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Abstract

In this paper, we focus on the response of housing investment to uncertainty in housing returns and interest rates. At the aggregate level, we regress quarterly housing starts on the levels and rolling standard deviations of housing returns and Treasury bill rates. We find that housing starts decline with higher volatility in either of these state variables. We further explore these results using data on individuals from the American Housing Survey. We estimate the probability of observing major additions and improvements by individual homeowners, again finding that investment is less likely in the face of greater uncertainty about aggregate housing returns or interest rates. Our empirical results are consistent with the predictions of the theoretical literature on irreversible investment under uncertainty.

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1 Introduction

Surprisingly little empirical work has been directed at understanding the relationship between investment and uncertainty. In part, the dearth of empirical studies in this area reflects the ambiguity of the associated theoretical literature, with models emphasizing different channels through which uncertainty might affect investment, some predicting a positive relation and others a negative relation. The goal of this paper is to sign the investment-uncertainty relation for residential real estate, one of the largest components of private domestic investment and a class of investments where data on the values and timing of investments are readily available.[2]

Following Leahy and Whited (1996), it is useful as a starting point to classify theories of investment under uncertainty according to whether the marginal revenue product of capital is concave or convex in some random variable.[3] In general, if the marginal revenue product of capital is concave, then greater uncertainty depresses investment, while a convex marginal revenue product of capital function produces a positive investment-uncertainty relation. When investments are irreversible, the marginal revenue product of capital is concave in the face of aggregate shocks to demand or costs (Dixit and Pindyck (1994), Caballero and Pindyck (1996), Novy-Marx (2005), among others). Intuitively, if a negative aggregate shock is realized in the future, the marginal revenue product of capital falls because investors cannot redeploy the installed capital. On the other hand, if a positive shock is realized in the future, additional capital will be deployed, limiting the rise in the marginal revenue product of capital. Hence uncertainty increases downside risk but not upside gains, depressing irreversible investments as long as current and future investments are linked through decreasing returns to scale, downward sloping demand, a limit on investment, or through some other mechanism.[4] Idiosyncratic shocks also lead to reduced investment, but as shown by McDon-

[2]The prior empirical housing investment literature does not consider the effects of uncertainty in market fundamentals on investment—see, for example, Kearl (1979), Poterba (1984), Rosen and Topel (1988).

[3]See Dixit and Pindyck (1994) and Adda and Cooper (2003) for extensive overviews of the literature on investment under uncertainty.

[4]Abel (1983) shows that if technology is linearly homogeneous and demand is perfectly elastic, the link

ald and Siegel (1986), in this case greater uncertainty raises the value of waiting relative to the value of investing (as opposed to reducing the value of investing relative to not investing, as in the case of aggregate shocks).

Convex investment returns might be driven through a number of channels. Roberts and Weissman (1981) show that the option to abandon a project can deliver convex returns, and Stiglitz and Weiss (1981) emphasize that bankruptcy can limit downside risk, making uncertain projects more attractive. Bar-Ilan and Strange (1996) show that time-to-build along with costly entry and exit can produce convex returns and hence a positive relation between uncertainty and investment. Other research has shown that the adjustment of flexible factor inputs to exogenous shocks can deliver convex returns via a Jensen's inequality (see, for example, Hartman (1976), Abel (1983), Caballero (1991), Leahy (1993), and Abel and Eberly (1994)).[5]

Not all of the mechanisms that link investment and uncertainty fit neatly into a taxonomy based on the curvature of the marginal revenue product of capital function. For example, Ingersoll and Ross (1992) show that interest-rate uncertainty exerts an ambiguous influence on investment because present values are convex in interest rates. Moreover, it is clear that care must be taken to carefully distinguish between the effects that uncertainty has on investment and the effects that uncertainty has on risk premia. If investors are risk-averse, then greater uncertainty boosts required returns and the desired level of the capital stock falls. Finally, Williams (1993) and Grenadier (2002) focus on the effects that the fear of pre-emption by other suppliers would have on the investment decision, showing that in some

between current and future investment is severed and irreversibility does not affect investment.

[5]Hartman (1972), Abel (1983), and Caballero (1991) demonstrate how uncertainty will increase the expected value of a marginal unit of capital if the marginal revenue product of capital is a convex function of the stochastic variable (a result of Jensen's inequality) and would thus increase investment. Pindyck (1993) argues that if all firms in an industry face identical realizations of the random variable impacting the industry, then taking account of the endogenous response of the equilibrium price will reverse the Hartman, Abel, and Caballero results. Abel and Eberly (1994) argue that in a world in which competitive firms face only idiosyncratic productivity shocks and use capital and a vector of costlessly adjustable inputs to produce nonstorable output, then the results of Hartman, Abel, and Caballero continue to hold. Abel and Eberly (1994) claim that the Pindyck criticism (Pindyck (1993)) only holds if the source of the uncertainty arises from demand shocks that affect the competitive price of the output.

cases the fear of pre-emption drives the equilibrium investment strategy back to the standard NPV rule.

The residential real estate market is an attractive test-bed for theories of investment under uncertainty. It is generally accepted that major real estate investments are irreversible—in effect, the supply curve for residential real estate is kinked at the existing stock since houses depreciate slowly and are difficult to turn to alternative uses (see Glaeser and Gyourko (2004)). With respect to housing demand, there is an extensive empirical literature documenting a downward-sloping demand curve for housing (see, for example, Hanushek and Quigley (1980), Poterba (1984), Rosen (1985), and Ermisch et al. (1996)).[6]

We begin by regressing aggregate housing starts on the levels and rolling standard deviations of interest rates and housing returns. We find that housing starts decline with higher volatility in either of these state variables, a result that is robust to different definitions of volatility, alternative functional forms for linking movements in the levels and volatilities of the state variables to aggregate housing start activity, and in the presence of controls for housing market risk premia. We then turn to consider individual investment decisions in order to shed light on the extent to which the aggregate results hold in the cross-section and at different scales of investment. Specifically, we test whether homeowners' decisions to significantly modify the characteristics of existing houses are affected by aggregate uncertainty. Consistent with our results for housing starts, we find that remodeling activity falls when aggregate uncertainty rises, a result that is robust to different specifications of the likelihood of observing remodeling, different definitions of volatility, the presence of geographic fixed-effects, and unobserved heterogeneity across houses and/or homeowners. Notably, we also find evidence that remodeling decisions are affected by housing tenure, the age of the house, and the homeowner's income and family size.

Our results add an important piece to the developing empirical literature on investment

[6]It should be noted that, while most empirical studies conclude that housing demand is downward-sloping in housing prices, considerable disagreement remains regarding the degree of downward slope, owing principally to the multidimensional nature of housing and the illiquidity of housing markets.

under uncertainty. Other studies that focus on real estate investment under uncertainty include Bulan et al. (2003), who examine condominium developments in Vancouver, Canada and find that uncertainty delays developments, though greater competition appears to attenuate these effects. Schwartz and Torous (2003) examine a larger sample of commercial real estate developments and find similar results. Quigg (1993) estimates a structural model of land values in Seattle, Washington and finds that the option to wait—the value of the real option to develop—is worth about 6 percent of the value of the land. Moel and Tufano (2002) find that gold price volatility delays decisions to close gold mines, consistent with the real options theory. Our study differs from these in that we consider the residential real estate market in the U.S. In addition, we study real estate investments at different levels of aggregation and of different scales.

This paper is organized as follows. In the next section, we summarize the comparative statics of models of aggregate and disaggregate investment under uncertainty. In section three we discuss our data sources and empirical results. The final section concludes.

