HONG KONG INSTITUTE FOR MONETARY RESEARCH

CAN ANCHORING AND LOSS AVERSION EXPLAIN THE PREDICTABILITY IN THE HOUSING MARKET?

Tin Cheuk Leung and Kwok Ping Tsang

HKIMR Working Paper No.16/2011

May 2011

Can Anchoring and Loss Aversion Explain the Predictability in the Housing Market?*

Tin Cheuk Leung

The Chinese University of Hong Kong

and

Kwok Ping Tsang

Virginia Tech

Hong Kong Institute for Monetary Research

May 2011

Abstract

We offer an explanation of why changes in house prices are predictable. Extending the static model in Leung and Tsang (2010), we analyze the housing market with loss averse sellers and anchoring buyers in a dynamic setting. A buyer's current offer price increases with the housing unit's previous purchase price, and the seller has the tendency to delay the sale of a housing unit that has a loss. We show that when both cognitive biases are present, changes in house prices are predicted by price dispersion and trade volume. Using a sample of housing transactions in Hong Kong from 1992 to 2006, we find that price dispersion and transaction volume are indeed powerful predictors of housing return. For forecasting both in and out of sample, the two variables perform as well as conventional predictors like real interest rate and real stock return.

Keywords: Housing Return Predictability, Price Dispersion, Anchoring, Loss Aversion, Hong Kong Housing Market

JEL Classification: R31, C53, D03

* First draft: December 2010. This work was partly undertaken while the second author was visiting and supported by the Hong Kong Institute for Monetary Research (HKIMR). We thank Charles Leung and Matthew Yiu for helpful suggestions. Tsang: Department of Economics, Virginia Tech, Pamplin Hall (0316), Blacksburg, Virginia, USA, 24061; byront@vt.edu. Leung: Department of Economics, Chinese University of Hong Kong, 914, Esther Building, Shatin, Hong Kong. We thank Debbie Leung, Fengjiao Chen, Jiao Lin and King Wa Yau for their help in extracting the EPRC data.

1. Introduction

The Hong Kong housing market is famous for its large number of transactions and sharp fluctuations in price. According to Figure 2, the average price per square feet in 2006 HK dollars went from about HKD4000 in 1996 to almost HKD7000 in 1997, and three years later in 2000 it dropped to about HKD3000. In 2003 we again see an upward trend in the house price. The large swings in house prices in Hong Kong have motivated studies on whether they can be justified by movements in economic fundamentals. Typically, house prices in Hong Kong are explained by variables like real GDP, real interest rate, land supply, population growth and real stock return. Peng (2002) shows that, in addition to variables like GDP, real interest rate and exchange rate, demographic changes and housing supply are also important factors that affect house prices in Hong Kong. Leung, Chow and Han (2008) confirm that GDP, real interest rate, land supply, and residential investment deflator are important determinants of long-run house prices in Hong Kong, and they also find equity price to be relevant in the short run. Glindro, Subhanij, Szeto and Zhu (2007), using a panel of Asia-Pacific economies which includes Hong Kong, again confirm that house prices in Hong Kong can be explained well by macroeconomic fundamentals.

While most studies on the Hong Kong housing market focus on the long run and fundamentals, and mostly on the level of house price, our paper offers an alternative and complementary investigation on the short-term changes of house price in Hong Kong from 1 to 12 months. Since our explanation relies on the concepts of loss aversion and anchoring, some discussion of the two concepts would be helpful. Kahneman and Tversky (1979) and Tversky and Kahneman (1991) propose the prospect theory, a set of "irrational" assumptions for explaining choice under uncertainty. First, gains and losses are examined relative to a reference point (in our case it is the initial purchase price). Second, the value function is steeper for losses than for equivalently sized gains. Third, the marginal value of gains or losses diminishes with the size of the gain or loss. Figure 1 plots the value function according to the prospect theory. Shefrin and Statman (1985) is an early application of the prospect theory to explain why investors hold on to "loser" stocks for too long. That is, sellers are loss averse when their dislike of loss is stronger than their preference for gain of the same size, and sellers' decision to sell the housing unit depends on the initial purchase price. In particular, sellers tend to delay a sale when they suffer from a loss. If sellers are rational, they should treat the amount paid initially as sunk cost.

