

Momentum traders in the housing market: survey evidence and a search model

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This paper studies household beliefs during the recent US housing boom. The first part uses the Michigan Survey of Consumers to document several stylized facts about households' attitudes towards housing. In particular, we show that towards the end of the boom (2004-5), there was a marked increase in the share of “momentum traders” who expected house prices to rise further and viewed housing as a good investment. The second part performs a cluster analysis to show that households sort into two types, whose views on housing are driven by credit market and house price considerations, respectively. The third part provides a simple search model of the housing market to show how a small number of momentum investors can have a large effect on prices without buying a large share of the housing stock.

Evidence from the Michigan Survey suggests that the housing boom had two distinct phases. During the initial boom years 2001-3, a large and increasing fraction of households believed that the time for buying a house was good. This fraction peaked at 85.2% in the last quarter of 2003. The most important reason – cited by up to 72% of households – was favorable credit conditions. At the same time, by these measures, enthusiasm about housing and credit was actually slightly weaker than at previous peaks during the last 25 years.

In a second phase of the boom, during 2004-2005, overall enthusiasm about housing and credit was already waning, and houses were increasingly viewed as “too expensive”. However, the number of agents who believed that prices would go up further or that houses were a good investment increased from 10% in 2003:Q4 to over 20% in 2005:Q5, a 25 year high. It thus appears that the boom was initially driven by a familiar force, namely good credit conditions. What was unusual about the recent boom is the surge in the number

of momentum investors in the housing market, which occurred precisely at the time when prices rose to their historical highs.

In terms of demographics, momentum traders are not strongly different from the rest of the population. They are somewhat older and richer, more likely to be male and have a college degree, and have fewer children. However, as is common in the literature, demographic characteristics explain little of the variation in beliefs. To learn more about the different views of the world implicit in survey responses, we turn to cluster analysis. In particular, we estimate a mixture density model on data about households' views on housing, inflation, interest rates and business conditions. The idea is to find a common themes in households' responses to many questions – formally a common vector of mean answers – that helps summarize behavior parsimoniously in terms of a finite number of types.

In the estimations for both phases of the boom, one cluster contains agents that mention favorable credit conditions as a reason for optimism about housing. A second cluster contains agents that care little about credit, but more about house prices. This second “price” cluster becomes more important in the second phase of the boom, and contains more momentum traders. Interestingly, price cluster agents are always more pessimistic about business conditions. There are no systematic differences between clusters in terms of beliefs about interest rates and inflation.

The third part of the paper considers the role of a small number of momentum traders on house prices. For the stock market, there is a standard argument for why even a small number of optimistic traders can push up prices in the presence of short-sales constraints (Edward Miller 1977.) Indeed, if investors are risk neutral and have unlimited wealth, and if stock cannot be sold short, then the competitive equilibrium price reflects the subjective valuation of the most optimistic investors in the market. Those investors use their wealth

to buy up all stocks in equilibrium. Less optimistic investors would like to short stock, but are constrained from doing so. As a result, they simply sell all stock to optimists at inflated prices.

While the standard argument is plausible for segments of the stock market where shorting is difficult (such as recent IPO shares), it does not work for the housing market: we do not observe a small number of optimistic speculators buying up all houses. One likely reason is that transaction costs are much higher in the housing market. In contrast to stocks, houses are not standardized assets traded in highly competitive markets. Instead, households search for a unique house that provides the best fit for them. Once they have found such a house they cannot easily exchange it for another equivalent house.

The fact that optimists cannot easily buy many houses might suggest that they have smaller effect on the price.¹ However, in a search market, the recorded price reflects only the transactions that actually take place. What matters for a boom is thus not optimists' share of total market capitalization, but optimists' share in the volume of transactions. In the housing market, a market where volume is much lower than in the stock market, optimists can drive up the price while spending much less wealth and obtaining a far smaller market share. Section 4 below we use a simple search model to illustrate the relationship between the number of momentum investors, transaction costs, volume, and prices.

