Understanding the Puzzling Risk-Return Relationship for Housing*

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Abstract

Standard theory predicts a positive relationship between risk and return, yet recent house price data show that housing returns vary positively with risk in some metropolitan areas but negatively in others. This paper rationalizes these cross-market differences in the risk-return relationship for housing, and in so doing, explains the puzzling negative relationship. The paper's explanation emphasizes the interaction of three local market factors: households' hedging incentives, housing supply constraints, and urban market growth. Using a simple conceptual framework, the paper shows that when the current house provides a hedge against the risk associated with the future housing consumption, households are willing to accept a lower return to compensate for price risk, so weakening the positive risk-return relationship. Further, in markets with less elastic housing supply and a growing population, hedging incentives can be sufficiently strong to make the risk-return relationship *negative*. Consistent with these predictions, the paper presents empirical evidence showing that in markets where hedging incentives are strong enough, there does tend to be a negative risk-return relationship. In addition, the estimates indicate that the impact of hedging on the risk-return relationship is larger in markets where housing supply is more constrained, and that the hedging and supply-constraint effects are present only in markets where population growth is sufficiently high.

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1 Introduction

The risk-return relationship is fundamental to finance. While a substantial literature focuses on the risk-return relationship for stocks, much less attention has been paid to housing. This omission is surprising: housing represents two-thirds of a typical American household's portfolio (Goetzmann, 1993; Brueckner, 1997; Bayer, Ellickson, and Ellickson, 2010), and house prices can be highly volatile. According to the Case-Shiller 10-city composite price index, for example, real house prices rose by over 80 percent between 2001 and 2006, then fell by over 40 percent between 2006 and 2010. Yet despite the dramatic nature of these recent price movements, little is known about the way expected housing returns vary with price risk.

Standard theory predicts that risk-averse agents require higher returns to reward higher risk. Merton (1973) shows in a well-known study that the conditional expected excess return on the aggregate stock market is a linear function of its conditional variance and its covariance with investment opportunities (the hedging component). In standard asset pricing models, the hedging component is considered negligible (e.g., Merton, 1980) and supply is assumed to be fixed (e.g., Lucas, 1978), implying a positive risk-return relationship for most financial assets.

The empirical fact motivating this paper is that this positive risk-return relationship does not always hold for housing.[1] Unlike other financial assets, much of the variation in house prices is local, not national (Goetzmann and Spiegel, 1997; Glaeser, Gyourko, Morales and Nathanson, 2010). Looking at data from local housing markets, an interesting pattern emerges: in some markets, such as San Francisco and San Jose, there is a significantly positive risk-return relationship for housing; while in others, such as Chicago and Cincinnati, the relationship is significantly negative. Figure 1 illustrates this pattern by plotting the correlation between conditional forecasts of real annual housing returns and the associated risk for these four metropolitan areas over the period 1975-2009.[2] The correlation evidence, seen through the lens of the standard theory, is rather puzzling. In particular, standard theory cannot explain why housing returns vary negatively with risk in some markets; nor can it explain why both the sign and magnitude of the risk-return relationship vary across these markets.

This paper explains the cross-sectional variation in the risk-return relationship for housing by appealing to three fundamental market factors: local hedging incentives, urban market growth, and housing supply

[1] This empirical puzzle arises not just for housing. A large literature, as discussed later, has documented conflicting evidence regarding the sign of the risk-return relationship in the aggregate stock market. Several studies have aimed to reconcile these conflicting findings (e.g., Scruggs, 1998; Guo and Whitelaw, 2006), though none of these papers looks at housing.

[2] The conditional forecasts of returns and risk are generated by a GARCH (1,1) model. The correlation evidence described here is only suggestive; a thorough empirical investigation of the risk-return relationship for housing will be presented in the core of the paper.

constraints. To that end, I preface the empirical work with a simple conceptual framework that generates transparent and testable predictions to bring to the data.[3]

The first prediction relates to hedging incentives. Local hedging incentives are present when households use their current home to hedge against future housing consumption risk (e.g., Cocco, 2000; Ortalo-Magne and Rady, 2002; Sinai and Souleles, 2005). Such incentives become stronger when households are more likely to move up the housing ladder within positively correlated markets (e.g., Han, 2010). In markets with strong hedging incentives, an investment in 'risky' housing today actually reduces the risk associated with future housing consumption, because the investment pays off well when households face a high price for their next home, and pays off poorly when the price of the next home is low. As a result, households are willing to pay a higher price (thereby accepting a lower return) for such a consumption hedge, just as they would pay a premium for any financial insurance.

Taking hedging incentives into account, this paper disentangles the two competing forces at work in the housing risk-return relationship. Higher risk implies more uncertainty associated with the current home investment, and therefore requires a higher rate of return (*a financial risk effect*). Higher risk may also increase the value of holding the current house as a hedge against future housing consumption risk, hence requiring a lower rate of return to compensate for this risk (*a consumption hedge effect*). Thus, the sign and magnitude of the risk-return relationship depend crucially on the relative strength of these two effects, which in turn varies with local households' hedging incentives. This generates the first testable prediction examined in the paper: *in markets with stronger hedging incentives, a lower financial return is required to compensate for house price risk.*

The second prediction relates to urban growth. The urban literature has long emphasized the interplay between real estate assets and urban dynamics.[4] And recently, Glaeser, Gyourko and Saks (2006) have stressed that "it is difficult to think sensibly about real estate in many contexts without understanding the urban equilibrium." In the context of the risk-return relationship, urban growth can be thought of as a comparative static shift in hedging demand. In markets where population growth falls behind the housing stock (referred to below as 'declining markets'), the abundance of vacant units should prevent house prices from rising and therefore mute the consumption hedge effect. In markets where population growth does not fall behind but house prices are insufficient to justify new construction ('slow-growing markets'), households are less likely to be concerned about being priced out of the local market, making

[3] The conceptual framework is presented in details in Section 3 and formalized in Appendix I.
[4] Examples include Alonso (1964), Kain (1962, 1968), Mills (1967), and Muth (1969).

the consumption hedge effect weak. Thus, for our discussion of the financial risk and consumption hedge effects, the most interesting markets are ones in which population growth is sufficiently high and new construction is profitable ('fast-growing markets'). This generates a second testable prediction: *unlike the financial risk effect that can be present anywhere, the consumption hedge effect should be strongly present only in fast-growing markets.*

The third prediction relates to supply constraints. Unlike other financial assets, the housing stock can be expanded relatively quickly in response to rising prices relative to costs (Spiegel, 2001), but diminishes only very slowly through depreciation (Glaeser and Gyourko, 2005). This implies an asymmetric impact of supply constraints on the two risk-return effects in fast-growing markets:[5] while the strength of the financial risk effect is independent of how quickly housing stock can be added, the extent to which the consumption hedge effect is capitalized into the risk-return relationship depends crucially on supply elasticities. That is, in markets where it is hard to increase supply, an increase in hedging demand translates mostly into changes in house prices and returns, and hence we should expect a stronger hedging effect in the risk-return relationship. And in markets where supply can adjust easily, this hedging effect is mitigated by increased construction. This generates a third testable prediction: *in fast-growing markets, the relative strength of the consumption hedge effect versus the financial risk effect should be stronger in markets where supply is more constrained.*

To test these three predictions, I use the Metropolitan Statistical Area (MSA) level repeat sales house price indices from the Federal Housing Finance Agency (FHFA, formerly OFHEO) between 1980 and 2007. To proxy expected return and risk, in the main analysis of the paper, I assume that households' expected return and risk can be reasonably approximated by the time-varying conditional forecasts of housing returns and risk generated from an AR(1)-GARCH(1,1) model. Within this framework, risk is measured as a function of the variance of forecast errors, which is consistent with the notion of unpredictability rather than variability of housing price changes. To the extent that the expected return and risk are both driven by some prevailing economic conditions uncaptured by the model, there might be a simultaneity problem. To address this concern, I employ an instrumental variable strategy developed by Pagan (1984), with instruments being constructed from the information on lagged price risk.

I then go beyond the standard risk-return analysis by combining house price data with Census data. This allows me to estimate the impact of hedging incentives, urban growth, and supply constraints on the risk-return relationship for housing, controlling for observable time-varying factors such as population

[5] In slow-growing and declining markets, since new construction is not profitable, supply constraints are irrelevant.

and income growth, as well as for permanent unobserved market factors. Since average hedging demand increases with the fraction of households who plan to move locally to a bigger house, I construct various measures of hedging incentives to account for time-varying cross-sectional differences in household mobility, the life-cycle tendency to 'move up,' and the expected price correlations across current and future markets. To explore the way that the risk-return relationship varies with urban growth, I group markets into three categories (as described above): fast-growing, slow-growing, and declining, depending on local population growth relative to the existing housing supply and the profitability of new construction. Within each category, to further explore cross-market variation in supply constraints, I distinguish between markets with higher and lower housing supply elasticities as captured by land scarcity and zoning restrictions.

Based on these rich data, a simple regression of the expected housing return on its associated risk yields a statistically significant coefficient of -0.05. However, this small negative average correlation masks important geographical variation in the risk-return relationship across markets. Controlling for urban market growth, I find that declining and slow-growing markets always exhibit a significant and positive risk-return relationship, suggesting a strong financial risk effect. In contrast, in fast-growing markets, the financial risk and consumption hedge effects are found to be simultaneously present, with the relative strength of the latter being determined by local hedging incentives and housing supply constraints.

To further gauge the magnitude of the hedging and supply-constraint effects in fast-growing markets, consider two cities that are identical except for the fact that the first is highly supply-constrained (e.g., San Francisco) and the second is not (e.g., Atlanta). Suppose initially that households in both cities have weak hedging incentives. In this case, a one-standard-deviation increase in risk is associated with a 37% *increase* in the expected return from the sample mean, reflecting the dominance of the financial risk effect. Now suppose that households in both cities have strong hedging incentives. In this case, a one-standard-deviation increase in risk is associated with a 13% *increase* in the expected return from the sample mean in less constrained cities, but a 59% *decrease* from the sample mean in more constrained cities. Both estimates confirm the role of hedging incentives in offsetting the standard positive risk-return relationship; the latter further indicates that more stringent supply constraints strengthen the consumption hedge effect to the extent that the estimated risk-return relationship is completely negative.

Overall, these results are consistent with each of the predictions above. Moreover, the findings are highly robust. They hold across sample markets and sample periods, for various measures of expected returns and risk, hedging incentives and supply constraints, and with a variety of controls for possible endogeneity.

In terms of its contributions, first, the paper documents a new dimension of geographical variation in house price movements by looking at cross-city differences in the risk-return relationship. Second, to rationalize the variation in the risk-return relationship, the paper emphasizes geographical differences in local market factors such as hedging incentives and supply constraints. These factors have not been central to studies of the risk-return relationship for standard financial assets. They are, however, crucial for understanding the risk-return relationship in the housing market, where scope for risk-sharing is very limited and new homes can be built in response to rising demand. Since current institutional arrangements have yet to provide a widely accepted financial instrument to reduce house price risk,[6] the self-hedging mechanism becomes particularly important. The findings in this paper further indicate that when households price house price risk, they not only take into account the hedging role of housing, but also factor in the importance of the local supply constraints and growth conditions.

The rest of the paper is organized as follows: Section 2 discusses the relationship between this paper and the prior literature; Section 3 presents a conceptual framework that explores geographic determinants of the risk-return relationship for housing; and Section 4 describes the data and construction of key variables. Section 5 contains the empirical analysis and findings, Section 6 provides robustness checks, and Section 7 concludes.

2 Relationship to the Prior Literature

This paper adds to several strands of the existing literature. First, the paper is closely related to a growing literature that aims to understand cross-market differences in house prices. In a series of papers, Glaeser, Gyourko and Saks (2003, 2006) and Glaeser, Gyourko, and Saiz (2008) explore the interactions among housing supply conditions, house prices, and urban market dynamics. A recent literature also points to the need to incorporate the hedging role of housing in understanding house price movements. For example, Sinai and Souleles (2005) find that in markets where rent volatility is greater, the price-to-rent ratio is also higher; Ortalo-Magne and Prat (2010) develop a spatial asset pricing model and show that house prices tend to be higher in markets with strong hedging demand. Building on these existing studies, the present paper takes a different focus on the risk-return relationship and highlights the *interactions* of geographical differences in three local market factors: hedging incentives, supply constraints, and urban market growth.

[6]Using different housing return measures, previous work finds a low correlation between housing and existing financial assets. See Goetzmann (1993), Gatzlaff (2000), and Flavin and Yamashita (2002). De Jong, Driessen and Van Hemert (2008) also find that economic benefits for homeowners of having access to the limited housing futures are small. These findings suggest that house price risk cannot be easily diversified.

This paper also adds to recent literature on the risk-return relationship for housing. For example, treating housing as a financial asset, Meyer and Wieand (1996) show that price risk increases expected housing returns in an asset-pricing context. Consistent with this view, Crone and Voith (1999), Cannon, Miller, and Pandher (2006) and Case, Cotter, and Gabriel (2011) provide careful empirical evidence that favors a positive risk-return relationship for housing. The current paper differs from these studies in terms of the focus – exploring the durable nature and hedging role of the housing asset – and in terms of the approach – measuring price risk by unpredictability as opposed to variability or sensitivity to the national stock or housing market. Using a time-varying risk measure, Dolde and Tirtiroglu (1997) find that the risk-return relationship tends to be positive in San Francisco but negative in Cincinnati, consistent with the evidence reported in Figure 1 of this paper.

More broadly, this paper is related to a large literature that studies the risk-return relationship for financial assets.[7] While classical risk-return models generally assume away hedging and supply effects, there has been recent research interest in relaxing these assumptions in asset pricing models. For example, Scruggs (1998) and Guo and Whitelaw (2006) emphasize the desire to hedge; and Spiegel (1998) and Braun and Larrain (2009) examine the impact of asset supply on asset prices. In this paper, my focus on households' intermporal hedging incentives and housing supply conditions complements these lines of research.