Anchoring is a phenomenon that buyers anchor their reservation price on a reference point (in our case it is the initial purchase price). That is, buyers are willing to pay more if the housing unit was first purchased at a higher price. The original source of the idea is in Tversky and Kahneman (1982). In an experiment, subjects are first given a random number between 1 and 100 and are then asked to estimate a number which is not related to the original random number (in their example it is the percentage of African countries). The subjects show a bias in their estimates toward the original random number. This anchoring heuristic has been documented in many other laboratory experiments, and readers can refer to Chapman and Johnson (2002) for a survey.

Studies in behavioral finance provide ample evidence of the two cognitive biases. Using non-experimental data, Odean (1998), Grinblatt and Keloharju (2001) and Shapira and Venezia (2001) show that stock market investors in various countries are reluctant to sell losers relative to winners. McAlvanah and Moul (2010) find that horseracing bookmakers anchor to previous odds when horses are withdrawn. In the art market, Beggs and Graddy (2009) find that buyers anchor to previous selling price, while Mei, Moses, Shapira, and White (2010) argue that art sellers are not loss averse. In the housing market, both Northcraft and Neale (1987) and Black and Diaz (1995) find that a buyer's opening offer is affected by the seller's asking price.

In Leung and Tsang (2010), we find strong evidence of anchoring and loss aversion in the Hong Kong housing market. Taking both cognitive biases as given, we begin with a theoretical model of the housing market with loss averse sellers and anchoring buyers. In our other study (Leung and Tsang 2010), we show that the positive correlation between house price, price dispersion and trade volume can be explained by loss averse sellers and anchoring buyers. But the model is static, and as a result it has no implications on housing return.[1] In this paper we extend the model to a dynamic setting to explain the predictive power of the two variables.[2] From the simulation results of the model, we learn that when both cognitive biases are present, housing return is predicted by price dispersion and transaction volume.

Next, the empirical part of this paper shows that price dispersion and trade volume in the housing market are indeed powerful predictors for housing return, complementing conventional macroeconomic variables. Price dispersion is defined as the deviation of house price from a hedonic pricing model that includes characteristics of the housing unit like size, age, floor, district, and time effects. Trade volume is simply the number of transactions each month. We show that the value of the two variables in the current month contains information on housing return from 1 to 12 months ahead. Moreover, the predictive power of the two variables is not reduced by including macroeconomics variables (real interest rate and real stock return). We also find evidence that the two variables can forecast housing return out of sample.

Genesove and Mayer (2001) and Bokhari and Geltner (2010) are two studies that are most relevant to this paper. Genesove and Mayer (2001) aim at explaining the positive price-volume correlation in the housing market. Using a sample of housing transactions in Boston in the 1990s, they find that sellers who suffer from nominal losses set a higher asking price and have a lower chance of a sale compared to those with nominal gains. Since such loss aversion behavior from sellers makes a transaction more likely

1 In this paper we use "housing return" and "change in house price" interchangeably. The conventional definition of housing return includes rental income.

2 There is also a literature that explains the predictability of the house price in a real business cycle (RBC) setting. Among others, please see Davis and Heathcote (2005), Kan, Kwong and Leung (2004), and Leung (2007).

during a boom, it can account for the positive price-volume correlation. Bokhari and Geltner (2010), using a sample of commercial real estate units with a sale price above US$5,000,000 in the 2000s, find both anchoring and loss aversion. In addition, they create a hedonic housing index that controls for the cognitive biases. Both papers do not explain how the two biases affect the housing market from a theoretical point of view. The current paper takes the first step towards explaining how the two cognitive biases can affect price dynamics. In particular, we ask if they can contribute to the predictability of house prices in the short run.

Of course, we do not argue that house price dynamics can be explained *solely* by the presence of loss averse sellers and anchoring buyers. Our model is not inconsistent with other macroeconomic and institutional explanations of house price. Instead, we take our results as evidence that cognitive biases are important for explaining the movements in house prices, complementing other economic fundamentals. When forecasting house price change, price dispersion and transaction volume contain information that traditional macroeconomic variables like real interest rate and real stock return do not.

2. Data Description

We use housing transaction data provided by the Economic Property Research Center (EPRC). The dataset covers most of the residential housing transactions from 1992 to 2006 in Hong Kong. It contains many aspects of each transaction, including prices, gross and net area, address, floor, age of the housing unit, and so forth.

Initially, there were about 2.1 million observations in the EPRC data. We drop some problematic observations. First, we drop observations with missing characteristics like prices, floor, and area. Second, we drop observations with outlier prices (i.e. top and bottom 0.1% of the data). Third, we exclude transactions of new housing units since the first hand property market is not entirely competitive. Lastly, it is a common practice in Hong Kong to sell a housing unit through a middleman first, and the middleman would "sell" the apartment to the buyer at the same price later. We drop such observations. This leaves us with 746,574 observations, and 371,590 housing units, in the second-hand housing market.