¹In fact, if agents in the simple competitive model above are constrained to hold one house per person, then a small number of optimists does not move the price: for the market to clear, there must be as many buyers as houses.

II. Housing Boom and Reasons for Buying a House

Panel A in Figure 1 shows the early 2000s housing boom in the United States that we focus on in this paper. The series shown in the figure presents quarterly data on the price-dividend ratio for housing until 2008:2: the market value of aggregate real estate from the Flow of Funds (B.100 line 4, including the value of residential structures held by nonfarm noncorporate businesses B.103, line 5) divided by NIPA expenditures on housing (NIPA Table 2.3.5, line 14). This ratio fluctuates around 14 and 15 during the 1990s, and stays consistently above 16 since 2002. Based on this series, house prices were high relative to their historical values, with pd-ratios above 17, during the years 2002-2006, and declined after 2006.

How is the market value of houses determined? Their value is more difficult to determine than the value of other assets, such as stocks. The reason is that houses do not change hands as often as stocks, and so we do not observe transaction prices as often as we do for stocks. If we count the number of existing homes that are sold each year, they only make 6 percent of the total number of existing homes. (This is measured from the American Housing Survey.) By contrast, each share of equity gets turned over at least once per year. (Annual volume divided by market capitalization for the NYSE is 120 percent.) The common approach to determining the market value of homes is thus to collect recent transaction prices and also apply them to similar homes that have not been on the market for a while.

Panel B in Figure 1 helps illustrate that the Flow of Funds value of homes also reflects recent transaction prices. The figure plots the growth rates in housing price-dividend ratios based on data from the Flow of Funds (dark/black line) and the Office of Federal Housing Enterprise Oversight (grey/green line), which measures prices changes in repeat sales or

refinancings on the same properties. To obtain a pd ratio, we divide the OFHEO house price index by the CPI rent index for primary residences (CUSR0000SEHA). Like the Flow of Funds measure, the OFHEO measure also peaks during the years 2002-2006 and declines after 2006. The same patterns arise in the S&P/Case-Shiller Home Price Index for the U.S., which is also based on repeat-sales pricing (not shown.)

How did households view the recent boom in the housing market? We read these views from their responses to the Michigan Survey of Consumers. The survey asks "Generally speaking, do you think now is a good time or a bad time to buy a house?" Figure 2 plots the fraction of "good time" answers to this survey question. Two facts emerge from the figure. First, the fraction fluctuates over time and peaks at 85.2% in the fourth quarter of 2003. This suggests that a large number of households were indeed enthusiastic about housing during the recent housing boom. Second, and perhaps more surprisingly, the enthusiasm during the recent boom was not higher than in other periods before: 85.6% in 1986:2, 87.5% in 1994:1, and 88.8% in 1999:1.

We also investigate the various reasons that households bring up in response to the questions "Why do you say so?" and "Are there any other reasons?" Three main reasons seem important. First, many households mention their view that credit conditions are good (interest rates are low, interest rates won't get any lower, lower down payments, credit is easy to get, credit will be tighter later, attractive variable mortgage rates). Indeed, Figure 2 shows that credit conditions are a major driver of households' overall thinking about house buys. Moreover, the figure indicates that the recent housing boom was not special in this regard compared to earlier periods.

The second reason behind households' attitudes is their expectation of future house price appreciation. Here, we collect any answers that reflect a belief that "house prices are go-

ing up”, “won’t get lower” or there will be “capital appreciation”. On average, 9.2% of households are optimistic about future house prices. Figure 2 shows that, starting in 2004, more and more households became optimistic *after* having watched house prices increase for several years. The percentage of these *momentum traders* rose to an all time high of 20.2% in 2005:3.

The third reason for why households think that now is a good time to buy a house is their view that “current house prices are low” or “good buys are available.” Figure 2 shows that this reason was definitely not behind the enthusiasm about housing during the recent boom. In fact, the fraction of households who thought that current prices are low was roughly 10% during the housing boom, and only increased dramatically after 2006.