2 Investment under Uncertainty: Comparative Statics

Irreversibility is a key friction in most models of investment under uncertainty and it is usually introduced with the assumption that the free entry of productive units requires a sunk cost, F. In addition, free entry assures that producers earn zero profits when adding another unit of housing services to the market, so that:

$$F \geq E_0 \left(\int_0^\infty P(t)A(t)e^{-\delta t}dt \right), \tag{1}$$

where $A(t)$ is average aggregate productivity of capital, $P(t)$ is the unit price of housing, and δ is the constant risk–free discount rate.[7] Equation (1) holds with equality at any

[7]It is further assumed that δ is greater than the drift in the stochastic price process to assure convergence and that cash flows are valued in a risk–neutral framework.

instant in which entry occurs and the expectation E_0 is over the distribution of the future marginal revenue product of capital, $P(t)A(t)$, accounting for possible (irreversible) entry of new productive units. Uncertainty arises from either idiosyncratic and/or aggregate shocks to productivity, $A(t)$, or to price, $P(t)$. Free entry also implies that the number of housing producers is endogenous so that the stochastic process $P(t)A(t)$ is regulated from above. The upper truncation of the distribution of aggregate expected revenues, $\overline{P}(t)A(t)$, arises because potential additions to the housing stock reduce the probability of future price increases.

This stylized market has been analyzed under a wide range of simplifying assumptions that render the problem sufficiently tractable to generate comparative statics. For example, Caballero and Pindyck (1996) focus on the effects of aggregate shocks to productivity and demand in a market characterized by an irreversible constant returns to scale production technology. Following Leahy (1993), they find that free entry implies that $E_0 \int_0^\infty P(t)A(t)e^{-\delta t}dt = F$ at $t = 0$, the time of entry or investment. The upper bound is strictly greater than expected revenues at time increments when investment does not occur, $\overline{P}(t)A(t) > E_0[P(t)A(t)]$ for all $t > 0$, so that irreversibility implies $E_0 \int_0^\infty \overline{P}(t)A(t)e^{-\delta t}dt > F$, due to the asymmetry of the price response to aggregate shocks. If in the face of negative shocks housing producers could disinvest and recoup the sunk cost, F, then the standard Marshallian result $E_0 \int_0^\infty \overline{P}(t)A(t)e^{-\delta t}dt = F$ would hold.

To derive comparative statics, Caballero and Pindyck (1996) set the drift and volatilities of the aggregate productivity shocks to zero so that aggregate stochastic demand shocks, assumed to follow a Brownian motion with an instantaneous drift, α_M, and standard deviation, σ_M, are the only remaining source of uncertainty. With this simplification, they find that $\partial(\overline{P}(t)A(t))/F)/\partial\sigma_M > 0$ because greater demand uncertainty, σ_M, raises the opportunity cost of investing and thereby raises the threshold required for a firm to pay the sunk cost F. The comparative static on the growth in demand is $\partial(\overline{P}(t)A(t))/F)/\partial\alpha_M < 0$ because for any $\overline{P}(t)A(t)/F$, a smaller value of α_M implies a lower expected price so less entry is needed to satisfy the zero profit condition. Additionally, the comparative static on the riskless discount rate, $\partial(\overline{P}(t)A(t))/F)/\partial\delta > 0$, since δ raises the threshold by directly lowering the expected present value of returns and by increasing the opportunity cost of investing in new housing units now rather that waiting and discounting the sunk cost F.

In another refinement of the basic model, Dixit and Pindyck (1994) focus on idiosyncratic and aggregate demand uncertainty, assuming a fully deterministic linear incremental production technology. Solving for the optimal investment strategy, they find that idiosyncratic demand uncertainty induces convexity in the payoff to producers because investment delay can reduce the individual producer's exposure to adverse shocks. This convexity leads to the usual comparative statics in the drift and volatility of the producer-specific demand shocks, with the expected value, or option value, of waiting rising with uncertainty. Industry-wide uncertainty reduces the expected value of investing relative to that of not investing. Thus, although investment still occurs when $E_0 \int_0^\infty \overline{P}(t)A(t)e^{-\delta t}dt > F$, the option value of waiting is not responsible for this wedge. Instead, the upper barrier on prices—induced by free entry—implies that the threshold price for entry is above the usual Marshallian zero profit condition. Overall, aggregate and/or idiosyncratic demand uncertainty produce delays in optimal investment, although the mechanisms through which these delays occur differs.

Other recent papers have focused exclusively on aggregate demand uncertainty, again assuming an irreversible linear production technology. Williams (1993) and Grenadier (2002) derive the symmetric Nash equilibrium development strategy for homogeneous producers and find that the optimal investment trigger is a decreasing and convex function of the number of producers. Thus, fear of preemption leads to immediate investment and a diminished option value to delay. The optimal option exercise trigger, though increasing in the volatility of the demand shocks, is again attenuated by free entry. The trigger level is also a decreasing function of the drift in stochastic demand, so that all else being equal, producers invest sooner when growth in demand is higher. Finally, as before the optimal investment trigger is increasing in interest rates so the value of the option would increase at higher exogenous riskless interest rates. These models suggest that in competitive markets with perfectly elastic demand and linear production technology, uncertainty would delay investment, but the dominant effect of preemption would drive investment back to the Marshallian zero profit condition. These countervailing effects suggest that, in aggregate, uncertainty may have no effect on investment delays.

Novy-Marx (2005) considers an economy with aggregate demand shocks in a market characterized by an increasing cost–to–scale production technology and heterogeneity in the opportunity costs of adjustment that is not directly associated with shocks to aggregate productivity. As in Dixit and Pindyck (1994) and Dixit (1993), Novy-Marx (2005) finds that prices are negatively skewed because aggregate industry capacity responds asymmetrically to aggregate demand shocks, since firms can add capacity quickly in response to rising demand but cannot adjust capacity as quickly to falling demand due to irreversibility. The degree of asymmetry in the equilibrium path of prices depends on the cost-to-scale of adding new capacity and the elasticity of prices with respect to supply. Under the assumed production technology, real option premia are found to be considerably higher than the rents to monopoly (or oligopoly) as in Williams (1993) or Grenadier (2002). The option value of waiting increases in volatility and the level of the interest rate and falls in the level of demand growth. In aggregate, firms have an incentive to delay investment due both to asymmetry in the price response and to significant positive option premia; overall, greater uncertainty depresses investment.

There are, of course, many impediments to testing the empirical implications of these models. First, a desire to maintain analytic tractability limits the number of state variables that can be considered. Hence most of these models consider only one state variable associated with either aggregate supply or demand shocks. Notably, all of the models in this literature assume that the riskless discount rate is constant and exogenous, thereby abstracting away from the effects of the level and dynamics of the term structure of interest rates. Most of the models consider either infinitesimally small homogeneous producers (Hartman (1972), Abel (1983), Caballero (1991), Leahy (1993), Williams (1993), and Grenadier (2002)) or monopolists (see Dixit and Pindyck (1994) for a survey), and most solve the models for only one type of production technology.[8] The models are usually solved in continuous time assuming instantaneous production responses in a competitive equilibrium with rational expectations, abstracting away from the realities of capital market imperfections or frictions arising from search.

Another important channel affecting the causal determinants of investment delays is the degree of cross-sectional heterogeneity among producers and the role of idiosyncratic producer-level shocks to demand and supply. The model developed by Novy-Marx (2005) highlights the importance of heterogeneity in productive decision-making and those of Dixit and Pindyck (1994) and Abel and Eberly (1994) the role of idiosyncratic shocks on aggregate equilibrium price dynamics and investment delays. The differing origins of these effects suggest that it should be important in empirical work to control for heterogeneity and to distinguish between individual producer decisions and aggregate market responsiveness to drift and volatility of fundamental state variables such as prices or interest rates.

As discussed, uncertainty affects irreversible investment in two ways: 1) through the effect of the firm's current investment on the expected path of its marginal profitability of capital and 2) through the effects of competitors' investments on the path of this marginal product. The first channel will always lead to a positive relationship between uncertainty and investment delays when demand curves are downward sloping and/or the production technology is characterized by decreasing returns to scale. The second channel leads to the same positive correlation since negative shocks will lead prices to fall and positive shocks will lead prices to be limited due to free entry. For these reasons, firm and aggregate level price elasticities of demand are important determinants of the relationship between uncertainty and investment in real world applications. Although there is not a consensus concerning the empirical magnitude of the U.S. aggregate price elasticity of demand for housing, as noted

[8]Novy-Marx (2005) explicitly accounts for the effects of cross-sectional heterogeneity in the equilibrium solution and Dixit and Pindyck (1994) solve for the optimal investment strategy with idiosyncratic producer-specific demand shocks.

at the outset, the bulk of evidence to date indicates that the demand-curve for housing is downward sloping. Still less is known about the underlying production technology for housing, rendering the relationship between uncertainty and housing investment an open empirical question.

