsymbol{S})$ increase simultaneously. For each set of correlations, we search for α^* that maximizes the conditional expectation in equation , which is evaluated as the mean of 10^6 simulations. In the simulation of random variable, $\boldsymbol{R}^s_{t+1}$ follows log normal distribution $\boldsymbol{r}^s_{t+1} = \ln(\boldsymbol{R}^s_{t+1}) \sim \boldsymbol{N}(\mathbf{0.08}, \mathbf{0.16^2})$, while $\boldsymbol{P}^h_{t+1}$ and $\boldsymbol{Y}_{t+1}/\boldsymbol{S}$ follow gamma distribution with parameters $\kappa_{P^h} = 2.13$, $\theta_{P^h} = 17.97$, $\kappa_{YS} = 0.01$, and $\theta_{YS} = 709.54$.

Figure 2: β_2 and confidence intervals in pooled cross-section regressions



Notes: The figure shows the sensitiveness of the coefficient on the interaction term of young household indicator and inelastic MSA indicator, β_2 in equation (11), to the cut-off age defining young households. The coefficients β_2 measure the extent to which that young households, for the purpose of hedging housing price risk, have a greater share of risky asset in their portfolio at times when the MSAs they live has less elastic housing supply. A lower bound of 95% confidence interval above zero indicates that the difference is significant at 5% level. MSAs are defined as inelastic if both the undevelopable land share and population are above the 75% percentile of their empirical distributions. Standard errors are clustered at MSA × year cells and are used to construct the 95% confidence intervals.

Table 1: Summary statistics

	All samples			Samples in elastic MSAs			Samples in inelastic MSAs		
	N	Mean	Std Dev	N	Mean	Std Dev	N	Mean	Std Dev
Panel A: Summary statistics of household variables (2011 PSID)									
Risk-asset share	3,906	0.17	0.3	2,252	0.15	0.29	1,654	0.2	0.32
age	3,906	45.95	16.44	2,252	45.01	16.09	1,654	47.24	16.84
Housing owner	3,906	0.63	0.48	2,252	0.63	0.48	1,654	0.63	0.48
Occupation	3,890	9.2	6.15	2,245	9.23	6.13	1,645	9.16	6.18
Health status	3,894	2.39	0.99	2,247	2.4	0.98	1,647	2.38	1.01
College degree	3,906	0.43	0.5	2,252	0.43	0.49	1,654	0.44	0.5
Family size	3,906	2.57	1.41	2,252	2.63	1.43	1,654	2.48	1.38
Gender (1=male, 2=female)	3,906	1.28	0.45	2,252	1.27	0.45	1,654	1.28	0.45
Married	3,906	0.61	0.49	2,252	0.61	0.49	1,654	0.6	0.49
Race	3,880	1.55	1.11	2,234	1.53	1	1,646	1.58	1.24
Mortgage payment (log)	3,875	4.34	4.74	2,232	4.45	4.71	1,643	4.19	4.77
Income	3,906	1.24	1.38	2,252	1.2	1.4	1,654	1.3	1.35
Total wealth	3,906	1.3	4.53	2,252	1.22	4.51	1,654	1.41	4.54
Family composition change	3,906	0.88	1.7	2,252	0.95	1.77	1,654	0.79	1.58
Panel B: Summary statistics of MSA variables									
Housing supply elasticity (Saiz (2010))	211	2.49	1.43	158	2.96	1.36	53	1.1	0.27
Undevelopable land share (Saiz (2010))	211	0.26	0.22	158	0.17	0.14	53	0.54	0.17
Cov(housing price growth, S&P returns)	56	27.12	26.59	30	23.76	22.19	19	40.79	30.26
Mean risk free savings of low income households	263	0	6.17	139	0.37	0.77	48	-1.78	14.34
Average unemployment rate (2007-2011)	254	7.53	2.1	152	7.49	2.42	52	8.05	1.39
Average population growth (2007-2011)	292	0.01	0.02	157	0.01	0.02	53	0.01	0.01
Average GDP growth (2007-2011)	266	0.19	1.94	149	0.25	1.48	50	-0.63	2
s.d. of real per capita income (2008-2012)	277	0.11	0.08	154	0.1	0.05	50	0.11	0.06