Momentum traders have observable characteristics that are notably different from those of other households. Table 1 shows that momentum traders are, on average, older and richer than other households. They also tend to have more college degrees and fewer children than non-momentum households. While these observable differences are statistically significant in a multinomial logit regression (not reported), they have essentially zero R^2 s in explaining the cross section of survey responses.

We thus proceed to investigate the survey data with cluster analysis. Here, the hope is that clusters will capture unobservable “types” who share similar views about the economy. We estimate statistical mixture models where the assumption is that within each cluster, survey responses to individual questions are independent, with probabilities that are constant within each cluster but different between clusters. The probability of each cluster is given by the mixture probability, and answers to each question can take on three possible values (which have multinomial distributions.)

We analyze survey answers to six questions about the economy. The first three questions

refer to households' expectations as to business conditions, interest rates, and inflation one year from now. The second three are questions that ask for the reasons behind households' views of housing. Here, about half of households announce two reasons, and we count both.

Table 2 reports estimations for both phases of the boom, 2002 & 2003 and 2004 & 2005. In Panel B, one cluster contains agents that mention favorable credit conditions as a reason for optimism about housing. A second cluster contains agents that care little about credit, but more about house prices. This second "price" cluster becomes more important in the second phase of the boom, and contains more momentum traders. Interestingly, price cluster agents are always more pessimistic about business conditions. There are no systematic differences between clusters in terms of beliefs about interest rates and inflation.

III. Momentum traders in a search model of the housing market

We consider a simple search model of the housing market, inspired by the contributions of William Wheaton (1990) and John Krainer (2001). It is also closely related to the standard Mortensen-Pissarides (1994) search model of the labor market.

Setup

Time is continuous and there is continuum of infinitely-lived households of measure 1. Households care for two goods. Numeraire consumption can be purchased in a frictionless spot market. Housing services are derived from indivisible housing units that must be bought in a search market. Households may own at most one house. Utility is quasilinear in housing and other consumption, and households discount the future at the constant rate r .

We introduce preference shocks to capture typical reasons for moving that are unrelated to price dynamics, such as changing jobs. In particular, when a household purchases a house, he is initially a "happy owner" who obtains housing services at the rate v . However, he may

be hit by a shock that makes him an “unhappy” owner who no longer obtains any services from the house. He can then sell the house and purchase a new one to again begin obtaining housing services. The preference shock that makes a household unhappy is driven by a Poisson process with arrival rate η . A household thus receives a moving shock on average every $1/\eta$ years.

At any point in time, there are at most three types of agents in the economy. Let μ_H and μ_U denote the number of happy and unhappy owners, respectively, and let μ_R denote the number of “renters” who do not own a house. Homeowners decide whether or not to put their house up for sale, which entails costs at the rate c . Renters decide whether to search for a house, which is free. If μ_S houses are for sale and μ_B households are searching, houses and potential buyers are matched at the rate $M(\mu_B, \mu_S) = m\mu_B^\alpha\mu_S^{1-\alpha}$. Once a house for sale is matched with a (potential) buyer, the seller makes a take-it-or-leave-it offer for a trade, and the buyer accepts or rejects the offer.

The supply of houses is fixed at $h < 1$. Renters’ and owners’ strategies specify probabilities of searching and putting the house up for sale, respectively. An equilibrium is a collection of strategies such that (i) each agent’s strategy is optimal given other households’ strategies (payoffs depend on what others do via the matching process), and (ii) the number of homeowners (happy plus unhappy) is equal to h at all dates. We focus on symmetric equilibria in which the probability of taking an action depends only on the current individual state (happy, unhappy, or renter) as well as calendar time.