Finally, there have been important recent advances in understanding the role of housing in explaining asset return variation, business cycles, and portfolio decisions. Examples include Lustig and Van Nieuwerburgh (2005, 2007), Yao and Zhang (2005), Yogo (2006) and Piazzesi, Schneider, and Tuzel (2007). This paper differs from this line of work in that it studies cross-market differences in house price risk premia, but abstracts from stock assets, borrowing constraints, the collateral role of housing, and changes in transaction costs.

3 Conceptual Framework

This paper is primarily empirical in its focus. To motivate the empirical analysis, I begin by setting out a stylized conceptual framework to illustrate the key sources of geographical variation in the risk-return relationship for housing.

[7] For example, Chou (1988), Harvey (1989), Goyal and Santa-Clara (2003), and Bali (2008) find a positive risk- return relationship, whereas Campbell (1987) and Glosten, Jagannathan, and Runkle (1993) find the opposite. See Bekaert and Wu (2000) for a review of the literature.

3.1 Financial Risk Effect and Consumption Hedge Effect

The dual investment/consumption role of housing has two very different implications for the risk-return relationship. If risk-averse households treat housing just as a financial asset, they will require higher returns to compensate for higher risk. Yet for most households, housing is also an important part of their consumption in all periods. If the price of the current house is positively correlated with future housing costs, then the investment in risky housing today provides a valuable hedge for future housing consumption. Hence, lower return would be required to compensate for the risk.

To illustrate this idea, here I provide a sketch of a simple consumption-based capital asset pricing model. The full model is set out in detail in Appendix I. The model consists of a large number of infinitely-lived households that enjoy both housing services h_t and a nondurable, numeraire consumption good c_t. There are only two assets: a risky owner-occupied housing asset that generates housing services every period and capital gains at the end of the holding period, and a riskless bond whose return is r_t^f.[8] The model presents a close parallel to the standard CCAPM of Lucas (1978), but the role of future dividends associated with financial securities in that model is replaced in our context by future rents associated with home ownership. Consequently, the basic asset pricing relation implies that the current value of housing is determined by the expected capital gains and rental services it provides in the future. This can be summarized by the following equation:

$$P_t = E_t \left[M_{t+1} \left(P_{t+1}(1-\delta) + Q_{t+1} \right) \right] \tag{1}$$

where P_t indicates house price at time t; M_{t+1} represents the present value of having one unit of non-housing consumption one period ahead; δ is the depreciation rate of the housing stock; and Q_{t+1} indicates future rents that households would have to pay if they did not choose to own now.

The key source of randomness in this model is the uncertainty surrounding future house prices.[9] To pin down the risk-return relationship, I make the following assumptions about the joint distribution of house price (P_t), rent (Q_t), and the marginal rate of substitution (M_t).[10] First, the shocks to price growth and to the intertemporal marginal rate of substitution are negatively correlated ($\rho_{PM} < 0$); that is, house price

[8]Given the extremely low correlation between housing and existing financial assets, adding a richer set of financial assets is unlikely to affect the house risk premium.

[9]Throughout the analysis, I treat house price risk as an exogenous phenomenon. Modeling the sources of house price risk is worthy of careful study in its own right and is beyond the scope of this paper. See Glaeser, Gyourko, Morales and Nathanson (2010), Sinai (2009), and Favilukis, Ludvigson, and Van Nieuwerburgh (2010).

[10]As shown in Appendix I, I assume house prices and rents follow a given stochastic process. The process of marginal rate of substitution, M_t, is derived as an equilibrium outcome by solving the utility maximization problem subject to market clearing conditions.

growth is slower in states where non-housing consumption is more valuable. This assumption is justified by the empirical evidence that house prices tend to vary positively with labor income (Davidoff, 2006) and that high labor income growth increases non-housing consumption growth, leading to a lower marginal utility of future consumption.

Second, I assume that the shocks to price growth and rent growth are positively correlated ($\rho_{PQ} > 0$). Within the same market, prices and rents are obviously linked through an arbitrage relationship, so shocks that increase house price growth are also likely to increase rent growth. More broadly, rents can be interpreted as future housing costs, which include the price of the next home if households ever move and buy again. In this case, the assumption $\rho_{PQ} > 0$ is justified by another important empirical observation: households tend to move among correlated housing markets (Sinai and Souleles, 2008).

Under these assumptions, Appendix I examines the risk-return relationship analytically. The key finding is that in an economy with exogenously fixed housing supply, the equilibrium housing risk-return relationship is characterized by

$$\frac{\partial E_t(r_{t+1})}{\partial \sigma^2_{r,t}} = -\frac{\frac{1}{2}\gamma + \rho_{PM} + (1-\gamma)\rho_{PQ}}{\gamma + 2(1-\gamma)\rho_{PQ}} \tag{2}$$

where $E_t(r_{t+1})$ is the expected total housing return conditional on information at time t, $\sigma^2_{r,t}$ is the associated conditional variance, and γ is a constant between zero and one.

The left-hand side of equation (2) defines the risk-return relationship for housing in a conditional mean-variance framework. The right-hand side of equation (2) shows that households care about house price risk only to the extent that it affects their future consumption — the latter includes both non-housing and housing consumption. This suggests two simultaneous but opposite risk-return effects. With a negative ρ_{PM}, the housing asset pays off poorly when households have a strong desire for more non-housing consumption and pays off well when such a desire is weak. In this case, greater price risk creates more uncertainty about future non-housing consumption. Because of this, households will require a lower price (thereby a higher return) to induce themselves to buy such an asset. This generates a positive risk-compensation component in the risk premium – a component that is common to all financial assets. On the other hand, with a positive ρ_{PQ}, the current home pays off well when households face high costs for future housing consumption and pays off poorly when such costs are low.[11] In this case, greater price

[11] Note that future housing costs can be interpreted either as rents or as the price of the future home. In the former case, the current home provides a hedge against uncertainty about the future rents that households would have to pay if they did not choose to own now. In the latter case, the current home provides a hedge against uncertainty surrounding the future home

risk increases the hedging value of the current home by reducing future housing consumption risk, and hence households are happy to pay a higher price (thereby requiring less return) for holding the current home. This implies a negative hedging correction term in the risk premium – a component that is unique to housing.

By emphasizing the dependence between prices of future and present housing consumption, this model implies a key source of geographical variation across markets in the risk-return relationship: local households' incentives to use the current home purchase to hedge future housing consumption risk. In markets where hedging incentives are weak, we should expect that housing behaves like other financial assets and that a high return is associated with higher risk. In markets where hedging incentives are strong, this positive relationship should be mitigated or even reversed. The sign and magnitude of the risk-return relationship will depend, therefore, on the strength of hedging incentives among local households. Intuitively, households' hedging incentives depend on the expected correlation between current and future housing markets and the expected size of the future house relative to the current one. The more positively correlated current and future markets are and the larger the size of the future home purchase, the stronger the hedging incentives will be.

Before proceeding, I should highlight one caveat about the mapping from the theory to the empirical work. The analysis so far has focused on the log total return process, $\ln\left(\frac{P_{t+1}+Q_{t+1}}{P_t}\right)$, which includes the dividend yield (Q_{t+1}). Empirically, one can proxy the dividends in housing markets by rents and compute the total return series. However, doing so implicitly assumes the direct comparability of owned units to rental units and of owners to renters. As documented by Glaeser and Gyourko (2010), rental units are very different from owner-occupied units and renters are very different from owners, consequently it is not feasible to construct rent series that are comparable to house price series for the national-wide cross-market analysis. For this reason, the empirical analysis below focuses on the capital return process, $\ln\left(\frac{P_{t+1}}{P_t}\right)$. To tie this return measure more closely to the theory, I show in Appendix I that the testable implications from equation (2) for the total return process essentially carry over to the capital return process.[12]

price if households choose to own now and move to a different home later.

[12] See Proposition 3 in Appendix I. The analysis is similar in spirit to Tauchen (2005). His work shows that implications for the stock volatility dynamics are essentially the same for either the total return process or the capital return process, because the capital gain return tends to dominate the total return.

3.2 Supply

Thus far, housing supply has been taken as exogenously fixed. Unlike most other financial assets, the housing stock can be expanded when supply is elastic and urban growth is high. To the extent that increases in price risk and in hedging incentives can elicit a supply response, their effects on expected returns may be muted. This section presents the housing supply function.

As shown in Figure 2, housing supply has a kink that occurs at the quantity of existing housing stock and at the price which equates to the long run marginal cost of supplying an additional housing unit. This kink breaks the supply function into two parts. The first part of supply function is a vertical line below the kinked point, which indicates that the housing stock is perfectly inelastic with respect to downward demand shocks. The second part of the supply function is depicted by a line that starts from the kink point and moves out to the right. This line indicates the marginal cost of developing a new house, which includes construction costs and necessary profit for developers, as well as land acquisition costs. A flat supply line corresponds to unconstrained markets. A close example is Atlanta, where there are almost no natural or regulatory barriers to overcome and thus the physical structure can be supplied highly elastically. In contrast, a rising supply line corresponds to constrained markets, where the cost of supplying a new house increases with the existing housing stock. An example is San Francisco, where the difficulty of acquiring good buildable sites has increased substantially because of land scarcity and zoning restrictions.

Because housing stock correlates almost perfectly with the population (Glaeser and Gyourko, 2005), the housing supply function naturally divides market into three types of urban economy: fast-growing, slow-growing, and declining. Under zero depreciation, an MSA is categorized as fast-growing if it satisfies two conditions: (1) population growth is sufficiently high so that the number of households does not fall behind the housing stock at the current price;[13] *and* (2) new construction is profitable. Graphically, fast-growing cities are represented by the northeastern region in Figure 2. Alternatively, an MSA is categorized as slow-growing if population growth is high relative to housing stock, *but* not sufficient to make new construction profitable. Graphically, this describes the case where the market equilibrium shifts along the vertical line, yet the new equilibrium price is still below the kink point. Finally, an MSA is categorized declining if the population is low relative to the housing stock at the current price. In this case, given the

[13] Population is an obvious indicator of urban growth (Helsley, 2003). Given the extremely tight link between population and housing stock (Glaeser and Gyourko, 2005), the difference between the two would naturally reflect the imbalance between housing demand and supply. However, what happens when we take into account the difference between the aggregate housing demand and the demand for owner-occupied housing, as well as changes in mortgage rates and expectations over future house price appreciation? Appendix II shows that the findings based on the population measure described here would remain robust even after accounting for these additional factors.

abundance of vacant housing units, house prices are likely to be below construction costs. Graphically, declining cities fall to the left of the vertical line at the existing price.

In practice, housing is subject to natural depreciation at a small but positive rate that is independent of market conditions. Thus, in evaluating whether an MSA is declining or growing, it is important to recognize the role played by depreciation. To see this, consider an MSA that experiences no change in population. According to the definition above, this is actually categorized as 'growing,' since with positive depreciation, existing supply falls but the number of households stays the same (see Figure 3). Even for an MSA that experiences a population loss, it is considered 'growing' as long as the resulting decrease in the number of households is less than the depreciation of housing stock. In this sense, a decline in population provides a necessary but not sufficient condition for an MSA to be categorized as 'declining.'

3.3 Empirical Predictions

To see how urban growth and housing supply conditions determine the relative strength of the consumption hedge effect versus the financial risk effect, I consider three categories of markets: fast-growing, slow-growing, and declining.

The most interesting category consists of fast-growing markets. Figure 4 illustrates how housing supply elasticity affects the risk-return relationship for markets in this category.[14,15] Consider an initial equilibrium at Point A. If hedging incentives are sufficiently strong, an exogenous increase in price risk would lead to an increase in hedging demand for housing. Since new construction is profitable, the effect of hedging demand on the risk-return relationship depends crucially on the extent to which new construction can catch up with demand. When housing supply is less elastic, illustrated by a steeper upward-sloping line, a positive hedging demand shock will have little impact on construction. Because the number of homes does not increase significantly, house prices must rise to adjust to the new market equilibrium (Point B). Thus, we should expect a stronger consumption hedge effect in the risk-return relationship. In contrast, if supply is relatively elastic, illustrated by a flatter supply line, new construction will quickly come on line, and the same hedging demand shock will translate mostly into quantity effects rather than price effects (Point C). In this case, we would expect a much weaker consumption hedge effect in the risk-return relationship.

On the other hand, if the only effect of price risk on housing return is the financial risk effect, there

[14] To keep the illustration simple, I do not show positive depreciation of housing stock in Figures 4-5. Incorporating positive depreciation into these figures is straightforward and would not change the key implications that I derive below.

[15] Glaeser and Gyouko (2005) and Glaeser, Gyourko, and Saks (2006) provide a similar graphical analysis to examine the role that housing supply plays in mediating urban dynamics. Unlike their work, the focus here is to examine how supply constraints influence the relative strength of the two risk-return effects.

should not be differences in the risk-return relationship between more and less constrained areas. Unlike the case described above, a financial risk effect brings a downward shock to housing demand. Since housing supply is perfectly inelastic with respect to downward demand shocks, whether new construction is profitable and how quickly housing stock can be added become irrelevant for the risk-return relationship. Putting these together, in fast-growing markets, the relative strength of the consumption hedge effect versus the financial risk effect increases with the degree to which housing supply is constrained.

A second category consists of slow-growing markets in which the equilibrium moves along the vertical part of the supply function when the city grows, yet the new equilibrium price is not sufficient to justify new construction. In this case, since new construction is not profitable, builders will not enter the market and hence housing supply will be inelastic with respect to both positive and negative demand shocks. Thus any demand shifts should be fully translated into price effects. However, in these markets, given the slow urban growth and below-cost house prices, households are unlikely to fear being priced out of the market even if they plan to move locally. Thus the consumption hedge effect in slow-growing markets, if any, should be much weaker relative to the corresponding effect in fast-growing markets. In contrast, the financial risk effect should remain strong.