A final concern in bringing these models to data is the usual assumption in the theoretical literature that agents are risk neutral. Obviously, an explicit treatment of preferences is beyond the scope of this paper; however, if investors are risk averse, volatility might reduce the likelihood of investment not because of valuable real option positions but because volatility enters the investors' discount rate directly. From the usual CAPM result, systematic risk would also reduce the likelihood of investment not because of the effect of irreversible investment but instead because investors cannot completely hedge systematic or market risk. This alternative channel for uncertainty highlights the importance of introducing controls for relative risk levels in empirical studies of uncertainty and investment in the housing market.

In summary, the theoretical predictions concerning the empirical relationship between uncertainty and investment delays in the housing market are far from conclusive. The varying empirical implications of the theoretical models reflect important differences in the assumptions concerning the underlying structure of demand and supply in these markets. Although prior empirical work suggests that demand is likely to be downward sloping in the housing market there is little empirical work that establishes the likely nature of the production technology. For these reasons, the relationship between uncertainty and investment delays in the housing market remains an open empirical question. The Jensen's inequality effect suggests a positive relationship between uncertainty and investment, whereas models abstracting from this potential effect predict that aggregate uncertainty in market fundamentals have either a neutral effect, because investment occurs at the Marshallian zero profit condition, or a strong depressant effect on investment.

3 Empirical Tests and Results

In this section we sign the investment-uncertainty relation for residential real estate investments. We begin with an analysis of aggregate housing investment data and then turn to disaggregate data. In both cases, we find evidence that greater aggregate uncertainty reduces investment.

3.1 Aggregate Specification

We begin by estimating a linear reduced-form model of housing investment where we regress aggregate housing starts on the level of the 90-day Treasury bill rate, housing returns, and rolling standard deviations of the bill rate and housing returns. The basic regression specification is given by:

$$\begin{aligned}(\text{Starts})_t &= \beta_0 + \beta_1(\text{Housing Return})_t + \beta_2(\text{Housing Return Vol})_t \\ &+\beta_3(\text{T-bill})_t + \beta_4(\text{T-bill Vol})_t + \epsilon_t,\end{aligned} \tag{2}$$

where ϵ_t is a mean-zero error and "Vol" denotes a rolling standard deviation. For all of our results, we report robust standard errors (Huber (1967), White (1982)). Our data are observed at a quarterly frequency from the first quarter of 1974 to the first quarter of 2005, for a total of 125 observations. We use starts rather than completions because starts are a more accurate measure of when a housing investment is initiated; moreover, starts do not translate into increases in supply until some months later, avoiding endogeneity problems with the housing return and Treasury bill series.[9]

We measure Starts with the total single-family housing starts series collected by the Bureau of the Census.[10] As shown in Panel A of Table 1, on average there are 282,032 housing starts per quarter, with a standard deviation of 71,348 starts. However, as can be

[9]Even were we to use completions, the fact that increments to housing supply are small relative to the existing stock would mitigate problems of endogeneity in supply and returns.

[10]Table Q-1, "New Privately Owned Housing Units Started in the United States, by Intent and Design".

seen in Figure 1, there is a strong seasonal component to the housing starts series, with substantially greater activity in the summer months. Hence we include quarterly dummy variables to capture these obvious seasonalities in the data.[11]

Housing returns are measured as the percentage change in the Conventional Mortgage Home Price Index (CMHPI) constructed by Freddie Mac. Freddie Mac constructs the index from a very large sample of transactions using a standard repeat-sales index methodology (Stephens et al. (1996)).[12] The volatility of housing returns is proxied with rolling two-year standard deviations of housing returns.[13]

Returning to Panel A of Table 1, we see that housing returns averaged 5.954 percent over the sample period, with a standard deviation of 3.926 percent, and housing return volatility averaged 2.726 percent with a standard deviation of 1.440 percent. The level and volatility of housing returns are positively correlated, with a correlation coefficient of 0.3104. Figure 2 displays a time-series plot of housing returns (Panel A) and return volatility (Panel B). The solid line in each panel shows the series we use in our regressions; the dashed lines are discussed below. As can be seen, early in the period relatively high inflation helped to produce rapid appreciation in housing values and significant housing return volatility. Housing returns slumped in the recession of the early 1990s, but rose steadily over the latter half of the sample. Housing return volatility was muted over most of the latter half of the sample, but jumped up late in the sample, reflecting the bull market in housing.

The risk-free discount rate is proxied with the yield on three month Treasury bills, taken from the Federal Reserve's monthly H.15 release. As shown in Panel A of Table 1, bill rates

[11]The upward trend over time evident in Figure 1 is suggestive of non-stationarity in the series, but formal tests reject the hypothesis of non-stationarity for these data in both their raw form and after the application of standard seasonal adjustment techniques.

[12]The transactions falling into Freddie Mac's sample are those associated with "conforming" mortgages—the largest and most liquid component of the housing market. So-called "jumbo" mortgages, associated with higher-value homes, are not included.

[13]We have experimented with the length of the subsamples—the "windows"—for calculating the rolling standard deviations of each state variable. Shorter windows (one year) result in standard deviations that are more highly correlated with the level of the state variable itself, affecting the precision of the estimates but not the signs of the coefficients. Longer windows (three years) do not have a material effect on our results. The two-year window is chosen because it is consistent with the sampling frequency of our disaggregate data, discussed below.

averaged 6.105 percent over the period with a standard deviation of 3.067 percent. The volatility of the risk-free discount rate is proxied with two-year rolling standard deviations of the bill yield. From Table 1 we see that bill rate volatility averaged 1.047 percent with a standard deviation of 0.741 percent over the period. It is apparent from Panel B that the level and volatility of T-bill rates are highly positively correlated, with a correlation coefficient of 0.6374. Figure 3 displays a time-series plot of the level (Panel A) and volatility (Panel B) of the bill rate over the sample period. The big run-up in bill rates in the late 1970s and early 1980s reflects the Fed's attempts to bring inflation under control in the wake of multiple oil price shocks. The period from about 1982 until the end of the sample is one of declining interest rates and, with a few exceptions, reduced short-rate volatility.

We control for the effects of uncertainty on risk premia using the spread of the 30-year fixed-rate conventional mortgages to 10-year Treasury rates. As shown in Table 1, this spread has averaged 1.735 percent over the sample period, with a standard deviation of 0.521 percent. As shown in Panel B of the table, the spread is strongly positively correlated with contemporaneous interest rate volatility, and negatively correlated with contemporaneous housing return volatility. At first blush, the negative correlation with housing return volatility seems counter-intuitive—greater return volatility ought to boost the risk of default, raising mortgage rates. However, this is a ceteris paribus result and here we are not holding fixed the level of returns. Apparently the level effect of housing returns—positively correlated with housing return volatility—generates mortgage spread contraction, on average, and hence the negative correlation with housing return volatility. Figure 4 displays the time-series of risk spreads. Mortgage risk spreads, like housing returns and interest rates, reach their peak in the early 1980s. The spread then declines until the fall of 1998 when spreads in most fixed-income markets jumped following the Russian default and the LTCM crisis.

Table 2 displays the results of regressing housing starts on the levels and volatilities of housing returns and interest rates. The four columns under the heading 'Linear' display the results for our linear regression specifications. In order to assess the incremental impact of each state variable and its volatility, we enter each level and volatility separately in models 1 and 2; model 3 includes both levels and the associated volatilities, while model 4 includes the mortgage risk spread.