We first consider a steady state in which the population weights μ are constant. We choose parameters such that only unhappy households put their houses up for sale, and all renters search for a house, that is, $\mu_B = \mu_R = 1 - h$ and $\mu_S = \mu_U$. (Details of the calculations are contained in a separate appendix to this paper.) In equilibrium, the number

of households who begin searching (because they become unhappy with their house) must be equal to the number of households who stop searching because they are matched:

$$\eta(h - \mu_U) = m(1 - h)^\alpha \mu_U^{1-\alpha}.$$

This condition uniquely determines the equilibrium number of unhappy agents. It is increasing in η , the rate at which households become unhappy. It is also decreasing in m – the faster unhappy sellers are matched with buyers, the fewer households are unhappy in steady state.

We assume that in the steady state selling and buying take the same amount of time on average. The average time for a house to be sold is μ_U/M , and the average time for a searcher to find a house is μ_R/M ; we thus require $\mu_U = \mu_R$. We then obtain a simple formula for the equilibrium price:

$$P = \frac{v}{r} - \frac{\eta}{r + \eta + m} \frac{v + c}{r}$$

The first term is the present value of the dividends that would be obtained if the house were always held by a happy owner. The second term is a discount that compensates the buyer for the inconvenience of future search. Indeed, the buyer knows that once he becomes unhappy he will not be able to sell the house immediately, but will have to forego dividends and incur search costs during the moving process. The discount vanishes as matching becomes infinitely fast ($m \rightarrow \infty$).

We choose parameters so that steady state trading and prices are roughly consistent with averages from the American Housing Survey. On average since 1983, about 6% of owner-occupied houses are traded per year, and the inventory of houses outstanding is about 3%. We thus set $(1 - h)/h$, the equilibrium share of houses on the market, equal to 0.03. In

addition, we set $1/m$, the average time to sell a house, equal to $0.03/0.06$ years, or 6 months. The parameter η is pinned down by the requirement that $\mu_U = \mu_R$. We obtain $\eta = 0.062$, which implies that a household becomes unhappy on average after about 16 years.²

We normalize the dividend rate to $v = 1$. The seller's cost c is hard to pin down. It incorporates not only direct transaction cost but also further nonpecuniary costs incurred in the moving process. To put it in perspective, we consider the total cost incurred during an average sale, that is, $c/2$, as a fraction of the value of the house. As a baseline case, we set this fraction to 10%. Given a value for the cost fraction, we choose the interest rate r to obtain a steady state price dividend ratio of 16, the average since 1983. In the baseline case, the implied interest rate is $r = 5.48\%$ and the cost is $c = 3.2$.

To study the price impact of a small number of momentum investors, we now consider a one time unanticipated shock that makes all renters – 3% of the total population – optimistic about future prices. In particular, renters believe that the value of the house is given by a price dividend ratio of 19 – the value at the top of the boom in 2005 – rather than by the steady state value of 16. However, once renters are matched and purchase a house, they realize that the dividend stream is simply the one for happy owners, and so they turn into happy owners themselves.

Figure 3 shows the behavior of prices and volume in a boom generated by the 3% households who become optimistic renters. The dark line in the left hand panel is the average home sale price. The average price increases to 19 on impact and then gradually reverts to the steady state value of 16. The dark line in the right hand panel shows home sales as a

²Households thus move about half as much as the typical US household. The difference arises because the households in our model are either owners or short-term renters who are actively searching for a new house to own (the average rental period is 6 months). We do not capture movements between rental units or moves between ownership and longer rental periods early or late in life, for example. This also explains why the fraction of renters (3%) in the model is much smaller than in the US population (about one third.)

percent of all homes, at an annual rate. Sales are initially higher than in the steady state, and also gradually revert. The model thus captures the fact that home sales increase during housing booms. Here we have chosen the parameter $\alpha = 0.57$ in order for sales on impact to rise to the rate observed at the top of the boom in 2005, 9.5%.