Finally, in declining markets, the deteriorating economic conditions limit the degree of households' incentives to hedge against local housing cost risk. Moreover, even with a temporary positive demand shock, it may elicit neither price response nor quantity response. This can be seen from a demand shift that pushes the equilibrium from E to F (Figure 5), at which point more vacant units are turned into occupied units but price and existing housing stock remain the same. This further prevents any hedging effect. On the other hand, we should still expect the financial risk effect to operate in declining markets, because once homes are built, "there is no lower bound on prices until they fall to zero" (Glaeser and Gyourko, 2005). Note that in the latter two categories, since new construction is not profitable, supply constraints are irrelevant.

This simple theoretical framework above generates four testable predictions regarding the cross-market variation in the risk-return relationship for housing.

1. In markets with weak hedging incentives, higher risk is associated with higher returns. This positive risk-return relationship is mitigated or even reversed in markets with strong hedging incentives.

2. While the financial risk effect can be present anywhere, the consumption hedge effect should be strongly present only in fast-growing markets.

3. In markets where both the financial risk and consumption hedge effects exist, the relevant strength of the consumption hedge effect increases with the degree to which supply is constrained.

4. These three sources of geographical variation are not independent of each other. In particular, supply constraints strengthen the consumption hedging effect only in fast-growing markets.

4 Data and Key Variables

The key variables for testing these predictions are expected housing return and risk, local hedging incentives, urban growth, and supply constraints. In this section, I discuss how I constructed each of these variables.

4.1 Expected Housing Return and Risk

The primary house price dataset consists of the Federal Housing Finance Agency (FHFA, formerly OFHEO) repeat-sales price indices of metropolitan-area-level prices, which track average house price changes in repeat sales or refinancing for the same single-family properties. The unit of analysis is a metropolitan area in one year. The FHFA series begins in 1975. But I use data beginning in 1980 because a large number of metropolitan areas are covered on a consistent basis from that year onward.[16] For the main analysis, I drop the post-2007 observations to avoid the special circumstances in the recent unprecedented financial crisis.[17] In addition, the main analysis uses the FHFA all-transaction price indices instead of the FHFA purchase-only price indices, because the latter begin in 1990 and include only 25 metropolitan areas. Nevertheless, the results based on the purchase-only indices are presented in Section 6.2 as a useful robustness check.

The distribution of FHFA annual real returns reveals a small number of returns greater 20% and less than -20% (about 1.5% of the distribution). To alleviate the effects of outliers, I winsorize the annual returns at the 1st and 99th percentiles prior to the construction of expected returns and risks.[18] To proxy expected returns and risk, I estimate an AR(1)-GARCH(1,1) model (Engle, 1982) based on quarterly

[16] The FHFA all-transaction HPI panel used in this paper is unbalanced both because the early FHFA series does not cover all metropolitan areas and because I have acquired a customized FHFA HPI series in an effort to construct a risk-return dataset that uses the same 4-digit MSA codes as other key variables in this paper. A detailed description of the FHFA HPI series used for this paper is provided in Appendix III.

[17] The results based on the 1980-2010 sample are presented in Table A3 in the appendices as an additional robustness check.

[18] More specifically, if the reported real annual return is above (below) its respective top (bottom) percentile, I assign it to the value of the observation at the top (bottom) percentile. This procedure is consistent with the standard practice in the finance literature, and enables me to limit the effect of outliers. The pattern of the risk-return relationship results does not change qualitatively when I winsorize the FHFA annual real returns at the 5th and 95th percentiles.

observations of real annual housing returns for each metropolitan area. Specifically, I express the housing return at time t in market i, r_{it}, as a function of past housing returns and a return shock. The conditional variance, σ^2_{it}, is modeled as a function of previous return shock, $u_{i,t-1}$, and previous conditional variance, $\sigma^2_{i,t-1}$.

$$\begin{aligned} r_{it} &= a_{i0} + a_{i1} r_{i,t-1} + u_{it} \\ \sigma^2_{it} &= b_{i0} + b_{i1} u^2_{i,t-1} + b_{i2} \sigma^2_{i,t-1} \end{aligned}$$

where $u_{it} \sim N(0, \sigma^2_{i,t})$. For each metropolitan area, I estimate an AR(1)-GARCH(1,1) process separately, and the resulting estimates are used to generate conditional forecasts of annual housing return and variance: the former is taken as the expected housing return, while the square root of the latter is taken as price risk. For each year, I use annual values imputed in the 3rd quarter to represent the expected housing returns and risk for that year.[19] To conduct a sensible time series analysis, I drop the MSAs for which the number of non-missing quarterly observations is less than 70. Among the remaining 313 MSAs, maximum likelihood estimates of the AR(1)-GARCH(1,1) model are obtained for 295 MSAs.[20]

The GARCH model assumes that households learn about changes in future returns only from information on past returns. This assumption is consistent with both anecdotal and survey evidence, namely that, "people seem to form their expectations on the basis of past price movements rather than any knowledge of fundamentals" (Case and Shiller, 1988). The econometric challenge is then to specify how the past price information is used to forecast the mean and variance of the return. The standard approach in the housing literature is to use the moving average and standard deviation of past returns in a rolling window to measure expected returns and risk (Sinai and Souleles, 2005). Note that this approach can be considered as a special case of an AR(1)-GARCH(1,1) specification in which the expected returns (volatility) is assumed to be an equally weighted average of the returns (squared residuals) from a finite number of past periods. However, the assumption of equal weights in a fixed window seems unattractive, as one would think the more recent events would be more relevant and therefore should have higher weights. In

[19] One important assumption underlying the GARCH approach is that households know the parameters of the local house price process, which is consistent with the empirical implementation of rational expectation models. By using quarterly data to estimate the GARCH model, I implicitly assume that households update their expectations of future house price movements using the newly revealed information in last quarter's asset returns. This assumption is reasonable, given that many local markets now release house price statistics quarterly, if not monthly.

[20] There are 18 MSAs for which the AR(1)-GARCH(1,1) model does not converge. However, this does not necessarily imply that the conditional variance is constant in these markets. An alternative explanation could be that the series of real housing returns in these MSAs are so noisy that a systematic pattern of conditional heteroscedasticity does not hold given the relatively short time-horizon observed for some MSAs.

contrast, the AR(1)-GARCH(1,1) specification lets these weights to be parameters to be estimated. Thus the model allows the data to determine the best weights to use in forecasting future returns and risk. In addition, GARCH risk explicitly incorporates the variance of return forecast errors. This is consistent with the notion of *unpredictability* about future housing returns, as opposed to *variability* in past house price movements — the latter is what is captured by the usual standard deviation measure.

The ARCH/GARCH families of models have been the workhorse of financial applications, particularly in the literature of the risk-return relationship (e.g., Ghysels, Santa-Clara, and Valkanov, 2005; Lundblad, 2007). For housing, the AR(1)-GARCH(1,1) specification is particularly suitable as it captures two important features of housing returns: they are predictable and mean-reverting. First, existing literature shows that housing returns follow distinct trends with current increases foretelling future increases and current declines foretelling future declines (Case and Shiller, 1990; Lamont and Stein, 1999; Goetzmann and Spiegel, 2002). The AR(1) specification in the conditional mean equation is consistent with this line of literature. Second, Glaeser and Gyourko (2010) show that changes in housing returns follow a dynamic and mean-reverting process, which is precisely what the GARCH specification is designed to capture (Engle, 2001). Since the virtue of the GARCH model is that a small number of lags appear to perform as well as or better than a model with many lags (Bollerslev, 1986), I use one lag to model the conditional variance. In addition, compared to the moving average and standard deviation measures, using GARCH measures of expected returns and risk also helps rule out a potential concern that the risk-return relationship may exist only because high returns mechanically translate into larger volatilities and hence larger risks.[21]

Table 1 presents summary statistics for the expected annual return and risk between 1980 and 2007 based on the winsorized FHFA sample. Overall, the sample mean of the price risk is of the similar magnitude as that of the expected return, indicating that housing markets feature high price risk. Furthermore, house price risk exhibits substantial variation both across markets and over time. For example, the cross-market mean of price risk increased by over 25% between 2003 to 2007, indicating a sharp increase in uncertainty in the wake of the financial market crisis.

Finally, it is worth noting that the finance literature often measures stock price risk by betas. In the context of Section 3.1, the concept of beta is equivalent to $\frac{Cov(r,M)}{Var(M)}$, which is captured by the first

[21] Consider a simple example where $r_t = a_0 + a_1 \times x_t + e_t$ and e_t follows a GARCH(1, 1) process. An *expected* shock to the return process would directly affect expected returns but not the risk forecast; while an *unexpected* shock would directly affect the risk forecast but not the expected returns. To see this, consider two cases. Case (1): Suppose there is an expected increase in x from time t to time $t+1$. This would obviously shift up the expected return $E_t(r_{t+1})$. But this does not change uncertainties about future housing returns. Case (2): Suppose there is an unexpected increase in e_t. This would translate into a higher GARCH risk estimate, as large forecast errors lead to large uncertainties about the future. However, conditional on today's information, such shock does not directly affect the expected future return.

correlation term in equation (2), ρ_{PM}. Empirically, beta is simply the regression coefficient of the asset return on the marginal rate of substitution between future and current non-housing consumption, which is in turn a function of non-housing consumption growth. Given the poor quality of consumption data, financial economists often model consumption growth in terms of a set of market factors, such as the return on a broad-based stock portfolio. However, for housing, the estimated beta relative to the stock market portfolio is virtually zero (Case and Shiller, 1990). I therefore choose not to explicitly model the housing beta correlation with the financial market. Instead, I focus on the second correlation term in equation (2), ρ_{PQ}. This term captures the correlation between prices of current and future houses and hence indicates local households' hedging incentives. Taking ρ_{PM} as given, the cross-market differences in the risk-return relationship should be attributed to variations in the local hedging incentives, which I turn to next.

4.2 Hedging Incentives

An empirical measure of hedging incentives should capture two different ingredients: (i) the probability that local households will trade up to a bigger house in the future, and (ii) the positive correlation between the market where local households currently reside and the market where they plan to move.

To capture the trading-up tendency, I rely on the age distribution of the local population at the MSA/year level. Life-cycle housing demand models typically assume an age-profile of housing tastes that follows an inverted U-shape. Based on the evidence presented in Banks, et al. (2004), I assume that homeowners aged 20-45 are likely to move to a bigger house in the future given their expectation about family expansion and income increases.[22] The Census provides the size of the population by age at the county level for each year since 1970. I aggregate the county-level data to the MSA level, and then compute the fraction of the population aged 20-45 in each year between 1980 and 2010. Table A2 in the appendices shows that there is large variation in this fraction, ranging from 20.10% (Punta Gorda, FL in 1980) to 55.55% (Jacksonville, NC in 1991). A higher fraction of population aged 20-45 indicates a stronger tendency to move up, and hence larger future housing cost risk to hedge against. Across markets, the cities of the Rust Belt are relatively 'older' than western region cities. For example, the mean age of population over the sample period is 39 in Pittsburgh and 34 in San Diego, while the mean fractions of population aged 20-45 in these two cities are 34.86% and 42.09%, respectively. These variations will prove

[22]In addition to age, other demographic variables, such as marital status and the number of children, also help predict households' tendency to move up the housing ladder. Unfortunately, the distribution of these variables at the MSA level is not available at an annual frequency during the sample period. Nevertheless, to the extent that marital status and the the number of children vary with the stage of the life-cycle, the age variable should capture most of the variation in these measures.

useful in identifying the hedging effect on the risk-return relationship.

To proxy the positive price correlation between current and future houses, I consider two distinct measures. The first measure is based on the fraction of the population that stayed within the same MSA in the past 5 years. To the extent that houses within the same MSA follow the same price process, the more likely households are to stay within an MSA, the more positively their current house value will be correlated with their future housing costs. Using the household-level data from the Integrated Public Use Microdata Series (IPUMS) in 1990 and 2000, I compute the fraction of the population who have stayed within the same MSA for the past 5 years.[23] Specifically, for each MSA, the fraction of recent emigrants who moved from a specific MSA to other areas in the last five years is considered as the MSA's out-migration rate. Since there are only two years' mobility data available, I assign the 1990 out-migration rate to years up until 1995 and the 2000 out-migration rate to years after 1995. The difference between one and the imputed out-migration rate is then taken as the fraction of population that stay within the same MSA. For Chicago and Cincinnati area, the average out-migration rates were both around 0.10; for San Francisco and San Jose, they were 0.19 and 0.18, respectively. The difference implies that, all else equal, average hedging incentives in the first two cities should be stronger, leading to a more negative risk-return relationship. This is consistent with what we see in Figure 1.

Despite being conceptually appealing, using within-MSA mobility to proxy hedging incentives implicitly treats owning the current home as a poor hedge for households that plan to move across MSAs. As shown by Sinai and Souleles (2008) and Sinai (2009), even for cross-MSA movers, the hedging benefit of homeownership can be substantial, as households tend to move among correlated markets. For each of the 44 largest MSAs, Sinai and Souleles (2008) compute the expected house price correlation between the given MSA and other MSAs, where the expectation is weighted by the probability that an average household in this MSA moves to each of the other MSAs. Using their estimates, I rank all 44 MSAs by the median of the expected price correlation with other MSAs. This rank variable complements the within-MSA measure of price correlation.

To empirically identify the relative strength of hedging incentives, both the likelihood of trading-up and the expected price correlation should be taken into account. Since the latter is measured in two ways, I construct two corresponding sets of dummies that indicate whether there are strong hedging incentives within a given MSA in a given year. The first measure is constructed based on the within-MSA mobility.