Notes: This table shows the summary statistics of the combined data using 2011 wave of PSID and MSA level datasets. For household level data from the 2011 PSID, we restrict the sample to those 1) with positive financial asset and 2) live in MSAs that we have the data of housing supply elasticities. The housing supply elasticities and the undevelopable land shares in MSAs are obtained from Saiz (2010). MSAs are defined as elastic (inelastic) if housing supply elasticities are below (above) the 25% percentile of the empirical distribution. Housing owner, occupation, health status, college degree, male, married, race are all dummy or category variables with respect to household head. A small number (0.01) is added to mortgage payment before taking log. Income and total wealth are relative measures in the sense that they have been divided by sample means. FHFA Purchase-Only Indexes are used for obtaining housing price growth in MSAs. Covariances between housing price growth and S&P returns are calculated using the yearly time series from 1992 to 2012.

Table 2: Correlation matrix

	Housing supply elasticity	Undevelopable land share	Cov(housing price growth, S&P returns)
Housing supply elasticity (Saiz (2010))	1.000 [211]		
Undevelopable land share (Saiz (2010))	-0.620(0.000) [211]	1.000 [211]	
Cov(housing price growth, S&P returns)	-0.382(0.007) [49]	0.412(0.003) [49]	1.000 [56]

Notes: The table shows the pairwise correlations between variables at the MSA level. The housing supply elasticity and undevelopable land share are obtained from Saiz (2010). FHFA Purchase-Only Indexes are used for obtaining housing price growth in MSAs. Covariances between housing price growth and S&P returns are calculated using the yearly time series from 1992 to 2012. Figures in brackets are number of observations, and figures in parentheses are significant levels.

Table 3: The effect of housing risk hedging on portfolio demand (PSID 2011)

	Dependent variable: risk-asset shares		
	(1)	(2)	(3)
β_1: Housing supply elasticity (Saiz (2010))	-0.022**		
	(0.0095)		
β_1: Undevelopable land share (Saiz (2010))		0.082*	
		(0.044)	
β_1: Cov(housing price growth, S&P returns)			0.0020**
			(0.00089)
Head's age	0.0024***	0.0025***	0.0013
	(0.00077)	(0.00077)	(0.00091)
Housing owner	0.061***	0.059***	0.049*
	(0.022)	(0.022)	(0.028)
Head has college degree	0.079***	0.079***	0.072***
	(0.013)	(0.013)	(0.017)
Family size	-0.018***	-0.019***	-0.017
	(0.0054)	(0.0054)	(0.011)
Head is female	-0.036**	-0.038**	-0.044*
	(0.018)	(0.018)	(0.023)
Married	0.017	0.017	0.0067
	(0.025)	(0.025)	(0.034)
Log of mortgage payment	-0.00021	-0.000020	-0.00089
	(0.0020)	(0.0021)	(0.0030)
Income over sample mean	0.026**	0.026**	0.044***
	(0.012)	(0.012)	(0.013)
Total wealth over sample mean	0.0071	0.0071	0.012**
	(0.0051)	(0.0051)	(0.0048)
Mean risk free savings of low income households	-0.00019	-0.00025	-0.00091**
	(0.00036)	(0.00037)	(0.00037)
Average unemployment rate (2007-2011)	-0.0082	-0.0073	-0.024
	(0.0070)	(0.0070)	(0.014)
Average population growth (2007-2011)	0.93*	0.93*	0.81
	(0.55)	(0.53)	(2.81)
Average GDP growth (2007-2011)	0.00019	0.0027	0.011
	(0.0062)	(0.0064)	(0.0097)
s.d. of real per capita income (2008-2012)	-0.023	-0.047	-0.12
	(0.17)	(0.17)	(0.30)
Constant	-0.073	-0.18	0.077
	(0.11)	(0.11)	(0.094)
Other individual controls	Yes	Yes	Yes
State dummy	Yes	Yes	Yes
N	3366	3366	1511
Adj. R-Square	0.20	0.20	0.26

Notes: This table reports the regression results of equation (10) using 2011 wave of PSID in combination with MSA level data. Estimations are by OLS. Column (1) to (2) uses the housing supply elasticity and undevelopable land share in Saiz (2010) as explanatory variables, and column (3) uses the covariance between housing price growth and S&P returns as explanatory variable. Other individual controls include category variables for household head's occupation, health status, family composition change, and race. Standard errors are clustered at MSAs and reported in parentheses. *, **, and *** denote statistically significant at the 10%, 5% and 1% level, respectively.