A hedonic regression is fitted to the data and we use the standard deviation of the residual as our measure of price dispersion. Since no hedonic regression is perfect, we expect our measure of price dispersion to be contaminated with unobserved heterogeneity. With that said, we try to minimize the problem by fitting the hedonic regression in every month. That is, hedonic prices and district fixed effects are allowed to be time-varying. Price is the 2006 HK dollar price per square feet of gross area, and the explanatory variables are floor and its square, age and its square, gross area and its square, net-gross ratio and its square, bay window size and its square, club dummy, and district dummies.

Table 1 gives the summary statistics. Not surprisingly, house price is highly persistent and we cannot reject a unit root. Monthly housing return, which we define as the change in real house price per square foot, has an annualized mean of almost 3%. We strongly reject a unit root, and the variable is slightly negatively autocorrelated. Price dispersion is about HKD580 on average, and we almost reject a unit root at the 10% level. Knowing that unit root tests have low power in a small sample, we can conclude that there is little evidence in the data that price dispersion is non-stationary. There are on average 4000 transactions per month, and the hypothesis that the number of transactions is a unit root is strongly rejected.[3]

Figure 2 plots the monthly price dispersion for the full sample with the average price per square foot. Price dispersion tracks the housing cycle closely (the correlation is 0.681). Trading volume shows a similar pattern in Figure 3, and the correlation of the two variables is 0.342. We can also observe some important turning points in the Hong Kong housing market. From the beginning of the sample till the last quarter of 1997, there was a housing boom in which the average price increased more than three times. With the Asian crisis and the "85,000 policy" of the Hong Kong SAR government, house prices have decreased to the 1992 level.[4] From the end of 2003 to the end of the sample, we observe another, though smaller, housing boom.

3. A Dynamic Housing Market with Anchoring and Loss Aversion

In Leung and Tsang (2010) we present a simple model of the housing market with loss averse sellers and anchoring buyers. The model is static, and we show that under some reasonable assumptions the two cognitive biases can explain the positive correlation among house price, transaction volume and price dispersion. To explain predictability of housing return, we need to extend the model to a dynamic setting.

There are N housing units to be traded each period. Each seller is matched with a buyer. Let α be the difference in reservation values between buyers and sellers, and for simplicity we let $\alpha \sim U(0,1)$, so that all matches have the gain of trade. Since α affects all housing units equally, we can think of it as a macroeconomic shock. In addition, there is an idiosyncratic shock ϵ, which is a specific shock to the difference in reservation values for each housing unit, and $\epsilon \sim U(0,1)$. We can think of ϵ as a term that captures the heterogeneities in buyers or sellers, or both. Nash bargaining implies that the price of the housing unit i can be written as:

3 For the same transaction, there are two different transaction dates. The first is called instrument date which is the date at which the transaction occurred. The second is called delivery date which is the date at which the transaction documents were delivered to the Land Registry. We use the instrument date as our definition of transaction date.

4 The reader can refer to the 1997 Policy Address for details: http://www.policyaddress.gov.hk/pa97/english/polpgm.htm

$$P_i = \frac{\alpha + \epsilon_i}{2}$$

If buyers anchor their reservation value of the previous transaction price, denoted as $P_{p,i}$, of the housing unit, the price can be written as:

$$P_i = \frac{\alpha + \epsilon_i + \gamma P_{p,i}}{2}$$

The parameter $\gamma > 0$ measures the strength of anchoring. If the seller is loss averse, the seller is more willing to sell the house when there is a profit than if there is a loss. Let π be the probability that the seller would sell the house when facing price P_i, we have:

$$\pi_i = \begin{matrix} \pi_h, & if\ P_i - P_{p,i} \geq 0 \\ \pi_l, & if\ P_i - P_{p,i} < 0 \end{matrix}$$

Loss aversion means $\pi_h > \pi_l$, and if sellers are rational we have $\pi_h = \pi_l$. This simple specification captures the idea that sellers hold on to losers (housing units that show a loss) longer and sell winners (housing units that show a gain) earlier.