[23]There are 236 MSAs for which the imputed fractions are available both in 2000 and in 1990. These MSAs are then merged with the GARCH risk and return estimates obtained from the FHFA sample to form the estimation sample. A detailed description of the computation of the 'staying-within-the-same-MSA' fraction is provided in Appendix III.

Specifically, an MSA in a given year is categorized as a market with strong hedging incentives if the fraction of the population aged 20-45 exceeds 35% *and* the fraction of the population staying within the same MSA in the last 5 years exceeds 82%; otherwise, it is categorized as a market with weak hedging incentives. Note that the cutoff points, 35% and 82%, are the 25^{th} percentile of the distribution of the age fraction and the 25^{th} percentile of the within-MSA mobility rate, respectively. I choose to use a discrete method of identifying hedging incentives to ease the interpretation of the empirical results. For the main empirical analysis, I also experiment with different cutoff points and find that the key results are not affected by the choice of these points.

A second measure of the hedging indicator is generated based on the cross-MSA price correlation. Specifically, an MSA in a given year is categorized as a market with strong hedging incentives if the fraction of people aged 20-45 exceeds 35% *and* the expected price correlation ranks between 1 and 20; otherwise it is categorized as a market with weak hedging incentives.

Table 2 presents summary statistics for the generated hedging incentive dummy variables. Based on the within-MSA hedging indicator, about 63% of markets (defined at the MSA-year level) have strong hedging incentives. Based on the cross-MSA hedging indicator, about 44% have strong hedging incentives.

4.3 Urban Growth

Section 3.2 divided markets into three types: fast-growing, slow-growing, and declining, depending on whether a market exhibits higher population growth relative to housing stock *and* whether new construction is profitable.

To empirically proxy the first condition, I assume all markets start from an initial equilibrium where the number of households equals housing units, and then compare the net decrease in the number of households with the decrease in housing stock.[24] The former is captured by $\frac{Pop_{i,t-1}-Pop_{it}}{HS}$, where Pop_{it} is the size of population at market i in year t, and HS is the average household size. The U.S. Census statistics indicate that the average household size has been relatively stable across states over the last twenty years, with a mean of 2.7 people per occupied housing unit.[25] Since the housing stock shrinks only through depreciation,

[24] This approach effectively compares the aggregate housing demand with the existing housing units. Alternatively, one can compare the demand for owner-occupied housing with the housing stock. Given that the focus here is on urban growth rather than on the owner-occupied housing demand, and given that population is a natural indicator of urban growth, a comparison between overall population and existing housing stock is more suitable for the purpose here. As shown in Appendix II, the empirical findings based on the population measure described here would remain robust even after accounting for the difference between the aggregate housing demand and the demand for owner-occupied housing.

[25] Ideally one would like to introduce time and spatial variation into the household size variable. In practice, there does not exist a data source that provides the MSA-level estimates of the household size at the annual frequency. However, given the

the decrease in existing housing stock is measured by $\delta H_{i,t-1}$, where δ is the depreciation rate and $H_{i,t-1}$ is housing stock from the last period. Using the American Housing Survey (AHS) data from 1985 to 1993, Glaeser *et al.* (2006) show that the upper bound of the average depreciation rate of housing stock is about 1 percent per year. Putting these together, the first condition a growing market must meet is equivalent to $\frac{Pop_{i,t-1}-Pop_{it}}{0.01H_{i,t-1}} \leq 2.7$.

The second condition is indicated by whether house prices are high relative to construction costs. Glaeser and Gyourko (2005) compare the distribution of the value of the housing stock with the cost of new construction and compute the distribution of houses priced above and below construction costs at the MSA level. Using the statistics they compute based on the 1990 Census data, I categorize an MSA as a market where average house price exceeds construction costs if over one-half of the housing stock was priced above the cost of new construction.

Following the discussion in Section 3.2 and combining the proxies for demand growth with the proxies for construction profitability, I categorize MSAs into three types: (a) fast-growing markets, i.e., markets with $\frac{Pop_{i,t-1}-Pop_{it}}{0.01H_{i,t-1}} \leq 2.7$ and with over one-half of their housing stock priced above the cost of new construction; (2) slow-growing markets, i.e. markets with $\frac{Pop_{i,t-1}-Pop_{it}}{0.01H_{i,t-1}} \leq 2.7$ and with less than one-half of their housing stock priced above the cost of new construction; (3) declining markets, i.e. markets with $\frac{Pop_{i,t-1}-Pop_{it}}{0.01H_{i,t-1}} > 2.7$.[26] The last condition is equivalent to the magnitude of the population decrease exceeding 0.027 times the previous period's housing stock, which is about 8000 people for an average MSA. Ideally, one would like to construct the market growth indicators based on time-varying market conditions. In practice, given that the data on the second condition are only available for 1990, I construct the market growth indicators by applying both criteria described above to the 1990 Census data. Implicit in this construction is the assumption that the decline and growth of urban markets are relatively stable throughout the sample period. The persistence of urban decline is justified by the durable nature of the housing stock (Glaeser and Gyourko, 2005). For markets that are growing, casual empirical observations suggest that while these markets' urban growth rates may differ from year to year, the relative degree of growth is generally persistent over time.

According to this definition, about 67% MSAs are categorized as fast-growing, 28% are slow-growing, and the remaining 5% are declining. Table A1 in the appendices lists the MSAs in each category. Compared

substantially smaller variation in household size relative to the variation in population and housing stock (Glaeser, Gyourko, and Saks, 2006) and given my use of the discrete rather than continuous measures of growing and declining markets, I believe that little is lost by using a constant household size.

[26] In declining markets, since there is no demand for new construction, the profitability of construction is irrelevant.

with the urban growth literature (e.g., Glaeser, *et al.* 2006), the fraction of MSAs that are categorized as 'declining' in this paper is somewhat smaller. This difference can be attributed to two factors. First, the existing literature typically categorizes a city as either 'declining' or 'growing', with 'declining' indicating population loss. In contrast, in this paper, a market is categorized as 'declining' if and only if the population loss is sufficient to offset depreciation of the housing stock. Thus, many markets with positive population loss, such as St. Louis, are categorized as 'slow-growing' rather than 'declining' as the population loss is not large enough. Second, instead of looking at cities as in the urban growth literature, this paper examines metropolitan areas. Even in metropolitan areas such as St. Louis, the demand for housing in the suburbs has increased despite the decrease in the city. This explains why the overall population loss in St. Louis could be slow relative to the depreciation of its existing housing stock.

4.4 Supply Constraints

The primary measure is the share of undevelopable land in a given MSA. Using GIS software and satellite imagery, Saiz (2010) measures the slope and elevation of every 90 square meter parcel of land within 50 kilometers of the centroid of the area and computes the fraction of the undevelopable land in each MSA. Since this fraction is computed purely based on geographical conditions, it should be relatively independent of changes in housing demand.

A secondary measure is the Wharton Residential Land Use Regulation Index (WRLURI) developed by Gyourko, Saiz, and Summers (2007). This index is constructed from data on state and local government policies. A higher value of the WRLURI indicates more stringent building restrictions. To the extent that new construction responds more slowly in markets with more stringent supply conditions, differences in these building restrictions across MSAs should reflect variation in the elasticity of housing supply.

Using the undevelopable land share, I generate a discrete measure of supply constraints that defines an MSA as 'more constrained' if the share exceeds 20% and 'less constrained' otherwise. Combining market growth indicators with this discrete constraint indicator, Table A1 in the appendices further divides sample MSAs into six categories: fast-growing and more constrained; fast-growing and less constrained; slow-growing and more constrained; slow-growing and less constrained; declining and more constrained; declining and less constrained. Using these categories allows me to empirically examine the risk-return relationship in a framework that jointly takes market growth and supply responses into account.

5 Empirical Evidence

5.1 Prediction 1: Financial Risk and Consumption Hedge Effects

The main prediction of the model is two simultaneous and opposite effects in the risk-return relationship for housing: the financial risk and consumption hedge effects. The relative strength of these two effects depends on local hedging incentives. To test this, I begin by estimating variants of the following model:

$$R_{it} = \delta_0 + \delta_1 R_{i,t-1} + \delta_2 X_{it} + \alpha RISK_{it} + \beta RISK_{it} \times HEDGE_{it} + m_i + \xi_t + u_{it} \tag{3}$$

where R_{it} is the expected housing return at market i in year t; $RISK_{it}$ is the expected house price risk at market i in year t; $HEDGE_{it}$ is a dummy variable that indicates whether market i is characterized by strong hedging incentives in year t; X_{it} is a vector of control variables that include population, income, population growth, income growth, and the hedge indicator; m_i is a market fixed effect; and ξ_t is a set of year dummies. Since housing returns and risk are likely to be serially correlated over time within a market, all standard errors are clustered at the MSA level. Given that the price risk term is constructed from separate regressions, the estimates of the asymptotic covariance matrix are also corrected using the bootstrap strategy.

The income and population variables account for major economic and demographic factors in housing markets, and are therefore included to control for the consumption demand for housing. In addition, since housing markets are highly inefficient in perfect asset market terms (Case and Shiller, 1989), the lagged housing return term is included to capture the potential inertia in house price movements.

Furthermore, by including MSA fixed effects, the model eliminates any permanent difference across MSAs, such as geographical constraints and local amenities. By including year dummies, the model absorbs unobserved time-varying macro shocks, such as changes in interest rates and in tax codes. To the extent that national housing returns matter for local housing markets, their effects would also be absorbed by year dummies.

The coefficients of interest are α and β. A finding of $\alpha > 0$ provides evidence for the basic financial risk hypothesis – higher expected return is required to compensate for higher risk. A finding of $\beta < 0$ is consistent with the consumption hedge hypothesis, since it indicates that the risk-return relationship is less positive in markets with stronger hedging incentives.

Identification of α and β relies on variation in the price risk and hedging incentives both over time and across markets. In particular, given the inclusion of the MSA and year fixed effects, identification of the financial risk effect comes from variation in the house price risk relative both to the average for a given MSA, and to the average for other MSAs at the same point of time. To the extent that the expected returns and risks are both driven by some prevailing economic conditions in an unspecified way, the estimate of the risk effect may be contaminated by a simultaneity problem. Following Pagan (1984), I use two lags of the price risk to instrument the price risk term in estimation equation (3). The resulting estimates thus provide valid inferences about the risk effects on expected returns. An alternative solution is to estimate a GARCH-in-mean model in which risk is not only simultaneously determined with returns but is also allowed to affect the expected returns directly. This approach is explored in Section 6.6 as an additional check.

Identification of the consumption hedge effect in the main analysis relies on the assumption that markets with weak hedging incentives form a valid counterfactual for markets with strong hedging incentives in evaluating the effects of price risk on housing returns. Given that the model has accounted for differences in observed time-varying factors and unobserved year and market fixed effects, this assumption is not unreasonable. Nevertheless, it is possible that some unobserved time-varying factors may induce a spurious correlation between the risk-return relationship and hedging incentives. To address these concerns, Sections 6.4 and 6.5 provide a set of checks that relax the exogeneity assumption on hedging incentives.

Estimates of equation (3) are reported in Table 3. For comparison purposes, column 1 presents the coefficients from a regression that does not include the interaction between risk and hedging incentives. This quantifies the average effect of price risk on expected returns. The result of this regression shows a negative and statistically significant relationship between risk and the expected housing return, which clearly contradicts with the conventional wisdom that high returns are needed to compensate for higher risk.

In column 2, the regression includes an interaction term of risk and hedging incentives, where the hedging variable is based on the within-MSA mobility measure. The entry for β quantifies the difference in the risk-return relationship between markets with strong hedging incentives and markets with weak hedging incentives. In this regression, the coefficient α is 0.11, while the coefficient β is -0.24 (both significant at the 1% level). Together, these coefficients indicate that a one-standard-deviation increase in price risk is associated with an increase of 0.16 percentage points in the expected return when local hedging incentives are weak, but a decrease of 0.19 percentage points in the expected return when hedging incentives are strong. The former accounts for a 24% *increase* over the sample mean of the return, while the latter accounts for about a 28% *decrease* from the sample mean. These effects provide strong support for the presence of the financial risk and consumption hedge effects.

Columns 3-4 repeat the estimation in columns 1-2, except that the hedging variable in column 4 is based on the cross-MSA hedging measure, and the underlying sample for column 3 is restricted to the sample where the cross-MSA hedging measure is available. This reduces the sample from $5,421$ to $1,097$ observations. In column 3 where the hedging incentive is not controlled, the estimated risk-return relationship is negative but only marginally significant. In column 4 where the the cross-market hedging incentive is controlled, the coefficient on α is 0.15 (with a t-stat. of 2.18), while the coefficient on β is -0.32 (with a t-stat. of -2.47). The estimated financial risk and hedging effects remain highly significant and economically substantial. In particular, in areas with strong hedging incentives, a one-standard-deviation increase in price risk reduces the expected return by 0.25 percentage points, which accounts for a 37% decrease from the sample mean. Note that these estimates cannot be compared with those in column 2, since the sample is now restricted to 41 largest MSAs and the hedging measure is different.[27]

Turning to other variables in these regressions, most of the estimates have the expected signs. For example, the coefficient on lagged returns is significantly positive across specifications. This is consistent with the previous studies that find inertia in housing prices (Case and Shiller, 1990). In addition, the coefficients on population and income growth are highly significant. The estimates in column 1 imply that, in the short run (reflected in the sum of coefficients on the level and growth), a one percent increase in population is translated to an over one percent increase in the housing return, while a ten percent increase in per capita income is associated with a three percent increase in the housing return. However, these effects tend to diminish in the long run, as reflected by level coefficients alone. These dynamic effects are consistent with the empirical observation that housing stock is fixed in the short run, but can respond to the rising demand over a longer term.