As can be seen from models 1-3, housing starts rise with housing returns and fall with the short rate, consistent with the comparative statics worked out in the previous section. More importantly, increases in housing return or interest rate volatility depress investment, as can be seen from the negative and significant coefficient estimates on Housing Return Vol and T-Bill Vol, respectively. Both of the state variables help to account for a significant share of the variation in housing starts, as can be seen by comparing the adjusted-R^2 values for models 1 and 2 to that for model 3.[14] When we include Spread—model 4—we find that it is not statistically significant, although the coefficient carries the expected sign. We also note that T-Bill Vol loses some significance in model 4, perhaps owing to its high correlation with Spread.

The last four columns of Table 2 display the results for Poisson regressions of starts on the same sets of independent variables. The Poisson framework explicitly takes account of the fact that our dependent variable is the count of the number of housing starts each quarter; hence the variable is bounded below at zero and takes on only integer values. The probability of observing y starts in a quarter, conditional on our vector of independent variables x, is given by:

$$f(y|x) = \frac{\mu(x)^y e^{-\mu(x)}}{y!}, \text{ for } y = 0, 1, 2, \ldots, \tag{3}$$

where the conditional mean is given by $\mu(x) = e^{x\beta}$, with β the set of coefficients to be estimated. These coefficients are estimated by standard maximum-likelihood techniques; it is worth noting that 100β gives the semi-elasticities of starts with respect to the independent

[14]Moreover, when the volatilities of housing returns and interest rates are excluded, the adjusted-R^2 value falls by approximately five percentage points, indicating that, while much of the explanatory power comes from the levels of the state variables, the volatilities account for an economically significant share of the variation in starts, as well.

variables (Schwartz and Torous (2003)).

Turning to the Poisson regression results in the last four columns of the table, we find that our results are robust to the functional form linking the levels and volatilities of the state variables to housing starts. Overall, all of the coefficients have the expected signs and are highly statistically significant. As with the linear regression specification, housing return and interest rate volatility depress investment. It is worth noting that the volatility of the T-bill rate remains highly statistically significant when Spread is included in the specification; moreover, the coefficient on Spread is also highly statistically significant, in contrast to the linear regression specification. These results suggest that, while our results are robust to the functional form chosen to link the state variables and their volatilities to Starts, it is important to take account of the fact that Starts is a count variable.

Overall, these results are consistent with models of investment under uncertainty that predict less investment under greater uncertainty, such as the models of irreversible investment in which the marginal revenue product of capital is concave. However, a number of issues raised at the outset remain unexamined. To what extent is cross-sectional heterogeneity important? Do the volatility-investment results hold up at the level of individual investments when we control for other potential drivers of housing investment? In the next section, we turn to household-level data in an attempt to shed light on these issues.

3.2 Disaggregate Specification

The various specifications that we consider nest within the mixed-logistic distribution (McFadden and Train (1998), Revelt and Train (1999)). There are at least two important motivations for adopting the mixed-logit specification in our application. First, the error components structure of mixed-logit induces correlations over time, an important feature given that we have repeated observations on each house. Second, the random coefficients structure allows for the possibility that the effects of the explanatory variables are heterogeneous in the sample, due to unobserved (and perhaps difficult-to-measure) heterogeneity across houses. Hence the more flexible mixed-logit specification provides a means for making robust inferences when, as we discussed in the previous section, we suspect unobserved heterogeneity might be present.[15]

Let y denote a vector of indicator variables that take the value one when a homeowner makes a major investment in a given period, and zero otherwise. Under the mixed-logit model, the unconditional probability of observing a time-sequence of additions y on house n is given by:

$$P_n(y|\mu, \Sigma) = \int P_n(y|\beta) g(\beta|\mu, \Sigma) d\beta, \tag{4}$$

where $P_n(y|\mu, \Sigma)$ denotes the mixed-logistic investment probability, $P_n(y|\beta)$ is the probability of observing y conditional on the coefficient vector β, and $g(\beta|\mu, \Sigma)$ is the probability density function for the distribution of the coefficient vectors in the population of houses. We assume that $g(\beta|\mu, \Sigma)$ is a multivariate normal distribution with mean vector μ and covariance matrix Σ. Conditional on β_n, the probability of observing a sequence of renovations on house n over T time periods is just the product of standard logits:

$$P_n(y|\beta) = \prod_{i=1}^{T} L_n(y_i, i|\beta), \tag{5}$$

where:

$$L_n(y_i = 1, t|\beta) = \frac{e^{\beta X_{n,t}}}{1 + e^{\beta X_{n,t}}}, \tag{6}$$

is the probability of observing an addition at time t on house n. In equation (4), we integrate over the population density $g(\beta|\mu, \Sigma)$ because we do not observe β. Our aim is to estimate the coefficients μ and Σ.

The integral in equation (4) does not have a closed form solution, so we approximate the solution through simulation. To simulate the investment probability, we make R draws from

[15] An additional advantage of mixed logit over standard logit is that it does not exhibit the independence from irrelevant alternatives. Moreover, McFadden and Train (1998) show that any choice model can be approximated by a mixed-logit model with an appropriate choice of the density for β. Here we work with the normal density.

the multivariate normal density with mean μ and covariance matrix Σ. For each draw β_r, we compute:

$$\tilde{P}_n(y|\beta_r) = \prod_{i=1}^{T} L_n(y_i, i|\beta_r) \tag{7}$$

and the results are averaged over the R draws. Hence the simulated probability is given by:

$$\tilde{P}_n(y|\mu, \Sigma) = \frac{1}{R}\sum_{r=1}^{R} \tilde{P}_n(y|\beta_r). \tag{8}$$

The simulated log-likelihood function is:

$$SLL = \sum_{n=1}^{N} \log(\tilde{P}_n(y|\mu, \Sigma)). \tag{9}$$

The values $\hat{\mu}$ and $\hat{\Sigma}$ that maximize (9) are maximum-likelihood estimates of μ and Σ. Any of a variety of methods for maximizing non-linear multivariate functions can be used to calculate $\hat{\mu}$ and $\hat{\Sigma}$; we make use of the panel mixed-logit estimator using Halton sequences developed in Train (1999).[16]

Our primary data source is the American Housing Survey (AHS) covering the period 1985 through 2003. After dropping observations with missing data, our sample consists of 51,544 houses in large metropolitan areas, for a total of 249,031 observations.[17] All of the survey waves collected information on whether or not, over the previous two years, the homeowner built any new additions. Using this information, we code our sequences of the

[16]Employing Halton sequences in the numerical integrations substantially reduces the time required to compute (8). For more details, the reader is referred to the sources cited in the text.

[17]In a separate data appendix, available upon request from the authors, we discuss the dataset and the construction of the variables used in the analysis. The AHS is an ongoing, biennial survey of randomly selected homes in the United States. The survey is sponsored by the U.S. Department of Housing and Urban Development and conducted by the Census Bureau. Approximately 53,000 interviews are conducted in each biennial survey from 1985 through 2003. For further detail on the survey, the reader is referred to the AHS web site (`http://www.huduser.org/datasets/ahs.html`).

binary dependent variables as follows:

$$Y = \begin{cases} 0 & \text{If no additions in previous 2 years, or} \\ 1 & \text{If one or more additions in previous 2 years.} \end{cases} \tag{10}$$

Table 3 displays a frequency table for our dependent variable by survey year.[18] We find that more than three percent of the data records in each survey year include a major remodeling investment. The types of additions that are included in our measure are new bedrooms, new bathrooms, kitchens, and other "big-ticket" items that are at least partially irreversible, and which have a major impact on the value of the home.[19] We include the lagged dependent variable as a regressor in order to introduce explicit dependence through time in the investment probabilities.

One notable difference between our aggregate and disaggregate methodologies concerns the measurement of the level of housing returns, interest rates, and risk spreads. The basic data on housing returns and interest rates are measured quarterly. However, all of our household-level variables are available bi-annually from the American Housing Survey. To be consistent with this sampling frequency, we construct two-year rolling means of the levels of the state variables for use in our logit estimation. As can be seen in Panel A of Figures 3 and 2 and in Figure 4, the rolling means closely track the underlying quarterly data. For the volatility series, we simply subset the data to the volatility readings corresponding to the dates of the survey waves, as shown in Panel B of Figures 3 and 2.