Home sales occur both when a seller meets an optimist, and when a seller meets a “sober” household. In the former case, the seller charges the optimist his valuation of 19. The price that a seller charges a sober household is shown as a light dashed line. It is always close to the steady state value of 16, although initially it is slightly higher. The average price mostly reflects the composition of the renter population. Initially, almost all renters are optimists and the price is close to 19. Later, more optimists have bought, and more sober households have become renters, resulting in a lower average price.

During the first three months of the boom, there are sufficiently many optimists in the market that some happy owners also put their home on the market, in the hope of selling to an optimist at an inflated price. (In this phase, happy owners are indifferent between putting the house for sale or not, and play a mixed strategy.) This is why home sales are much higher in this phase than their steady state rate of 6%. Moreover, since all happy owners take the same action, this means in particular that some houses that have just been bought are immediately put back on the market. The light line shows the rate at which houses are “flipped”. House flipping also explains why sellers initially charge sober households a price higher the steady state value of 16: the seller, who has the bargaining power, appropriates the flippers’ speculative gain.

The bottom line from the exercise is that a small fraction of optimistic households can have a large price impact, even if they buy only a small fraction of houses during a modest increase in trading volume. Three features of the model are important for these results.

First, the price is set in a bilateral negotiation. The transaction price for a purchase by an optimist thus reflects the optimist's valuation. Second, optimists account for a large share of transactions so that they drive the average transaction price. Importantly, optimists can account for a large share of transactions even though they make up only 3% of the population. Finally, there are sufficient transaction costs so that happy owners do not flood the market with houses. This keeps trading volume low.

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Footnote

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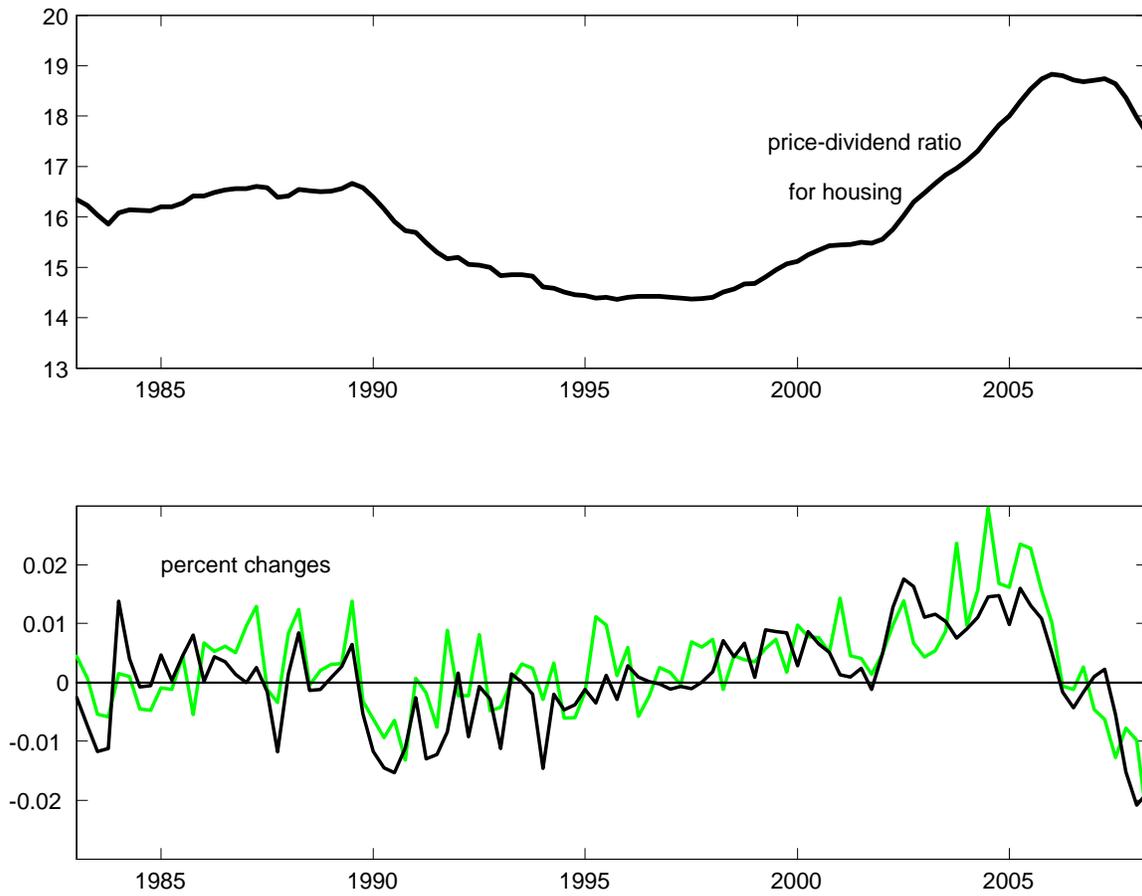