5.2 Prediction 2: Urban Growth Effect

The evidence so far lends support to the basic prediction from the model: the relative strength of the consumption hedge effect versus the financial risk effect increases with local households' hedging incentives. But if the cross-sectional variation in the sign and magnitude of the risk-return relationship is indeed explained by hedging incentives, there are several additional implications that one should see in the data.

[27] Among the 44 MSAs for which the cross-MSA hedging measure is available, there are 3 MSAs for which the AR(1)-GARCH(1,1) model does not converge. This explains why the estimation is restricted to 41 MSAs.

I now turn to testing three additional implications regarding geographical variation in the risk-return relationship.

Prediction 2 indicates that the consumption hedge effect should be strongly present only in markets where urban growth is sufficiently high, while the financial risk effect can be present anywhere. To test this prediction, I estimate models of the form

$$\begin{aligned} R_{it} \;=\;& \delta_0 + \delta_1 R_{i,t-1} + \delta_2 X_{it} + \alpha_1 RISK_{it} \times FAST_i + \alpha_2 RISK_{it} \times SLOW_i + \alpha_3 RISK_{it} \times DEC_i \\ & + \beta_1 RISK_{it} \times HEDGE_{it} \times FAST_i + \beta_2 RISK_{it} \times HEDGE_{it} \times SLOW_i \\ & + \beta_3 RISK_{it} \times HEDGE_{it} \times DEC_i + m_i + \xi_t + u_{it} \qquad (4) \end{aligned}$$

where $FAST_i$ is an indicator for whether MSA i is a fast-growing market; $SLOW_i$ is an indicator for whether MSA i is a slow-growing market; and DEC_i is an indicator for whether MSA i is a declining market. These indicators are constructed as in Section 4.3, and are available for about half of the areas covered in our sample. The control vector contains variables specified for equation (3) and the interactions of growth dummies with hedging incentives. The uninteracted urban growth effect is absorbed by market fixed effects. The estimation is instrumented by lagged price risk terms. Compared to the baseline model, this specification is less restrictive because it allows both the financial risk and consumption hedge effects to vary across market types. The coefficients of interest are those on the interactions of risk terms with growth dummies. If Prediction 2 holds, then we should expect that $\alpha_1 > 0$, $\alpha_2 > 0$ and $\alpha_3 > 0$; $\beta_1 < 0$, $\beta_2 \leq 0$, and $\beta_3 = 0$.

One reasonable concern related to including urban growth dummies in the housing return regressions is that the correlations may exist only because housing market conditions help shape the dynamics of future urban growth. This concern is relieved to some extent in our setting since the measure of urban growth variables does not vary over time. Moreover, even if one suspects that changes in housing returns are correlated with the urban market growth, there is no obvious reason that such changes would affect the interaction of urban growth and price risk, especially after accounting for market-fixed effects and other time-varying market conditions.

Table 4 indicates that the data are generally consistent with Prediction 2. Column 1 presents estimates based on the within-MSA hedging indicator. The coefficients on the interaction of price risk and growth dummies are significantly positive in fast-growing, slow-growing, and declining markets, indicating that the financial risk effect operates in all types of market. Turning to the coefficients on the hedging interaction terms, only the coefficient in fast-growing markets is significantly negative, indicating the presence of the consumption hedge effect in these markets. In contrast, the corresponding coefficients in slow-growing and declining market are both insignificant. Together, estimates in column 1 confirm the importance of urban market growth in explaining cross-market variation in the risk-return relationship for housing. Unlike fast-growing markets that are characterized by both the financial risk and consumption hedge effects, slow-growing and declining markets exhibit the financial risk effect only. These findings are consistent with Prediction 2.

Column 2 repeats the estimation of equation (4) but uses the cross-MSA hedging indicator. The estimates are largely in line with the estimates in column 1. The only exception is that the estimated coefficient on the price risk term for declining markets is no longer statistically significant, probably due to a much smaller set of observations within this category.

Looking at the risk estimates in Table 4, the analysis in Section 3.3 also suggests two additional testable implications. First, the financial risk effect in fast-growing, slow-growing, and declining markets should be equal in magnitude. This is because housing supply is perfectly inelastic with respect to downward demand shocks. A dominance of the financial risk effect puts downward pressure on housing demand. In this case, whether new construction is profitable and whether urban growth is high are irrelevant, and one should expect the magnitude of the financial risk effect to be the same across markets with different urban growth rates. This is tested by running the model with and without imposing $\alpha_1 = \alpha_2 = \alpha_3$. Asymptotically, the likelihood ratio under the null should follow a chi-square distribution with two degrees of freedom. The likelihood ratio test statistic based on estimates in column 1 is 2.72, with a p-value of 0.3356, indicating that the null hypotheses $\alpha_1 = \alpha_2 = \alpha_3$ cannot be rejected at the traditional 1, 5, or 10% levels. To gauge the magnitude of the difference in the financial risk effects, note that the estimates from column 1 imply that the largest difference in α's between any two types of market is 0.03 ($\alpha_1 = 0.09$, with a t-stat. of 2.71; $\alpha_3 = 0.12$, with a t-stat. of 1.73). I interpret this difference by referring to the implied difference in effects of a one-standard-deviation increase in risk on the expected return between declining and slow-growing markets, which is about 0.045% (0.03×0.0149). This constitutes less than 1% of one standard deviation of expected returns, suggesting that the estimated financial risk effects between slow-growing and declining markets (and hence between any two types of market) are indeed close in magnitude.

In contrast, the consumption hedge effect should depend crucially on whether urban growth is sufficiently high. In markets where economic conditions are deteriorating and urban population is not sufficient to justify new construction, future housing costs are less likely to be a concern for local households. As a result, one should expect the strength of the consumption hedge effect to be different between fast-growing markets and other markets. This is confirmed by the finding that β is statistically significant only in fast-growing markets. Furthermore, the likelihood ratio test statistic associated with the null hypotheses $\beta_1 = \beta_2 = \beta_3$ is 3.48 with a p-value of 0.0125, indicating that the null indeed can be rejected at the 2% level. For completeness, I also test the joint hypotheses $\alpha_1 = \alpha_2 = \alpha_3$ and $\beta_1 = \beta_2 = \beta_3$. The likelihood ratio test rejects the joint hypotheses at 1% level, further confirming the importance of urban market growth in explaining the cross-market variation in the risk-return relationship. Column 2 shows that these results remain robust when we use the cross-market hedging indicators instead.

5.3 Prediction 3: Supply Constraint Effect

The baseline specification (equation 3) implicitly restricts the estimated risk-return relationship to be the same across markets with different supply constraints. However, Prediction 3 indicates that the consumption hedge effect should be stronger in markets with more stringent supply conditions. In these markets, new construction is slow to catch up with housing demand; consequently, a positive hedging demand shock will translate mostly into price effects, rather than quantity effects. To test this prediction, I estimate models of the form

$$\begin{aligned} R_{it} &= \alpha RISK_{it} + \beta RISK_{it} \times HEDGE_{it} + \gamma RISK_{it} \times HEDGE_{it} \times CONSTRAINT_i \\ &\quad + \delta_0 + \delta_1 R_{i,t-1} + \delta_2 X_{it} + m_i + \xi_t + u_{it} \end{aligned} \tag{5}$$

where $CONSTRAINT_i$ is an index for housing supply elasticity in MSA i — a higher value of $CONSTRAINT_i$ indicates more stringent housing supply conditions. The control vector X_{it} contains variables specified for equation (3) and the interaction between the hedging indicator and the constraint index. Note that the supply-constraint term alone is indistinguishable from unobserved MSA heterogeneity. As before, the estimation is instrumented by lagged price risk terms.

Here the coefficient of interest is the coefficient on the triple interaction, γ, which is predicted to be negative in the presence of supply-constraint effects. Unlike equation (3), this model's focus is not on comparing markets with strong and weak hedging incentives. Rather, for a given level of hedging incentives, this model tests whether the strength of the consumption hedge effect is systematically associated with the elasticity of housing supply. To illustrate how γ is identified, consider two cities with different supply conditions, such as San Francisco and Atlanta. We first restrict our attention to San Francisco and compare the risk-return relationship in periods when hedging incentives are strong with the risk-return relationship in periods when hedging incentives are weak. Since the hedging indicator varies over time within the MSA, it is likely to generate variation in the estimated risk-return relationship. We then compare this difference with the similarly computed difference in Atlanta, where housing supply is much less constrained. The fact that house prices may be on average higher in San Francisco than in Atlanta is controlled for by including income and population, MSA fixed effects, and year dummies. Average differences in the risk-return relationship across periods with strong and weak hedging incentives and across markets with more and less constrained supply are controlled for using the uninteracted hedging indicator, its interaction with supply constraint, and market fixed effects. Thus the estimate of γ is identified by the variation in the interaction of time-varying hedging incentives and MSA-specific supply constraints.

Table 5 presents estimates of variants of equation (5). The first two columns present the estimates using the within-MSA hedging indicator. In column 1, the supply constraint variable is based on the the undevelopable land share developed by Saiz (2010). The coefficient on the house price risk term alone is 0.12 (with a t-stat. of 2.18), confirming the presence of the financial risk effect. The coefficient on the interaction term between risk and hedging incentives is -0.09 (with a t-stat. of -1.37), suggesting that the consumption hedge effect does not appear to be significant when housing supply is considered the least constrained by land scarcity. The key coefficient on the triple interaction term, γ, is -0.96 (with a t-stat. of -4.01). This implies that in areas with strong hedging incentives, everything else equal, a one-percentage-point increase in risk is associated with a reduction of the required return by five percent points, when we move from an MSA at the 10th percentile of the undevelopable land share (e.g., Omaha, NE-IA) to an MSA at the 90th percentile (e.g., Oakland, CA). Thus, the hedging effect increases with the supply constraint in a significant and substantial way, consistent with Prediction 3.

Column 2 repeats the estimation in Column 1 but uses the Wharton Residential Land Use Regulation Index. The remaining two columns of Table 5 present estimates based on the cross-MSA hedging indicator, with the supply constraint measured by the unbuildable land share in Column 3, and by the Wharton Residential Land Use Regulation Index in Column 4. Across all specifications, we see a familiar pattern: the coefficient on the risk term alone is significantly positive; the coefficient on the interaction term between hedging and risk is insignificant; the key coefficient on the triple interaction term is strongly negative and statistically significant. Together, these results are highly consistent with the results in column 1, providing further support for Prediction 3.

For completeness, I also fit a specification where the price risk term is interacted with the supply constraint directly. The estimated coefficient on this interaction is small and statistically insignificant, consistent with the model's implication that, unlike the consumption hedge effect, the financial risk effect is independent of supply constraints given the durable nature of housing.

5.4 Prediction 4: Joint Effects of Hedging, Growth, and Supply

The estimation so far has suggested that there are three distinct sources of geographical variation in the risk-return relationship for housing: hedging incentives, market growth, and supply constraints. Prediction 4 indicates that these three sources of geographical variation are not independent of each other. Rather, the strengthening impact of supply constraints on the hedging effect appears only in markets where urban growth is sufficiently high and new construction is profitable. To test this prediction, I now repeat the estimation in equation (5) but allow all the risk terms – the risk term alone, and its interactions with hedge indicator and supply measures – to be interacted with market growth dummies. The effects of supply measures, market growth dummies, and their interactions are absorbed by market fixed effects. Compared with the previous specifications, this specification is more comprehensive because it allows geographical variation in the risk-return relationship both within markets of a given growth type and across markets of different growth types.

To see how the model is identified, one can make use of the fact that price risk and hedging incentives vary over time within each MSA and that the degree of supply constraint varies within each market growth type. More specifically, I group all MSAs into different categories, with each category jointly defined by supply constraints and market growth types. Since price risk and hedging incentives vary over time within *and* across MSAs in each category, I can include MSA fixed effects and year dummies and still identify the coefficient on the interaction terms.[28]

Column 1 in Table 6 presents the estimates based on the within-MSA hedging indicator and the share of undevelopable land. As before, I find that, in all types of markets, the coefficients on the risk term alone are positive and statistically significant, and that the coefficients on the interaction term between hedging and price risk are statistically insignificant. A new finding that emerges from this specification is that the coefficients on the supply constraint interaction terms are significantly negative only in fast-growing markets. This indicates that the supply constraint enters the risk-return relationship and strengthens the consumption hedge effect only when the population growth is high relative to existing housing stock and

[28] This strategy would not work if the specification were based on the cross-MSA hedging measure, which is available for only 41 MSAs. In this case, there is not enough cross-MSA variation in supply constraints for declining markets.

new construction is profitable. These results remain robust when we move to Column 2, where supply constraints are measured by the WRLURI indices.

Column 3 repeats the estimation in column 1, but uses a discrete measure of supply constraints defined at the end of Section 4.4. The resulting estimates allow me to disentangle and quantify the degree of financial risk and consumption hedge effects in different categories of fast-growing markets. Consider two fast-growing markets, identical except for the fact that the first is more supply constrained (e.g., San Francisco) and the second is not (e.g., Atlanta). What happens if there is a one-standard-deviation increase in price risk? The top panel estimates in Column 3 imply that this would *increase* the expected return by 37% from its sample mean in markets where hedging incentives are weak. However, in markets where hedging incentives are strong, the same one-standard-deviation increase in price risk would *increase* the expected return by only 13% from its sample mean if markets are less constrained; and *decrease* the return by 59% from its sample mean if markets are more constrained.

In conclusion, the evidence in Tables 6 reveals three important and interacting sources of geographical variation in the risk-return relationship for housing. First, in markets where households have strong incentives to use their current home to hedge against future housing consumption risk, less financial return is required to compensate for price risk. Second, such hedging effect is strong only in fast-growing markets where urban growth is sufficiently high. Third, among fast-growing markets, the strength of the hedging effect increases with the degree to which housing supply is constrained.