Table 4 displays pooled means and standard deviations for the variables used in our disaggregate models. The American Housing Survey sample begins in 1985 compared to 1975 for the aggregate data, hence we miss the high-inflation period of the late 1970s and early 1980s. As a result, the average housing return, Treasury bill rate, and risk spread are

[18]The year 1985 is omitted because, as we discuss below, we use the first lag of the investment indicator as an explanatory variable. This causes the observations of the first survey year to drop out because we do not have survey data prior to 1985.

[19]The median value of additions made in 1987 is $2,500, a figure that rises to $5,000 by 2001 (the average sizes are much larger, reflecting a high degree of skewness toward high value additions in the sample).

lower than in the aggregate sample, as are the average volatilities of housing returns and interest rates. Housing returns average 4.980 percent in the disaggregate sample compared to 5.954 percent in the aggregate sample, with similar magnitude declines for the other variables. The risk spread averages 1.676 percent versus 1.735 percent in the aggregate sample. This data limitation likely works against our finding a role for uncertainty in housing investment, because we are excluding the period of greatest uncertainty over the past 30 years.

There are numerous alternative theories of the processes driving housing investment. Goetzmann and Spiegel (1995) propose that housing investment tends to cluster either at the time a family moves into a home (what we call the effects of *tenure*), or just before a home is put up for sale (the effects of being *on-the-market*). The AHS data allow us to test tenure effects against the real option model. To control for the effects of tenure, we include the variable "Recent Mover", which is a dummy variable that takes the value one when the respondent indicates that the family moved in at some time during the previous year. In our sample, we identify between 6 and 12 percent of the observations in each survey wave as recent movers. Unfortunately, there are not enough houses up for sale in the survey periods for us to reliably test on-the-market effects.

It is possible that older buildings require more renovation and updating than newer buildings. In order to control for possible age effects on the probabilities, we include the "Age" variable which gives the age of the structure in years. From Table 4, we see that the "average" house is 33 years old, but there is variation in the ages of houses in the sample. In fact, the structures range in age from newly built to nearly 80 years old.

Finally, the size of the family and the household income represent additional factors that might influence the probability of investment, independent of shifts in uncertainty over the aggregate state variables. Large families in small houses or wealthy families might be more likely to build additions, regardless of whether or not the option to invest is in the money, and vice-versa. In order to control for this possibility, we include the variable "Persons", which measures the number of persons in the household and "Income" which measures household income. As shown in Table 4, on average there are slightly less than three people living in each house, with a standard deviation of nearly a person and a half. Mean household income was slightly over $53,000.

The estimation results are displayed in Table 5.[20] The first four standard logit specifications are analogous to those in our aggregate regressions. The column labeled 'Regional Fixed Effects' displays results where we have included regional fixed-effects (not reported for sake of brevity), and the column labeled 'Mixed Logit' displays the results for the mixed logit model which accounts for cross-sectional heterogeneity.[21] As can be seen, with respect to housing returns and Treasury bill rates, the results for standard logit models 1-3 are very similar to those for the aggregate regressions. The volatility coefficients are negative and statistically significant in all three specifications. Moreover, as in the aggregate regressions, investment rises with housing returns and falls with interest rates. When we include Spread in model 4, the Treasury bill volatility coefficient reverses sign and is statistically insignificant, perhaps owing in part to the high correlation of the Spread and T-Bill Vol variables in this shorter sample. The inclusion of regional fixed-effects and controls for cross-sectional heterogeneity do not alter our basic results, as shown in the last two columns of the table.

Panel B of Table 5 shows the estimated standard deviations of the coefficients in the mixed logit model. Recall that under the mixed logit model, the coefficients (or, as in this case, subsets of the coefficients) are assumed to be normally distributed throughout the population. In this model, we assume that housing returns and interest rates and their volatilities are normally distributed in the population, reflecting unobservable sources of heterogeneity in the link between the levels and volatilities of the state variables and the likelihood of investment. To the extent that unobserved sources of heterogeneity are important, they will be picked up in a wide standard deviation of the coefficient in the population.

[20]Note that here we report the raw coefficient estimates, which technically are not the marginal effects of the regressors because the logit function is nonlinear. Except where noted, we focus on the signs and statistical significance of the raw coefficient estimates; using the true marginal effects does not alter any of these conclusions.

[21]In order to protect the confidentiality of the respondents, the AHS blurs geographic identifiers at levels of disaggregation below region. Hence we cannot include more detailed geographic fixed effects.

The results in Panel B indicate very little evidence of cross-sectional heterogeneity in the effects of housing returns—it would appear that while housing returns might vary in the cross-section, the effects of housing returns on investment are clear-cut. There is greater evidence of heterogeneity in the effects of housing return volatility, bill rates, and bill rate volatilities, each displaying a wide standard deviation, with each estimated standard deviation being highly statistically significant. The estimated mean coefficient for Housing Return Vol is -0.131, with an estimated standard deviation of 0.1938, indicating that, despite substantial heterogeneity, the bulk of the distribution remains in negative territory. The distribution of coefficients for the T-Bill variable also indicates that the negative sign on the mean estimate is robust, but the wide standard deviation of T-Bill Vol indicates that, for a significant mass of the population, the coefficient is likely positive. Taken together with the results for model 4 where we include Spread, these estimates suggest some caution in interpreting the effects of interest rate volatility on investment.

Of the other control variables, the coefficient on the lagged investment indicator, $y(t-1)$, is positive and highly significant, indicating that an investment in the previous sample period is predictive of investment in the current survey period. Somewhat surprisingly, recent movers are less likely to remodel, as indicated by the negative and significant coefficient on "Recent Mover". One possible explanation for this result is that recent movers have already optimized the configurations of their homes in the process of searching for a house to purchase. Another explanation, which we analyze in greater detail below, could be due to an interaction with Age—it could be that Recent Movers tend to cluster in new construction, where we would naturally expect to see less renovation.

The results indicate that, as expected, larger households are more likely to remodel, as are households with higher incomes. Curiously, older homes experience *less* remodeling, counter to our priors discussed earlier. We examine this issue, as well as the counter-intuitive sign on the Recent Mover variable, in Table 6. In the second and third columns, we display results for standard logit specifications where we have split the sample on Age. In column two we report results for new construction, defined as houses less than five years old. In column three we report results for the rest of the sample. The first thing to note is that in neither case do our basic conclusions on aggregate uncertainty and investment change—greater uncertainty depresses investment. However, moving further down the table, we see that for new construction, Age is negative but statistically insignificant, while it remains statistically significant for older homes. In column three we explore whether age effects might be nonlinear by including the square of age as an independent variable. As can be seen, there is evidence of nonlinearity in that the coefficient on the square of age is positive. Hence it would appear that for "old enough" homes, the probability of observing investments rises.

Notably, the importance of the lagged investment indicator increases with the age of the house, as can be seen by comparing the coefficients on $y(t-1)$ in the second and third columns of the table. For new houses, the coefficient on $y(t-1)$ is 0.657, while for old homes the coefficient is 1.264. Hence, in terms of marginal effects, lagged investments are roughly twice as predictive of current investment for old homes than for new homes. These results are consistent with the conjecture that older houses, when improved, experience more sizable improvements.[22]

Finally, we note that the effects of tenure depend importantly on the age of the house. In the second column, we see that the coefficient on Recent Mover is -0.332 and highly statistically significant—recent movers in new homes are much less likely to invest, all else equal. In the third column, we see that this coefficient rises to -0.095, suggesting that, all else equal, recent movers in older homes are more likely to invest than recent movers in new homes. Nevertheless, regardless of the age of the home, recent movers are still less likely to invest than those who have not recently moved, consistent with the idea that potential homeowners optimize the configuration of their house over the set of available homes when

[22]The AHS data on the costs of additions and improvements indicate that, conditional on observing at least one addition or improvement over the survey period, younger houses do experience lower total investment, on average, than older houses. However, consideration of the scale of investments is beyond the scope of this paper.

searching for a house to purchase.