Figure 1. Housing price-dividend ratio, quarterly data 1983:1-2008:2. Top panel: Levels. Bottom panel: Percent changes. The black lines are pd-ratios computed from Flow-of-Funds data, while the green lines are based on the OFHEO HPI index and CPI rents.

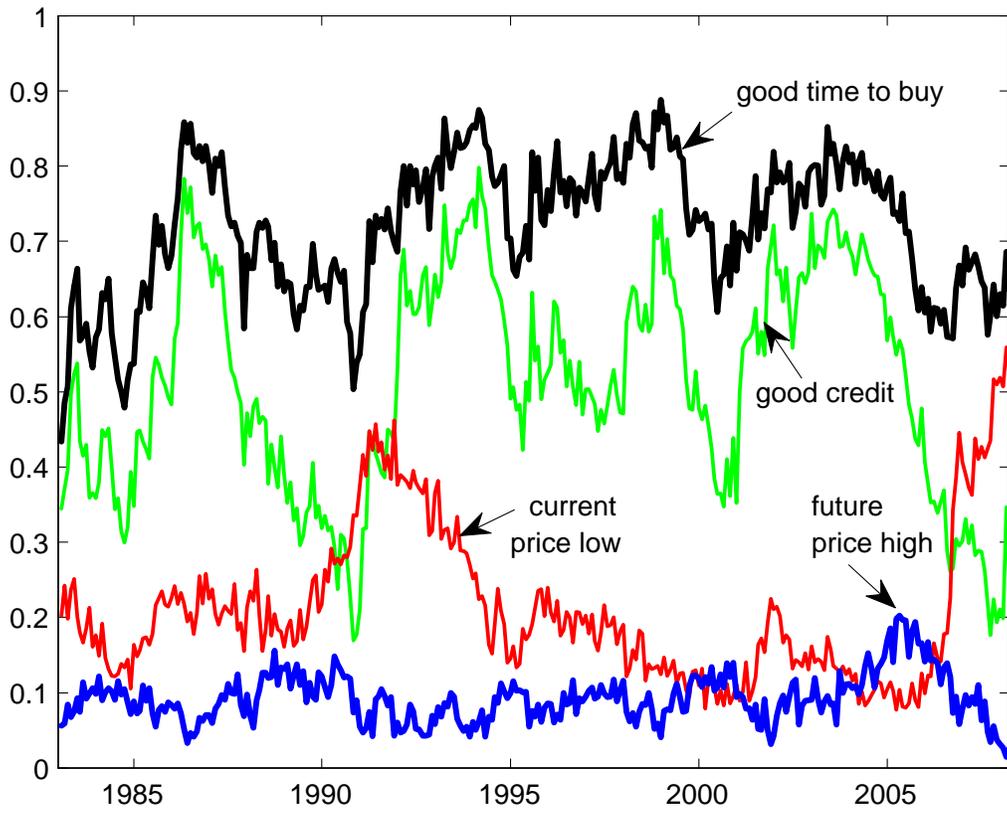


Figure 2. View about housing, Survey of Michigan Consumers.