6 Robustness Checks

6.1 Sensitivity to Alternative Samples

The results from Section 5 are based on a 1980-2007 sample. One reasonable concern is that this sample includes 2001-2007 data, and this period could be unusual due to significant changes in credit standards and unrealistic expectations of housing capital gains (Gabriel and Rosenthal, 2011). To the extent that these factors cannot be fully captured by year dummies combined with market fixed effects, one may suspect that the estimated risk-return relationship would be biased.

Two pieces of evidence suggest that in practice these factors are not significant sources of bias. First, I re-estimate all the models in Tables 3-5 by restricting the sample to 1980-2000. Innovations in mortgage instruments and over-optimism regarding housing appreciations, while also present before 2001, do not appear to be primary drivers for housing demand. For example, using data from the 1983 to 2001 Survey of Consumer Finance, Gabriel and Rosenthal (2005) show that the increase in homeownership in the 1990s was driven primarily by household demographic factors that had little to do with innovations in mortgage finance. Thus, a focus on the pre-2001 period allows us to avoid the special circumstances present in the recent decade.

The top panel of Table 7 reports the results from the baseline estimation for the 1980-2000 sample. Columns 1-2 use the within-market and cross-market hedging indicators, respectively. Here we see the familiar pattern of point estimates – a positive point estimate on the price risk term alone and a negative estimate on the interaction of hedging incentives and price risk (all significant at the 10% level or lower).

The top panel of Table 8 reports the results from the urban growth regressions for the 1980-2000 sample. In column 1 where the within-market hedging indicator is used, the coefficients on the risk terms alone are positive and statistically consistent in all types of markets, while the estimated hedging effect is significantly negative only in fast-growing markets. In column 2 where the cross-market hedging indicator is used, the financial risk estimates remain strong and significant in the fast- and slow-growing markets, and the estimated hedging effect is economically strong and statistically significant only in fast-growing markets, despite a much smaller sample. The results are largely consistent with Prediction 2.

Finally, the top panel of Table 9 presents the estimates of supply constraint effects for the 1980-2000 sample. Similar to Table 5, I have experimented with different measures of supply constraints (the undevelopable land share in columns 1 and 3, and the WRLURI in columns 2 and 4) and different measures of hedging incentives (the within-market indicator in columns 1 and 2, and the cross-market indicator in columns 3 and 4). Across all specifications, the basic pattern is again consistent with Prediction 3: the financial risk effect always dominates the risk-return relationship in markets with weak hedging incentives; the consumption hedge effect is negligible in markets that are considered the least supply constrained, but increases substantially with the degree to which supply is constrained.

As an additional way to address the concerns associated with the rapid credit expansion and overly-optimistic expectations that occurred during the recent housing "bubble," I repeat the main estimation by restricting the sample to areas that are considered to have experienced less dramatic house price changes during the 2000s. As shown in Haughwout, Lee, Tracy, and van der Klaauw (2011), while house prices were rising in many parts of the country over the period leading up to the crisis, these increases were particularly pronounced in four so-called "bubble" states – Arizona, California, Florida, and Nevada.[29]

[29] My use of the language of "bubble states" here follows strictly from Haughwout, Lee, Tracy, and van der Klaauw (2011). They show that in each of these four states, average house prices more than doubled between 2000-2006; after 2006, house prices declined rapidly in each of these four states with much of the earlier gains given back within just two years.

A focus on the metropolitan areas in "non-bubble" states allows us to examine whether the estimated hedging effect remains robust in the absence of "bubble" factors.

The bottom panels of Tables 7-9 present results based on the 1980-2007 sample excluding cities in the "bubble" states. Across all these tables, the predictions of the theory are again borne out – with weak hedging incentives, the financial risk effect is present in all types of markets; with strong hedging incentives, the consumption hedge effect is present only in fast-growing markets, and such effect increases with the degree of supply constraints.

Taken together, the evidence remains remarkably stable after removing from the sample the "bubble periods" or "bubble areas" for which the ease of credit access and over-optimism in expectations are often considered to be the most prevalent.[30] These findings reinforce the evidence about the hedging, urban growth, and supply constraint effects established in the main analysis.

6.2 Sensitivity to Alternative Price Indices

Estimates reported so far are based on the FHFA all-transaction price index, which includes data from both home purchases and refinancings. To the extent that the appraised home value used for refinancing purposes cannot truly reflect actual buyers' willingness to pay, the estimated risk-return relationship would mis-represent the actual risk premium or discount required by home buyers. Fortunately, FHFA also publishes a purchase-only index, which begins in 1991 and covers 25 metropolitan areas. To increase the number of observations in this small sample, I extend the sample period to 2010.

Table 10 reports results based on the FHFA purchase-only index. These estimates are necessarily less precise because they are based on smaller samples and therefore are not the main focus of the analysis. The first three columns control for within-market hedging incentives. Column 1 shows that the risk-return relationship is positive in markets with weak hedging incentives, but negative in markets with strong hedging incentives. Moreover, the strength of the negative hedging effect increases with land scarcity (column 2), and with the degree of zoning restrictions (column 3). Columns 4-6 report similar patterns when the cross-market hedging indicators are used. Together, the evidence here is again consistent with the main predictions.

[30]For completeness, I also repeat the main estimation for the sample between 1980-2010 — this is the longest window for which both the FHFA data and the Census data are available for most MSAs. As shown in Table A3 in the appendices, the evidence there is again consistent with the main predictions.

6.3 Alternative Expected Return and Risk Measures

Section 4.1 shows that the AR(1)-GARCH(1,1) measures of expected return and risk are both conceptually consistent and empirically suitable for the purpose of testing the risk-return relationship. Nevertheless, it is useful to discuss alternative return and risk measures and their suitability in the current analysis.

One natural approach to obtaining expectations of housing returns and risk is to conduct surveys to directly elicit information on households' expectations about future prices (Case and Shiller, 1988; 2003). However, conducting surveys for a national sample of households over time is extremely costly, making this approach infeasible for the analysis in this paper.

Previous studies of the housing risk-return relationship have often explicitly or implicitly used realized returns to proxy for expected returns (e.g., Crone and Voith, 1999). This approach is less suitable in our context because the theoretical model discussed in the paper requires expected and therefore *ex ante* measures of returns.

A more common way to measure expected returns and risk in the housing literature is to use the moving average and standard deviation of past returns. Following this convention, I measure the expected annual returns and risk as the moving mean and standard deviation of observed annual returns over a rolling window of the past 12 quarters. I then repeat the main estimation of the risk-return relationship. Table 11 reports the results. The patterns resemble those reported in Table 10. In all specifications, the direction of the estimates is consistent with the main predictions: a positive risk-return relationship in areas with weaker hedging incentives, a negative risk-return relationship in areas with stronger hedging incentives; and stronger hedging effects in more supply constrained areas. Together, these findings provide reassuring support for results from the main analysis.

While the moving average and standard deviation measures of returns and risk are intuitively appealing, they are limited in several ways. First, there is no clear guidance on how long this moving window should be. If it is too long, then it will not be so relevant for today; if it too short, the estimates will be very noisy. Second, the assumption of equal weights of past returns in a fixed window is unnecessarily restrictive. Finally, averaging over adjacent windows induces substantial serial correlation, leading to a potential bias in the estimated risk-return relationship. For these reasons, I present this analysis as a useful robustness check rather than adopting this approach as the preferred specification.

Finally, to examine whether the findings are robust to a different lag structure in the construction of return forecasts, I have also estimated an AR(2)-GARCH(1,1) model to generate expected returns and risk for each metropolitan area in each year. Based on these measures, I repeat the estimation of the risk-return relationship. The resulting estimates of the risk-return relationship, as reported in Table A4 in the appendices, do not differ qualitatively from the results as for the AR(1)-GARCH(1,1) measures. This is yet another piece of evidence for the robustness of the main findings of this paper.

6.4 Endogeneity of the Within-Market Hedging Indicator

The within-market hedging indicator is constructed based on local out-migration rates. Presumably, local out-migration rates are driven by changes in economic opportunity, which are often related to housing market conditions. Thus, one may question whether the within-market hedging variable is endogeous to the risk-return relationship analysis. More concretely, suppose that some areas are in the process of undergoing fundamental transitions. Such transitions are purported to have two distinct effects. First, strong economic growth encourages local households to stay locally. Second, in markets in the process of transition, households might forecast that a strong economy would be accompanied by high returns and low risk. If these two assertions are both correct, there would be a negative correlation between the probability that households stay within the same MSA and the estimated risk-return relationship, even if hedging incentives were absent.

To address this concern, one needs instrumental variables that generate exogenous variation in local households' out-migration rates but that are independent of housing returns and risks. I consider the following two candidates: the fraction of the population engaged in a licensed occupation and the fraction of company establishments engaged in a licensed business, both of which vary over time and across MSAs. Underlying this identification strategy is an empirical observation — occupational licensing directly affects approximately 16% of U.S. workers over the sample period. Pashigian (1979) and Kleiner, Gay, and Greene (1982) find that occupations that require state licenses significantly restrict licensees' cross-state geographical mobility. The licensees' geographical mobility is restricted not only because of license requirements, but also because of their strong ties to local markets through reputation, client networks, and professional expertise related to local markets. For these reasons, one would expect that cities with a larger fraction of licensed workers, such as lawyers, dentists, and real estate agents, have lower out-migration rates, and hence stronger hedging incentives. At the same time, conditional on local income, population, and other market characteristics, the fractions of licensed workers and establishments are unlikely to affect the risk-return relationship, making them suitable instruments.

Using the County Business Pattern from the U.S. Census, I compute the fraction of workers and the fraction of business establishments engaged in licensed occupations for each MSA for years between 1990-2007.[31] Table 12 displays the results of the IV estimation. Column 1 controls for both price risk and within-market hedging incentives. The IV-estimated coefficient on the risk term alone is 0.11, and the IV-estimated coefficient on the hedging interaction term is -0.38. Both estimates are statistically significant at the 10% level or lower. Column 2 adds an additional interaction term among the Wharton regulation indices, hedging incentives, and price risk. The IV-estimates of financial risk, consumption hedge, and supply constraint effects are again consistent with what we expected. Thus the null hypothesis that the hedging effect is due to a spurious correlation between out-migration rates and the risk-return relationship can be rejected.

6.5 Endogeneity of the Cross-Market Hedging Indicator

The main empirical section also establishes that the risk-return relationship is less positive in markets where households are more likely to move to other correlated MSAs. One potential concern is that households do not move randomly. For example, Sinai and Souleles (2008) argue that shocks that induce the correlation in house prices also induce labor market flows. This is because households often move among cities that are similar in amenities, industry structure, and demographics. The similarity in these market fundamentals further leads to a correlation in house prices among these cities. Some of these market fundamentals are not fully controlled for in the current specification, and might bias the estimate on the uninteracted hedging indicator term. However, there are no obvious reasons to expect that this type of move would affect the coefficient on the interaction of hedging and price risk in equation 3.

Another argument for non-random cross-market moves is that households may choose to move among markets that are correlated in house prices simply because they are constrained to move to where they can afford to move. This is again consistent with the idea that the current home purchase serves as a hedge, especially for those who are concerned about being 'priced out of the market' in the future. In this case, we should still expect that households require less return to compensate for price risk in markets that are highly correlated with their subsequent markets.

Nevertheless, to the extent that the cross-market migration flows are driven by house price differences (Saks, 2008) or productivity differences (Van Nieuwerburgh and Weil, 2010), and to the extent that these

[31] Kleiner, Gay, and Greene (1982) measure the effects on migration patterns of state or local occupational licensing. They consider 14 universally licensed occupations: accountants, architects, engineers, lawyers, dentists, pharmacists, physicians, surveyors, insurance agents, real estate agents, registered nurses, practical nurses, barbers, and cosmetologists. In this paper, I consider an occupation as licensed if it belongs to one of categories specified above.

differences are related to the risk-return relationship in some unspecified way, it would be ideal to have some exogenous predictors of the cross-market hedging indicator that is independent of the price correlation across markets. Sinai and Souleles (2008) provide a way that helps to address this problem. They show that, in the expected price correlation they computed (which I used to construct the cross-market hedging indicator), the propensity to move among highly correlated markets is not driven by relative house price changes in these markets. In particular, they re-compute the cross-MSA moving weights by explicitly setting the difference between any two MSAs in annual house price growth over the prior year to zero. The resulting adjusted expected cross-MSA price correlation is consistent with the original price correlation both in magnitude and in distribution. This provides reassuring support for using the expected price correlation to control for the cross-market hedging incentives. In particular, we can confirm that the estimated consumption hedge effect is not due to a spurious relationship that runs from cross-market price differences to cross-market moves.

6.6 GARCH-in-Mean Model

In the main analysis, I employ a two-step estimation procedure: the first to estimate the expected return and risk and the second to estimate the risk-return relationship. One concern with the two-step approach is that estimates are consistent but less efficient. More importantly, even the most flexible specification in Section 5.4 implicitly restricts the estimated risk-return relationship to be the same across all MSAs of the same type. Given the local nature of housing markets, one may question whether this restriction is too strong. In this subsection, I address these two concerns by separately estimating the GARCH-in-mean model (Engle, Lilien, and Robins, 1987; Bollerslev, Engle, and Wooldridge, 1988) for each MSA. The advantage of the GARCH-in-mean model over the two-step estimation is that housing returns and risk are estimated simultaneously in a consistent framework in which the conditional variance is directly tied to expected returns. In addition, the two-step procedure will only yield valid inferences provided that an instrumental variable approach is employed (see Pagan, 1984), whereas GARCH-in-mean does not share this problem.