Table 4: Estimations by age subsample (2011 PSID)

	Dependent variable: risk-asset shares					
	subsample: households' age<61			subsample: households' age>=61		
	(1)	(2)	(3)	(4)	(5)	(6)
β_1: housing supply elasticity (Saiz (2010))	-0.019*			-0.041		
	(0.0100)			(0.026)		
β_1: undevelopable land share (Saiz (2010))		0.14***			-0.067	
		(0.047)			(0.100)	
β_1: cov(housing price growth, S&P returns)			.0021**			0.0059
			(0.00081)			(0.0050)
N	2710	2710	1230	656	656	281
Adj. R-Square	0.20	0.21	0.23	0.18	0.18	0.35

Notes: This table reports the regression results of equation (10) by age subsamples using 2011 wave of PSID in combination with MSA level data. Estimations are by OLS. Controls are the same as those in Table 3. To conserve space, only selected coefficients are reported. Standard errors are clustered at MSAs and reported in parentheses. *, **, and *** denote statistically significant at the 10%, 5% and 1% level, respectively.

Table 5: Estimations with interaction with the strength of hedging incentive (2011 PSID)

	Dependent variable: risk-asset shares		
	Interact with housing status		
	(1)	(2)	(3)
β_1: Housing supply elasticity (Saiz (2010))	-0.011		
	(0.010)		
β_1: Undevelopable land share (Saiz (2010))		0.094**	
		(0.047)	
β_1: Cov(housing price growth, S&P returns)			0.0019**
			(0.00083)
Strong hedger * housing supply elasticity (Saiz (2010))	-0.036***		
	(0.014)		
Strong hedger * undevelopable land share (Saiz (2010))		0.22**	
		(0.086)	
Strong hedger * cov(housing price growth, S&P returns)			0.0018*
			(0.0011)
Strong hedger	0.14***	0.018	0.067
	(0.039)	(0.028)	(0.053)
N	2710	2710	1230
Adj. R-Square	0.21	0.21	0.24

Notes: This table reports the regression results of equation (10) with added interaction terms between the explanatory variables and an indicator "stronger hedger" that represents the strength of hedging incentive based on both households' housing consumption profiles and housing status. The sample is restricted to households with head's age less than 61. Strong hedger is a dummy that equals one for households that (1) head's age is less than 36, (2) do not own housing, and (3) do not own other real estate asset, and zero otherwise. Estimations are by OLS. Controls are the same as those in Table 3. To conserve space, only selected coefficients are reported. Standard errors are clustered at MSAs and reported in parentheses. *, **, and *** denote statistically significant at the 10%, 5% and 1% level, respectively.

Table 6: Robustness checks with alternative waves of the PSID (PSID 2001, 2005, 2009)

	Dependent variable: risk-asset shares
	(1)
β_1: Young households (age<36)	-0.051***
	(0.017)
β_2: Young households (age<36) × inelastic MSA	0.034*
	(0.020)
Head's age	0.0015***
	(0.00054)
Housing owner	0.094***
	(0.015)
Head has college degree	0.13***
	(0.011)
Family size	-0.011***
	(0.0040)
Head is female	-0.0089
	(0.012)
Married	0.030**
	(0.013)
Mortgage payment	-0.0016
	(0.0014)
Income	0.0088***
	(0.0031)
Total wealth	0.0036**
	(0.0015)
Constant	0.085*
	(0.046)
Other individual controls	Yes
MSA × year dummies	Yes
N	11676
Adj. R-Square	0.21

Notes: This table reports the regression results of equation (11) using the alternative samples of unbalanced short panel constructed with the 2001, 2005 and 2009 waves of PSID. Estimation is by OLS. The base group consists of old households whose heads have age greater than 40. Other individual controls include category variables for household head's occupation, health status, family composition change, and race. Standard errors are clustered at MSA × year cells and reported in parentheses. *, **, and *** denote statistically significant at the 10%, 5% and 1% level, respectively.