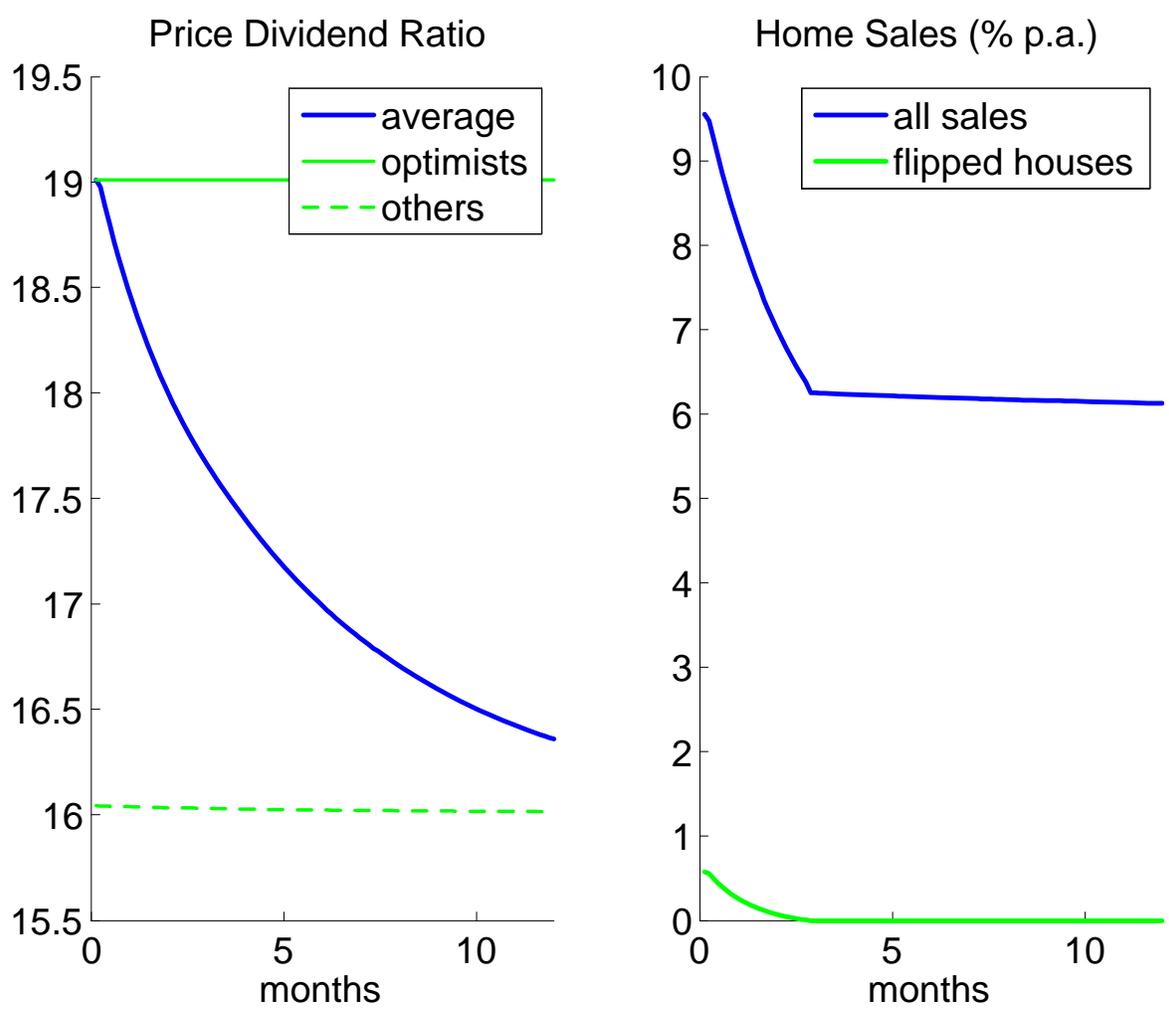


Figure 3: Search model implications for prices and home sales with 3% optimistic renters.