Specifically, for each metropolitan area, I estimate the quarterly real housing return $r_{i,t}$ and its conditional risk $\sigma^2_{i,t}$ as:

$$r_{i,t} = a_{i,0} + a_{i,1} r_{i,t-1} + \theta_i \sigma^2_{i,t} + u_{i,t} \quad (6)$$

$$\sigma^2_{i,t} = b_{i,0} + b_{i,1} u^2_{i,t-1} + \lambda_i \sigma^2_{i,t-1} \quad (7)$$

where $u_{i,t} \sim N(0, \sigma_{i,t}^2)$; $\sigma_{i,t}^2$ is the variance of the error term $u_{i,t}$, conditioned on information available at time $t-1$. The lagged housing return term in equation (6) captures possible inefficiencies in the housing markets. In order to accommodate a relatively short time series in each market, I choose a parsimonious specification in which all other time-varying factors that could possibly affect housing returns are captured by the residual term u_{it}.

The maximum likelihood estimates of the model (6) and (7) are obtained for 135 MSAs between 1990-2007.[32] The key parameter, θ_i, permits a natural test for the risk-return relationship within each MSA. Areas like Sioux City exhibit a strongly positive risk-return relationship ($\theta_i = 78.72$ with a s.e. of 32.38). Conversely, areas like Providence-Fall River-Warwick exhibit a strongly negative risk-return relationship ($\theta_i = -63.81$ with a s.e. of 20.05). Note that the out-migration rates are 0.21 and 0.11 in these two cities, respectively. Together, the evidence is consistent with the hypotheses that households in Providence-Fall River-Warwick have stronger hedging incentives and that stronger hedging incentives help weaken or even reverse the positive risk-return relationship for housing. To see if this pattern systematically holds in the data, I match the MSA-specific GARCH-in-mean estimates with the Census data in 1990 and estimate the following relationship:

$$\widehat{\theta_i} = \gamma_0 + \gamma_1 HEDGE_i + \gamma_2 X_i + \eta_i \tag{8}$$

where $\widehat{\theta_i}$ equals the estimated θ_i if the estimated value is statistically significant at the 5% level, and 0 otherwise. $HEDGE_i$ is the hedging indicator based on the 1990 within-MSA measure. In addition, the control vector X_i includes population, income and their growth rates in 1990. I restrict the sample to the MSAs that are categorized as 'fast-growing' markets. The estimated γ_1 is -25.84 with a standard error of 13.42. Thus, stronger hedging incentives are associated with a smaller θ_i, consistent with the most basic prediction of the model.

While the GARCH-in-mean specification presents a natural fit for estimating the relative strength of the financial risk effect versus the consumption hedge effect, it is limited by the data in several ways. First, the small sample size prevents me from testing other key components of the risk-return relationship, such as supply constraints.[33] In addition, the relatively short time series restricts the within-market analysis to a quarterly frequency, rather than at the annual frequency as in the main analysis. The latter is more consistent with households' expected housing transaction horizon given the durable nature of housing. For

[32] To conserve space, the estimates for each individual MSA are not reported but are available from the author upon request. See footnote 20 for an explanation for the non-convergence in some MSAs.

[33] Matching converged GARCH-in-mean estimates with supply data reduces the sample size down to 40, which is not sufficient for testing supply constraint effects.

these reasons, the GARCH-in-mean model is presented as a specification check rather than the main focus of the analysis.

7 Conclusion

While financial economists have long been interested in the risk-return relationship for stocks, there have been little examination of the risk-return relationship for housing. In this paper, I show that the dual financial-asset/consumption-hedge role of housing, coupled with the impact of urban growth and housing supply, makes the analysis of risk and return quite different for housing than for other assets.

Examination of MSA-level housing market data reveals several important patterns in the risk-return relationship for housing. First, I find evidence in support of the hypothesis that in markets where households have stronger incentives to use their current home purchase to hedge against future housing consumption risk, lower return is required to compensate for price risk. This explains why housing returns vary positively with risk in some markets, but negatively in others. Furthermore, since housing stock can be added in response to rising demand but disappears slowly through depreciation, regulatory and geographical constraints on housing supply should strengthen the consumption hedge effect but not affect the financial risk effect. My finding of a stronger consumption hedge effect in more supply-constrained markets is consistent with this. Finally, I find that the financial risk effect, consumption hedge effect, and the associated supply constraint effect are simultaneously present only in markets where urban growth is sufficiently high to justify new construction. In other markets, only the financial risk effect remains strong. These results suggest that a thorough understanding of the risk-return relationship for housing requires an equilibrium framework in which house prices and quantities are jointly determined.

Table 1: Summary Statistics of Expected Housing Return and Risk[a]

	expected return (%)					*risk forecast* (%)				
	mean	s.d.	p10	p50	p90	mean	s.d.	p10	p50	p90
1980	-0.90	5.22	-6.66	-1.20	6.55	3.74	1.21	2.54	3.49	5.24
1981	-3.50	4.96	-9.71	-3.18	3.16	4.32	1.86	2.42	3.79	6.61
1982	-1.48	5.95	-7.65	-1.90	6.66	5.12	3.10	2.63	4.12	9.00
1983	-0.51	5.61	-6.22	-1.18	5.39	5.34	3.11	2.70	4.29	9.33
1984	-2.66	5.53	-9.12	-3.08	4.55	5.32	2.89	2.82	4.44	8.76
1985	0.13	6.04	-6.96	-0.65	8.74	4.47	2.11	2.48	3.91	7.23
1986	3.30	6.10	-1.87	1.84	13.61	3.55	1.51	2.11	3.14	5.79
1987	2.07	6.36	-3.52	0.91	11.64	3.43	1.17	2.31	3.18	4.81
1988	-0.98	5.72	-8.12	-1.06	6.79	3.21	1.09	2.16	2.88	4.62
1989	-1.99	5.19	-7.30	-2.55	3.09	3.49	1.43	2.25	3.16	5.06
1990	-1.86	4.80	-6.70	-2.57	3.87	3.67	1.46	2.40	3.33	5.45
1991	-3.70	4.18	-8.63	-3.54	0.64	3.27	1.11	2.31	2.97	4.78
1992	-0.41	2.28	-3.43	-0.25	1.76	2.87	0.77	2.13	2.70	3.72
1993	-1.49	2.85	-5.46	-1.10	1.33	2.62	0.63	2.01	2.54	3.37
1994	0.65	3.08	-2.90	0.61	4.16	2.35	0.63	1.70	2.25	3.06
1995	-1.56	4.08	-7.12	-0.75	3.05	2.50	0.70	1.76	2.41	3.31
1996	1.51	1.69	-0.53	1.52	3.49	2.39	0.72	1.68	2.28	3.21
1997	-0.95	2.29	-3.81	-0.71	1.92	2.27	0.69	1.50	2.18	3.14
1998	3.31	1.72	1.40	3.25	5.33	2.19	0.65	1.45	2.12	2.95
1999	1.73	2.04	-0.42	1.37	4.00	2.12	0.67	1.33	2.03	2.98
2000	0.05	3.82	-3.58	-0.95	4.67	2.25	0.68	1.56	2.17	3.09
2001	2.68	3.38	0.01	1.61	6.73	2.12	0.65	1.44	2.02	3.00
2002	4.88	3.35	1.83	3.73	10.67	2.14	0.61	1.51	2.06	2.94
2003	2.28	3.25	-0.41	1.00	7.43	2.05	0.57	1.45	1.95	2.74
2004	3.50	4.01	0.06	1.69	9.93	2.11	0.61	1.46	2.00	2.83
2005	3.87	6.63	-1.89	1.05	16.75	2.32	0.72	1.55	2.19	3.30
2006	3.82	6.13	-1.84	1.46	14.37	2.43	0.74	1.61	2.28	3.45
2007	1.48	3.64	-3.61	1.30	5.79	2.54	0.89	1.59	2.29	3.79

[a]Data Source: Federal Housing Finance Agency (FHFA) all-transaction house price indices. To proxy expected returns and risk, I estimate an AR(1)-GARCH(1,1) model based on quarterly observations of real annual FHFA housing returns for each metropolitan area. Before the estimation, I winsorize the FHFA real annual returns at the 1% and 99% levels to remove the influence of outliers. The estimates generate conditional forecasts of annual housing return and variance: the former is taken as the expected housing return, while the square root of the latter is taken as price risk.

Table 2: Summary Statistics of Hedging Incentives[a]

Variable	mean	s.d.	min.	max.
within-MSA hedging indicator	0.63	0.48	0	1
cross-MSA hedging indicator	0.44	0.50	0	1
fraction of population 20-45	0.38	0.04	0.20	0.56
fraction of population staying within-MSA	0.84	0.04	0.61	0.97

[a]The hedging indicator is a dummy variable that equals 1 if households at a given MSA in a given year have strong hedging incentives, and 0 otherwise. See Section 4.2 for how the within-MSA and cross-MSA hedging indicators are constructed.

Table 3: Financial Risk and Consumption Hedge Effects on Expected Returns (1980-2007)[a]

Variable	1	2	3	4
risk	-0.05^{*}	0.11^{***}	-0.08^{*}	0.15^{**}
	(-1.81)	(2.92)	(-1.68)	(2.18)
risk × hedge		-0.24^{***}		-0.32^{**}
		(-2.73)		(-2.47)
lagged return	0.41^{***}	0.41^{***}	0.46^{***}	0.46^{***}
	(16.50)	(16.55)	(9.97)	(9.67)
population growth	1.15^{***}	1.15^{***}	1.59^{***}	1.60^{***}
	(7.40)	(7.42)	(6.39)	(6.51)
income growth	0.33^{***}	0.33^{***}	0.55^{***}	0.55^{***}
	(12.11)	(12.19)	(7.46)	(7.58)
population size	0.06^{***}	0.06^{***}	0.06^{***}	0.06^{***}
	(5.54)	(5.12)	(2.99)	(3.23)
income level	-0.03	-0.03	-0.05	-0.04
	(-1.30)	(-1.64)	(-1.06)	(-0.86)
hedge		-0.0013		-0.0065
		(-0.47)		(-0.55)
hedge measure		within-market		cross-markets
N	5421	5421	1097	1097

[a]The dependent variable is the expected return. The risk terms are instrumented by lagged risk terms. Columns 1 and 2 are restricted to the sample for which the within-market hedging incentives are available, while columns 3 and 4 are restricted to the sample for which the cross-markets hedging incentives are available. All specifications include MSA fixed effects and year dummies. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 4: Urban Growth Effects on the Risk-Return Relationship (1980-2007)[a]

Variable	1	2
risk × fast	0.09***	0.13*
	(2.71)	(1.82)
risk × slow	0.11**	0.09*
	(1.98)	(1.85)
risk × decline	0.12*	0.15
	(1.73)	(1.32)
risk × hedge × fast	−0.20**	−0.37*
	(−2.40)	(−1.73)
risk × hedge × slow	0.06	0.11
	(0.87)	(0.34)
risk × hedge × decline	−0.11	−0.21
	(−0.75)	(−0.73)
hedging measure	within-market	cross-markets
N	2577	1013
	Likelihood Ratio Test	
$\alpha_1 = \alpha_2 = \alpha_3$	2.72	0.48
(p-val)	(0.3356)	(0.6372)
$\beta_1 = \beta_2 = \beta_3$	3.48	1.52
(p-val)	(0.0125)	(0.0273)
$\alpha_1 = \alpha_2 = \alpha_3$, $\beta_2 = \beta_2 = \beta_3$	4.89	3.85
(p-val)	(0.0008)	(0.0108)

[a]This table reports the estimates of the risk-return relationship controlling for cross-market differences in urban growth. The dependent variable is the expected return. Hedging incentives are based on the within-MSA measure in column 1 and based on the cross-MSA measure in column 2. The risk terms are instrumented by lagged risk terms. All specifications include control variables specified in Table 3, the interactions of growth dummies with hedging incentives, MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 5: Supply Constraint Effects on the Risk-Return Relationship (1980-2007)[a]

Variable	1	2	3	4
risk	0.12^{**}	0.07^{**}	0.12^{*}	0.13^{*}
	(2.18)	(1.98)	(1.75)	(1.69)
risk $\times$ hedge	-0.09	0.01	0.15	-0.13
	(-1.37)	(1.25)	(1.14)	(-0.52)
risk $\times$ hedge $\times$ constraint	-0.96^{***}	-0.58^{*}	-1.62^{*}	-0.64^{**}
	(-4.01)	(-1.76)	(-1.90)	(-2.38)
hedging measure	within-market	within-market	cross-markets	cross-markets
supply constraint	undeveloped land	WRLRUI	undeveloped land	WRLRUI
N	4751	4751	1072	1072

[a]This table reports the estimates of the risk-return relationship controlling for cross-market differences in supply constraints. The dependent variable is the expected return. Hedging incentives are based on the within-MSA measure in columns 1-2 and based on the cross-MSA measure in columns 3-4. The supply constraints are measured by undevelopable land share in columns 1 and 3, and by the WRLRUI in columns 2 and 4. The risk terms are instrumented by lagged risk terms. All specifications include control variables specified in Table 3, the interactions of supply constraints with hedging incentives, MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 6: Joint Effects of Hedging, Growth, and Supply on the Risk-Return Relationship (1980-2007)[a]

Variable	1	2	3
		fast-growing markets	
risk	0.17*	0.15**	0.17*
	(1.94)	(1.98)	(1.68)
risk × hedge	−0.06	0.07	−0.11*
	(−0.58)	(0.02)	(−1.75)
risk × hedge × constraint	−0.86***	−0.62*	−0.33***
	(−2.76)	(−1.79)	(−3.02)
		slow-growing markets	
risk	0.19*	0.11*	0.19*
	(1.89)	(1.68)	(1.72)
risk × hedge	−0.04	−0.20	0.10
	(−1.14)	(−1.45)	(0.88)
risk × hedge × constraint	0.16	−0.22	0.23
	(1.45)	(−0.89)	(0.42)
		declining markets	
risk	0.18*	0.17*	0.20*
	(1.72)	(1.72)	(1.81)
risk × hedge	0.52	−0.21	0.15
	(0.35)	(0.65)	(0.42)
risk × hedge × constraint	−1.51	−0.23	−0.17
	(−0.82)	(−0.64)	(−0.85)
hedging measure	within-market	within-market	within-market
supply constraint	undevelopable land	WRLURI	discrete land measure
N	2536	2536	2536