4 Conclusion

Using aggregate data on housing starts and disaggregate data on housing additions and alterations, we found strong evidence that housing investment falls when uncertainty over aggregate housing returns rises. The evidence for a link between interest rate uncertainty and housing investment is strong at the aggregate level, but at the disaggregate level the results are less clear, perhaps owing to a high degree of collinearity between interest rate volatility and risk spreads, but perhaps also indicating that the effects of interest rate volatility operate through their effect on risk premia—our reduced-form estimation approach is incapable of resolving this issue cleanly. Our results are consistent with theoretical models that produce a marginal revenue product of capital function that is concave in some random variable, such as models of irreversible investment under uncertainty.

We also found evidence that, at the disaggregate level, factors unrelated to aggregate uncertainty are also important determinants of housing investment. Larger households and households with higher incomes are more likely to invest, all else equal. We found evidence for nonlinear effects of house age on investment—homeowners in new homes invest less often, but those in older homes invest at a rising rate. Recent movers invest less often, consistent with matching models for housing choice.

Table 1: Summary Statistics for Variables Used in Aggregate Regressions

Panel A displays the means and standard deviations for the variables used in the aggregate regressions. The variable 'Starts' is the total number of housing starts (in thousands of starts) each quarter. The variable 'Housing Return' is the annualized return on housing, as measured by the CMHPI. 'Housing Return Vol' is the rolling two-year standard deviation of the CMHPI. 'T-bill' is the annualized yield on 90-day Treasury bills; 'T-bill Vol' is the two-year rolling standard deviation of these yields. 'Spread' is the difference between the 30-year conforming fixed-rate mortgage rate and the 10-year Treasury rate. Aside from Starts, the variables are expressed in percent. Panel B displays pairwise contemporaneous correlations for the variables. The sample period is the first quarter of 1974 to the first quarter of 2005, for a total of 125 observations.

Panel A: Means and Standard Deviations

Variable	Mean	Std. Dev.
Starts	282.032	71.348
Housing Return	5.954	3.926
Housing Return Vol	2.726	1.440
T-bill	6.105	3.067
T-bill Vol	1.047	0.741
Spread	1.735	0.521

Panel B: Correlations

	Starts	Housing Return	Housing Return Vol	T-bill	T-bill Vol	Spread
Starts	1.0000					
Housing Return	0.4135	1.0000				
Housing Return Vol	-0.1747	0.2745	1.0000			
T-bill	-0.4535	-0.0015	0.2800	1.0000		
T-bill Vol	-0.4267	-0.0083	0.2776	0.6212	1.0000	
Spread	-0.2079	-0.0137	-0.1567	0.3788	0.5866	1.0000

Table 2: Housing Starts and Uncertainty

The columns under the heading 'Linear' display the results for linear regressions of housing starts on different combinations of controls for housing returns, housing return volatility, the T-bill rate, the volatility of the T-bill rate, and the mortgage spread, all defined as in Table 1 above. The last four columns display the results for Poisson regressions using the same sets of dependent and independent variables as in the first four columns. Below each coefficient estimate is its robust standard error. Estimates suffixed with * are significant at the 10 percent level, those suffixed with ** are significant at the five percent level, and those with *** at the one percent level. The row labeled 'Adj.-R^2' gives the adjusted-R^2 value for the linear regressions. The row labeled F gives for each model the test statistic for the null hypothesis that all of the slope coefficients in the specification are zero; all of these are rejected at better than one percent significance. The sample size is 125 quarterly observations from 1974:Q1 through 2005:Q1.

	Linear				Poisson			
	1	2	3	4	1	2	3	4
Housing Return	8.832***		7.484***	7.391***	.031***		.025***	.027***
	(1.226)		(.939)	(.929)	(.001)		(.001)	(.002)
Housing Return Vol	-10.906***		-4.361*	-7.981***	-.041***		-.018***	-.032***
	(3.283)		(2.583)	(2.826)	(.004)		(.004)	(.005)
T-Bill		-8.541***	-7.802***	-6.277***		-.031***	-.028***	-.023***
		(1.774)	(1.443)	(1.436)		(.002)	(.002)	(.002)
T-Bill Vol		-19.185***	-17.269***	-12.092*		-.08***	-.075***	-.052***
		(7.319)	(5.985)	(6.965)		(.01)	(.01)	(.012)
Spread				-10.838				-.049***
				(8.862)				(.015)
Constant	240.657***	327.408***	295.488***	308.211***	5.498***	5.814***	5.706***	5.766***
	(12.741)	(11.844)	(11.339)	(17.274)	(.015)	(.016)	(.018)	(.03)
Q1 Dummy	-31.278**	-20.848*	-28.928***	-33.931***	-.121***	-.086***	-.108***	-.134***
	(12.639)	(11.759)	(9.568)	(9.525)	(.016)	(.016)	(.016)	(.017)
Q2 Dummy	57.539***	75.551***	59.733***	59.4***	.194***	.26***	.209***	.208***
	(12.935)	(11.852)	(9.792)	(9.548)	(.015)	(.015)	(.015)	(.016)
Q3 Dummy	48.949***	55.326***	49.861***	50.599***	.171***	.197***	.179***	.185***
	(12.708)	(11.859)	(9.623)	(9.351)	(.015)	(.015)	(.015)	(.016)
Adj.-R^2	0.531	0.590	0.736	0.739				
F	26.937	34.199	46.568	39.266				

Table 3: Frequency of Investments by Survey Year

The table shows, for each two-year period ending in the given survey year, the number of houses for which an addition is noted (second column) and the fraction of valid observations in each period accounted for by these investments (third column).

Survey Year	# Obs With $y = 1$	Percent of Valid Obs
1987	1,307	4.8
1989	1,089	4.0
1991	1,079	3.9
1993	1,010	3.5
1995	1,612	6.0
1997	1,272	5.2
1999	1,575	5.5
2001	1,369	5.1
2003	1,459	4.8

Table 4: Summary Statistics for Variables Used in Panel Logits

The table displays pooled means and standard deviations for each variable used in our panel logit specifications for housing additions and improvements. It is important to note that the 'Housing Return', 'T-bill', and 'Spread' variables are defined as two-year rolling means of these variables; in our aggregate regressions, we used point observations of these variables. Here we use rolling means to be consistent with the two-year survey period in the American Housing Survey, the source of information for the additions and improvements data, as well as the 'Recent Mover', 'Income', 'Age', and 'Persons' variables. These data are observed from 1985-2003 on a bi-annual frequency. The total number of observations is 249,031.

Label	Definition	Units	Mean	Standard Deviation
$y(t-1)$	Lagged investment indicator	0/1	0.039	0.193
Recent Mover	Indicator of recent move-in	0/1	0.092	0.289
Income	Household income	$K	53.415	75.147
Age	Age of house	years	33.858	22.477
Persons	Number of persons in household	persons	2.748	1.437
Housing Return	Rolling 2-yr Average Return	percent	4.980	2.019
Housing Return Vol	Rolling 2-yr Std. Dev.	percent	1.977	0.680
T-Bill	Rolling 2-yr Average Yield	percent	4.755	1.729
T-Bill Vol	Rolling 2-yr Std. Dev.	percent	0.712	0.487
Spread	FRM30 less 10-yr Treasury, Rolling 2-yr Average	percent	1.675	0.285

Table 5: Housing Additions and Improvements and Uncertainty

Panel A displays the results for our mixed logit specifications of the probability of observing an addition or major improvement to a home over each two-year AHS survey period. Columns 1-4 are standard logit specifications where each logit coefficient is fixed. The column labeled 'Regional Fixed Effects' shows the results for a standard logit specification with fixed effects for the AHS' four geographic regions (for brevity, the fixed effects are suppressed). The column labeled 'Mixed Logit' gives the results for the mixed logit model where the 'Housing Return', 'Housing Return Vol', 'T-Bill' and 'T-Bill Vol' logit coefficients are assumed to be normally distributed in the population. The estimated standard deviations of the random coefficients are displayed in Panel B. Robust standard errors, clustered at the level of each house, are displayed beneath each coefficient estimate. The sample includes 249,031 observations.