TABLE 1: OBSERVABLE CHARACTERISTICS OF MOMENTUM TRADERS

					percent			
	age	income/yr	male	married	white	black	college	#children
momentum	48.2	67403	48	57	77	5	46	0.55
non-momentum	47.3	60247	43	57	76	9	41	0.68

Note: This table reports average characteristics of households who justified their view that now is a good time to buy (Michigan Survey of Consumers, variable HOM) with “house prices are going up”, “house prices won’t get lower” or there will be “capital appreciation” (variables HOMRN1, HOMRN2) during the housing boom years 2004 and 2005, and those households who did not. We compute averages with survey weights.

TABLE 2: UNOBSERVABLE HETEROGENEITY, CLUSTER ANALYSIS

PANEL A: SINGLE CLUSTER (POPULATION AVERAGES)

	2002 & 2003			2004 & 2005		
	higher/better	same	lower/worse	higher/better	same	lower/worse
next-year forecasts:						
business conditions	0.40	0.42	0.18	0.32	0.49	0.19
interest rates	0.44	0.38	0.19	0.72	0.23	0.05
inflation	0.34	0.33	0.34	0.34	0.38	0.28
views about housing:	positive	no mention	negative	positive	no mention	negative
credit	0.68	0.29	0.03	0.63	0.32	0.05
current house prices	0.16	0.77	0.07	0.10	0.77	0.13
future house prices	0.09	0.90	0.01	0.15	0.83	0.02
(1/N) log L		-5.0025			-4.9536	
mean, max s.e.		0.0035, 0.0045			0.0035, 0.0046	

PANEL B: TWO CLUSTERS

	2002 & 2003						
		cluster 1			cluster 2		
cluster prob		0.33			0.68		
next-year forecasts:	higher/better	same	lower/worse	higher/better	same	lower/worse	
bus. condition	0.32	0.45	0.23	0.44	0.41	0.15	
interest rates	0.45	0.35	0.21	0.42	0.39	0.19	
inflation	0.35	0.36	0.29	0.33	0.31	0.36	
view about housing:	positive	no mention	negative	positive	no mention	negative	
credit	0.03	0.89	0.03	1	0	0	
current house prices	0.15	0.67	0.18	0.17	0.81	0.02	
future house prices	0.11	0.86	0.03	0.08	0.92	0	
(1/N) log L		-4.9412					
mean, max s.e.		0.0085, 0.0241			0.0038, 0.0057		
	2004 & 2005						
		cluster 1			cluster 2		
cluster prob		0.40			0.60		
next-year forecasts	higher/better	same	lower/worse	higher/better	same	lower/worse	
bus. condition	0.24	0.53	0.23	0.36	0.47	0.16	
interest rates	0.72	0.22	0.06	0.74	0.22	0.04	
inflation	0.34	0.39	0.27	0.33	0.38	0.29	
views about housing:	positive	no mention	negative	positive	no mention	negative	
credit	0	0.86	0.14	1	0	0	
current house prices	0.09	0.61	0.30	0.11	0.86	0.03	
future house prices	0.19	0.75	0.06	0.13	0.87	0	
(1/N) log L		-4.80435					
max, mean s.e.		0.0056, 0.0072			0.0036, 0.0059		

Note: This table reports parameter estimates for a mixture of multinomial distributions $1/N \log L$, where $L = \prod_{n=1}^N \omega_n \sum_{c=1}^C p(c) \prod_{q=1}^Q \mu_{i,1}(c)^{a_{i,1}^n} \mu_{i,2}(c)^{a_{i,2}^n} (1 - \mu_{i,1}(c) - \mu_{i,2}(c))^{a_{i,3}^n}$ for household n and one of three possible answers a_i^n of household n to question q (with $Q = 6$ in both panels), and cluster c . The cluster probabilities are the mixture probabilities p_c for $c = 1$ or 2 . Panel A has $C = 1$ clusters, while Panel B has $C = 2$ clusters.