[a]This table reports the estimates of the risk-return relationship controlling for cross-market differences in both urban growth and supply constraints. The dependent variable is the expected return. The hedging incentives are based on the within-market measure. Supply constraints are measured by the undevelopable land share in column 1, the WRLRUI in column 2, and by a dummy variable based on the undevelopable land share in column 3. The risk terms are instrumented by lagged risk terms. All specifications include control variables specified in Table 3, the necessary interaction terms, MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7: Financial Risk and Consumption Hedge Effects on Expected Returns[a]

(Robustness Checks Based on Alternative Samples)

Variable	1	2
underlying sample	all markets, 1980-2000	
risk	0.10^{***}	0.12^{*}
	(2.64)	(1.91)
risk × hedge	-0.28^{***}	-0.32^{***}
	(−3.52)	(−2.89)
N	4053	844
underlying sample	"non-bubble" markets, 1980-2007	
risk	0.08^{*}	0.10^{*}
	(1.81)	(1.70)
risk × hedge	-0.21^{***}	-0.27^{**}
	(−3.15)	(−1.86)
N	4866	838
hedging measure	within-market	cross-markets

[a]This table repeats the baseline regressions in columns 2 and 4 of Table 3 for alternative samples. The top panel is based on all markets from the 1980-2000 period; the bottom panel is based on "non-bubble" markets (as categorized in Haughwout, Lee, Tracy, and van der Klaauw, 2011) from the 1980-2007 period. The dependent variable is the expected return. The risk terms are instrumented by lagged risk terms. Hedging incentives are based on the within-MSA measure in column 1 and based on the cross-MSA measure in column 2. All specifications include MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 8: Urban Growth Effects on the Risk-Return Relationship[a]

(Robustness Checks Based on Alternative Samples)

Variable	1	2
underlying sample	all markets, 1980-2000	
risk × fast	0.09^{*}	0.12^{**}
	(1.78)	(2.01)
risk × slow	0.07^{**}	0.10^{*}
	(2.12)	(1.76)
risk × decline	0.08^{*}	0.09
	(1.69)	(1.58)
risk × hedge × fast	-0.18^{***}	-0.32^{***}
	(−3.21)	(−2.63)
risk × hedge × slow	0.15	−0.15
	(0.92)	(−1.21)
risk × hedge × decline	−0.12	0.11
	(−1.33)	(0.32)
N	1992	781
underlying sample	"non-bubble" markets, 1980-2007	
risk × fast	0.12^{**}	0.17^{*}
	(2.01)	(1.86)
risk × slow	0.14^{**}	0.18^{*}
	(1.98)	(1.92)
risk × decline	0.15^{*}	0.20
	(1.78)	(1.62)
risk × hedge × fast	-0.25^{***}	-0.34^{**}
	(−2.56)	(−1.98)
risk × hedge × slow	0.08	−0.12
	(1.27)	(−0.79)
risk × hedge × decline	0.15	0.47
	(0.45)	(0.53)
N	2347	832
hedging measure	within-market	cross-markets

[a]This table repeats the estimation of urban growth effects on the risk-return relationship in Table 4 for alternative samples. The top panel is based on all markets from the 1980-2000 period; the bottom panel is based on "non-bubble" markets (as categorized in Haughwout, Lee, Tracy, and van der Klaauw, 2011) from the 1980-2007 period. The dependent variable is the expected return. Hedging incentives are based on the within-MSA measure in column 1 and based on the cross-MSA measure in column 2. The risk terms are instrumented by lagged risk terms. All specifications include MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 9: Supply Constraint Effects on the Risk-Return Relationship[a]

(Robustness Checks Based on Alternative Samples)

Variable	1	2	3	4
underlying sample	all markets, 1980-2000			
risk	0.15*	0.10**	0.14*	0.12*
	(1.92)	(2.05)	(1.75)	(1.70)
risk × hedge	−0.05	0.07	0.15	−0.21
	(−1.27)	(1.32)	(1.32)	(−0.81)
risk × hedge × constraint	−0.87**	−0.45**	−0.78*	−0.43**
	(−2.32)	(−2.82)	(−1.82)	(−2.32)
N	3556	3556	823	823
underlying sample	"non-bubble" markets, 1980-2007			
risk	0.13*	0.09*	0.14*	0.10*
	(1.86)	(1.92)	(1.83)	(1.89)
risk × hedge	−0.08	0.02	−0.07	−0.08
	(−0.72)	(0.76)	(−0.57)	(−0.71)
risk × hedge × constraint	−0.78***	−0.35**	−1.42***	−0.56**
	(−3.21)	(−2.03)	(−3.12)	(−2.29)
N	4237	4237	838	838
hedging measure	within-market	within-market	cross-markets	cross-markets
supply constraint	undeveloped land	WRLRUI	undeveloped land	WRLRUI

[a]This table repeats the estimation of supply effects on the risk-return relationship in Table 5 for alternative samples. The top panel is based on all markets from the 1980-2000 period; the bottom panel is based on "non-bubble" markets (as categorized in Haughwout, Lee, Tracy, and van der Klaauw, 2011) from the 1980-2007 period. The dependent variable is the expected return. Hedging incentives are based on the within-MSA measure in columns 1-2 and based on the cross-MSA measure in columns 3-4. The supply constraints are measured by undevelopable land share in columns 1 and 3, and by the WRLRUI in columns 2 and 4. The risk terms are instrumented by lagged risk terms. All specifications include MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 10: Hedging and Supply Effects on the Risk-Return Relationship[a]

(Robustness Checks based on FHFA Purchase-Only Price Indices)

Variable	1	2	3	4	5	6
risk	0.42^{*}	0.76	0.82^{*}	0.30^{*}	0.32	0.34
	(1.69)	(1.54)	(1.68)	(1.98)	(1.51)	(1.26)
risk × hedge	-0.67^{*}	-0.48	-1.16	-1.05	-0.18	0.35
	(-1.78)	(-1.63)	(-1.08)	(-1.43)	(-1.35)	(0.89)
risk × hedge × constraint		-1.68^{*}	-0.49^{**}		-0.82^{**}	-0.67^{*}
		(-1.92)	(-2.01)		(-1.97)	(-1.73)
N	311	311	311	317	317	317
hedging measure	within -market	within -market	within -market	cross -markets	cross -markets	cross -markets
supply constraint		undev. land	WRLURI		undev. land	WRLURI

[a]This table repeats the estimation of hedging and supply effects on the risk-return relationship in Tables 3 and 5 using the FHFA purchase-only house price indices between 1990-2010. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 11: Hedging and Supply Effects on the Risk-Return Relationship[a]

(Robustness Checks based on Alternative Housing Return and Risk Measures)

Variable	1	2	3	4	5	6
risk	0.24^{***}	0.27^{***}	0.19^{***}	0.25^{***}	0.37^{*}	0.31^{**}
	(4.21)	(3.85)	(2.78)	(3.13)	(1.82)	(1.98)
risk × hedge	-0.35^{***}	-0.05	-0.18	-0.47^{**}	-0.19	0.12
	(-5.29)	(-0.45)	(-0.95)	(-2.40)	(-0.11)	(0.53)
risk × hedge × constraint		-0.53^{***}	-0.46^{**}		-0.54^{**}	-0.61^{*}
		(-3.79)	(-2.19)		(-2.33)	(-1.89)
N	2185	2185	2185	570	570	570
hedging measure	within -market	within -market	within -market	cross -markets	cross -markets	cross -markets
supply constraint		undev. land	WRLURI		undev. land	WRLURI

[a]This table repeats the estimation of hedging and supply effects on the risk-return relationship in Tables 3 and 5 using alternative measures of housing returns and risks, which are constructed as the moving mean and standard deviation of real annual housing returns over a rolling window of the past 12 quarters. The sample period is 1990-2004. The t-statistics are adjusted for the intra-MSA correlation and reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

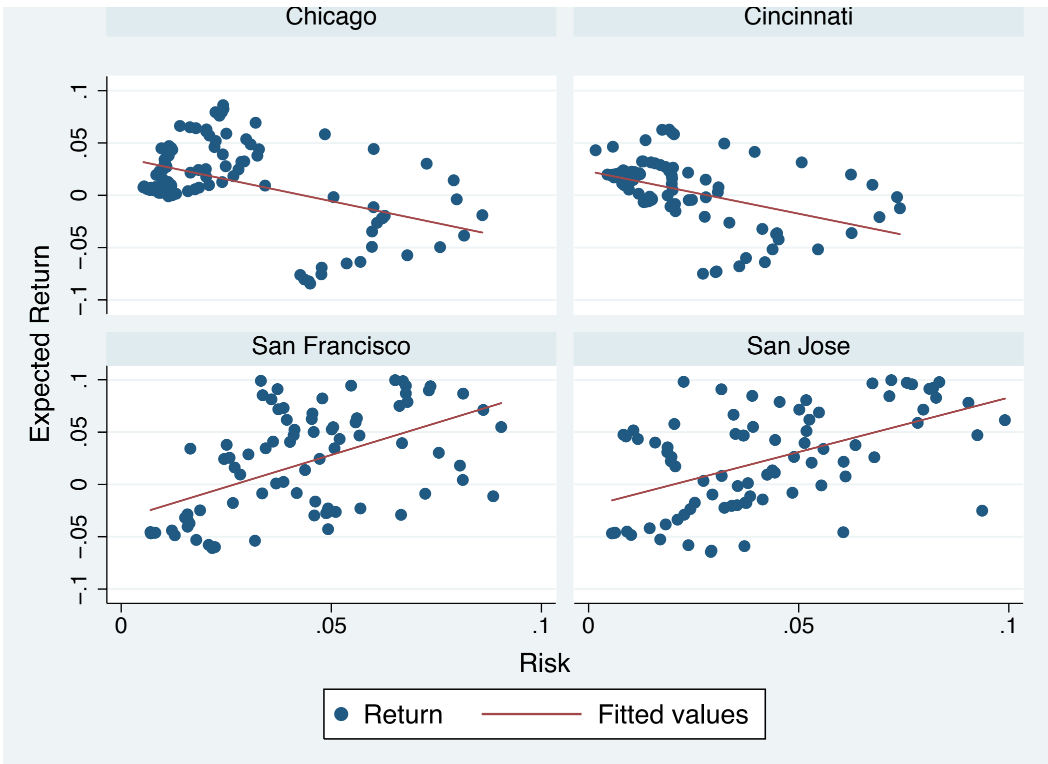
Table 12: Hedging and Supply Effects on the Risk-Return Relationship[a]

(Robustness Checks based on IV Regressions)

Variable	1	2
risk	0.11^{*}	0.13^{*}
	(1.87)	(1.89)
risk × hedge	-0.38^{**}	-0.12
	(-2.08)	(-1.48)
risk × hedge × constraint		-0.67^{**}
		(-1.98)
N	3657	3035
hedging measure	within-market	within-market
supply constraint		WRLRUI

[a]This table presents the IV estimation of hedging and supply effects on the risk-return relationship. The hedging terms are instrumented by the fraction of the population engaged in a licensed occupation and the fraction of licensed business. The risk terms are instrumented by lagged risk terms. All specifications include hedging term, population and income levels and their growth rates, lagged return term, MSA fixed effects and year dummies. To conserve space, I only report the coefficients on risk terms. The t-statistics are adjusted for the intra-MSA correlation and are reported in parentheses. $***$, $**$, and $*$ denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Figure 1: Correlation Between Housing Return and Risk



Source: House price data are obtained from the FHFA all-transaction HPI and are made real by deflating with net-of-shelter consumer price indices (CPIs) published by the Bureau of Labor Statistics. Expected housing return and risk are conditional forecasts generated by applying a GARCH(1,1) model to quarterly series of real annual housing returns within each MSA. The correlation coefficient is −0.83(0.16) in Chicago, −0.81(0.15) in Cincinnati, 0.85(0.23) in San Francisco, and 0.88(0.14) in San Jose. Standard errors are included in parentheses.

Figure 2: Housing Supply Function

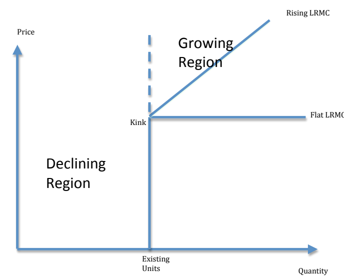


Figure 2.pdf

Figure 3: Stable Demand and Positive Depreciation

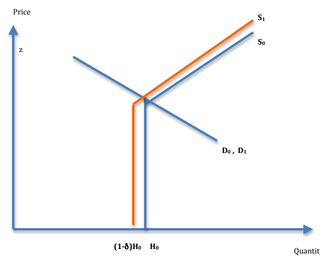


Figure 3.pdf

Figure 4: Demand Shift in Fast-Growing Region

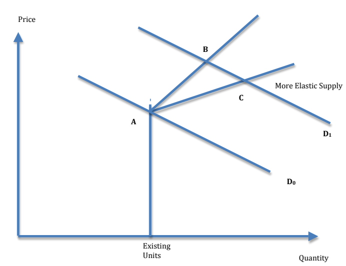


Figure 4.pdf

Figure 5: Demand Shift in Declining Region

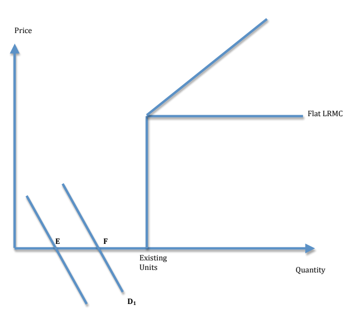


Figure 5.pdf

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