Panel A: Coefficient Estimates and Standard Errors

	Standard Logit					
	1	2	3	4	Regional Fixed Effects	Mixed Logit
Housing Return	.021***		.021***	.075***	.021***	.021***
	(.005)		(.005)	(.01)	(.005)	(.005)
Housing Return Vol	-.025*		-.048***	-.091***	-.047***	-.131***
	(.015)		(.017)	(.019)	(.018)	(.028)
T-Bill		-.008	-.015**	-.027***	-.015**	-.030**
		(.006)	(.007)	(.008)	(.007)	(.011)
T-Bill Vol		-.048**	-.046**	.009	-.047**	-.082**
		(.022)	(.022)	(.024)	(.022)	(.050)
Spread				-.428***		
				(.07)		
Constant	-3.477***	-3.347***	-3.322***	-2.759***	-3.313***	-3.202***
	(.042)	(.044)	(.065)	(.118)	(.071)	(.070)
$y(t-1)$	1.217***	1.222***	1.216***	1.213***	1.213***	1.013***
	(.031)	(.031)	(.031)	(.031)	(.031)	(.041)
Recent Mover	-.061*	-.058*	-.067**	-.075**	-.064*	-.079*
	(.034)	(.034)	(.034)	(.034)	(.034)	(.035)
Persons	.157***	.157***	.157***	.158***	.159***	.163***
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Income	.0006**	.0006**	.0006**	.0005**	.0006**	.0006**
	(.0003)	(.0003)	(.0003)	(.0002)	(.0003)	(.0002)
Age of House	-.003***	-.004***	-.004***	-.004***	-.003***	-.005***
	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)

Panel B: Estimated Standard Deviations of Coefficients in Mixed-Logit Model

Variable	Standard Deviation	Robust Std. Err.
Housing Return	0.0007	0.0019
Housing Return Vol	0.1938***	0.0270
T-Bill	0.0665***	0.0128
T-Bill Vol	0.2198**	0.1194

Table 6: Sample Split on Age, Quadratic Age

Columns 2 and 3 of the table display the results for standard logit specifications where we split the sample on Age as indicated. The last column displays the results for a standard logit specification where we include the square of age as an independent variable. The row labeled 'N' shows the sample sizes.

	Sample Split		
	Age $<$ 5	Age $\geq$ 5	Age^2
Housing Return	.048***	.017***	.019***
	(.016)	(.005)	(.005)
Housing Return Vol	-.152***	-.033*	-.046***
	(.053)	(.018)	(.017)
T-Bill	-.041*	-.01	-.011*
	(.022)	(.008)	(.007)
T-Bill Vol	-.112*	-.04*	-.05**
	(.066)	(.024)	(.022)
Constant	-2.34***	-3.473***	-3.132***
	(.211)	(.07)	(.068)
$y(t-1)$	.657***	1.264***	1.215***
	(.13)	(.032)	(.031)
Recent Mover	-.332***	-.095**	-.111***
	(.084)	(.04)	(.034)
Persons	.074***	.164***	.154***
	(.021)	(.006)	(.006)
Income	-.00009	.0006*	.0005**
	(.0005)	(.0003)	(.0002)
Age of House	-.034	-.002***	-.018***
	(.028)	(.0005)	(.002)
Age^2			.0002***
			(.00002)
N	18296	230735	249031

Figure 1: Housing Starts

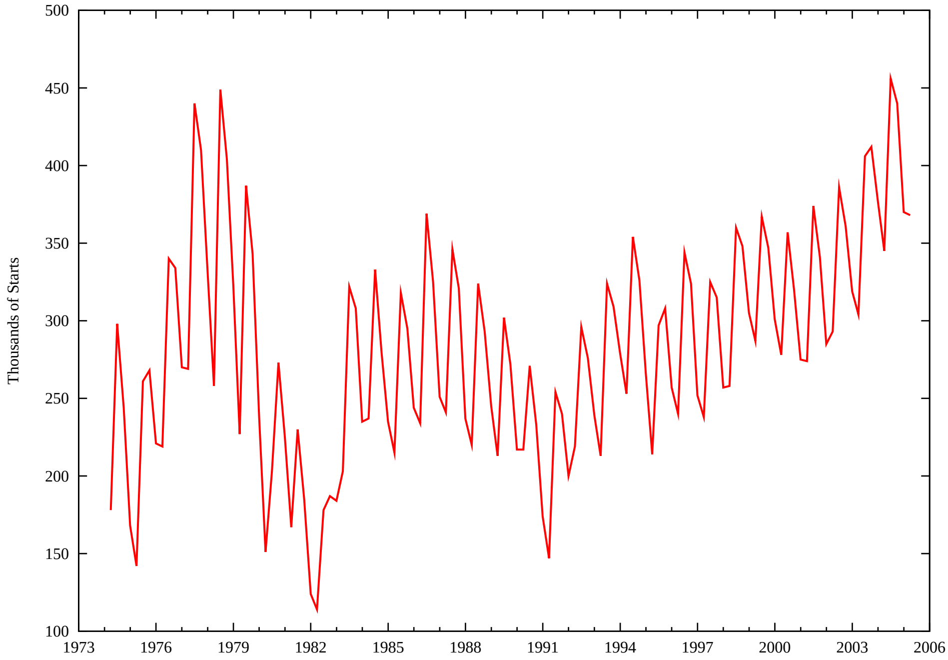
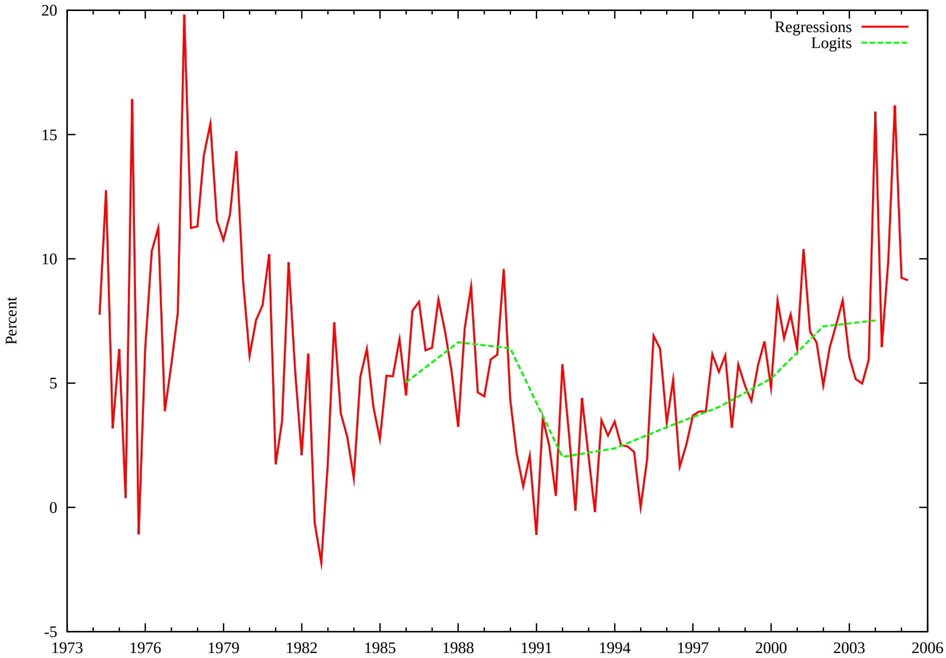


Figure 2: Housing Returns and Volatility

Panel A: Housing Returns



Panel B: Housing Return Volatility

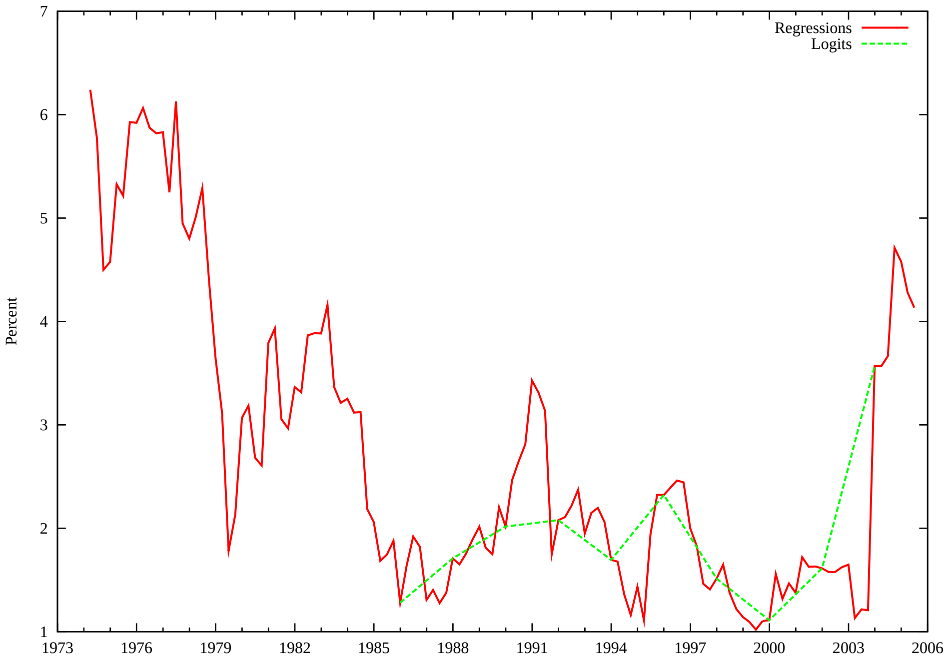
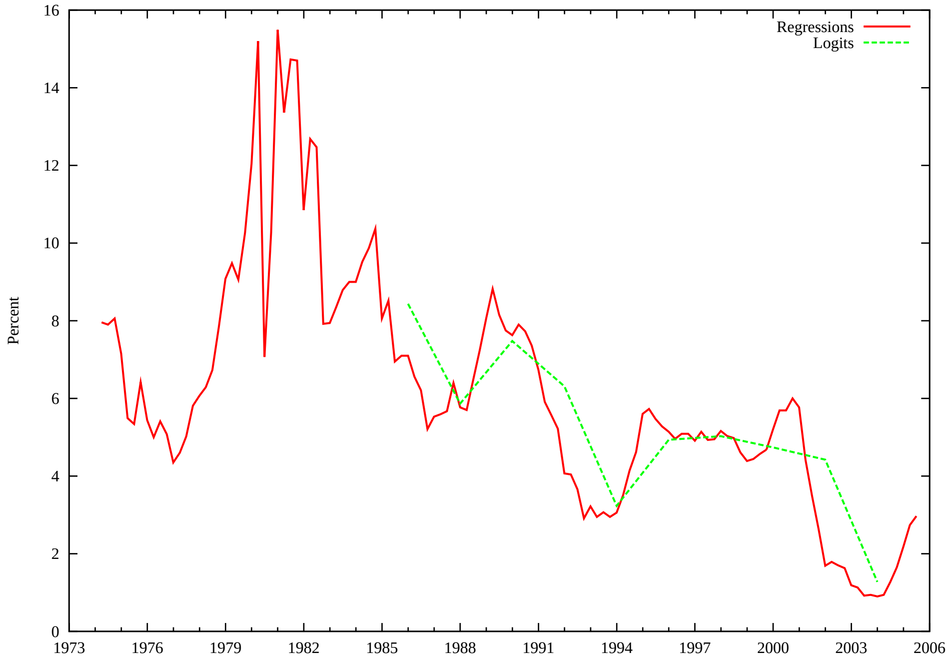


Figure 3: Short-Term Interest Rates and Volatility

Panel A: Short-Term Interest Rates



Panel B: Short-Term Interest Rate Volatility

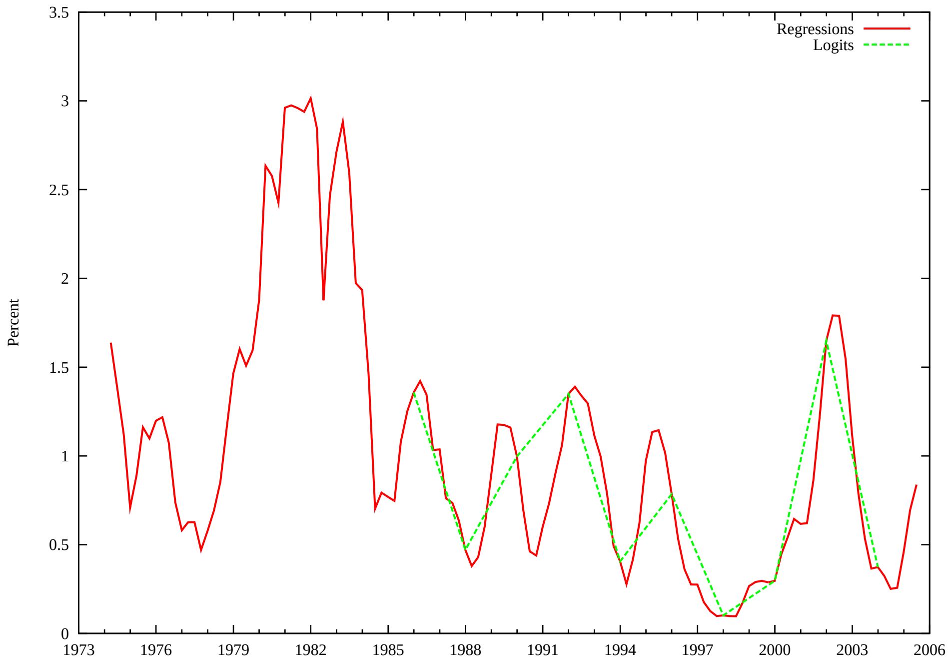
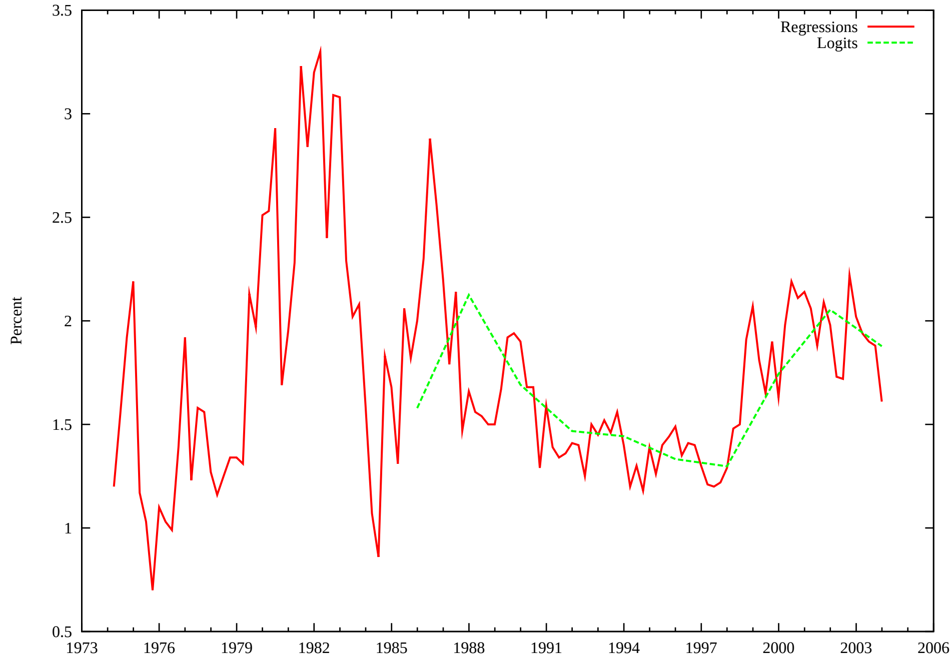


Figure 4: Mortgage to 10-Year Treasury Risk Spread



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