If a transaction is made, the previous price $P_{p,i}$ will be replaced by P for the housing unit. In the next period, the owner of the housing unit i will meet a buyer with newly drawn α and ϵ_i. If a transaction is not made, $P_{p,i}$ will stay the same and the owner of the housing unit i will also meet with a buyer, i.e. newly drawn α and ϵ_i, in the next period.

We are not able to obtain a closed-form solution for the model. To illustrate the implications of the model, we instead simulate data from the model as follows: the number of housing units is 1,000, the number of periods is 200, and the number of simulations is 500. We consider four calibrations of the parameters:

1) No loss aversion and no anchoring: $\pi_h = \pi_l = 0.5$ and $\gamma = 0$
2) No loss aversion and anchoring: $\pi_h = \pi_l = 0.5$ and $\gamma = 0.8$
3) Loss aversion and no anchoring: $\pi_h = 0.8, \pi_l = 0.2$ and $\gamma = 0$
4) Loss aversion and anchoring: $\pi_h = 0.8, \pi_l = 0.2$ and $\gamma = 0.8$.[5]

[5] It can be shown easily that when $\gamma > 2$ equilibrium price is non-stationary.

We calculate the correlations among price, price dispersion (defined as the standard deviation of the price), and number of transactions, and report the average correlations of the 500 runs. We also run a predictive regression for the log change in house price from the current to the next period on a constant, the current price dispersion, transaction volume, and lagged price change. We check whether the mean of the coefficients is significantly different from zero for the 500 runs. Finally, to measure predictability, we calculate the first-order autocorrelation of the average house price of the 500 runs. The simulation results are reported in Table 2.

When neither anchoring nor loss aversion is present, the three correlations are all close to zero. Housing return is close to white noise, and neither price dispersion nor transaction volume can explain housing return. When either one of the cognitive biases is present, the correlations become non-zero. Return is negatively autocorrelated, which is consistent with the data, but it is mainly predicted by its own lag rather than by price dispersion and transaction volume (except for the no anchoring case where return is predicted by transaction volume). When both biases are present, all correlations turn positive, as they are in the data, and both price dispersion and transaction volume now predict housing return.[6]

How do the results depend on the magnitudes of the parameters? We consider four cases in which both cognitive biases are present:

1) Strong anchoring $\gamma = 1$ and strong loss aversion $\pi_h = 0.9,\ \pi_l = 0.1$

2) Weak anchoring $\gamma = 0.6$ and loss aversion $\pi_h = 0.6,\ \pi_l = 0.4.$

3) Strong anchoring $\gamma = 1$ and weak loss aversion $\pi_h = 0.6,\ \pi_l = 0.4$

4) Weak anchoring $\gamma = 0.6$ and strong loss aversion $\pi_h = 0.9,\ \pi_l = 0.1.$

Table 3 presents the simulation results. For all four cases, the correlations are positive, though we are still not able to reproduce the stronger correlation between price and dispersion than that between price and volume. Returns are predictable in all cases, but the predictive power of price dispersion seems to rely on a strong loss aversion. The predictive power of transaction volume only depends on the presence of loss aversion.

4. Predicting Housing Return

In this section we present empirical evidence that price dispersion and trade volume are indeed good predictors for housing return, as the theoretical model suggests. In Table 4 we regress real housing return of a k-month horizon on a constant, log of price dispersion, log of number of transactions and the k-month lagged housing return:

6 Still we are not able to reproduce the stronger correlation between price and dispersion than that between price and volume.

$$R_t^{(k)} = \beta_0 + \beta_1 D_t + \beta_2 N_t + \beta_3 R_{t-k}^{(k)} + \epsilon_t$$

We use Newey-West standard errors to account for serial correlation. Price dispersion is a powerful predictor of housing return at all horizons. For each 1% change in price dispersion, housing return is predicted to drop by 0.8% in the 1-month horizon and more than 0.5% for all other horizons. A rise in trade volume predicts an increase in housing return, though the magnitude decreases with the horizon. Lagged return is significant at the 1-month horizon as housing return is negatively correlated as shown in Table 3, though the lagged return has no predictive power at longer horizons. At the 1-month horizon, we are able to explain almost 19% of the variance of housing return.

While the overlapping data in Table 4 may bias our results towards finding predictability, we report non-overlapping results in Table 5 by taking the end of each quarter, half-year and year to create non-overlapping samples for 3, 6 and 12-month horizons. Price dispersion continues to be a significant predictor of housing return, though the magnitude is a bit smaller. Trade volume matters at the 1-month horizon but not for others. We are able to explain over 30% of the variance of housing return at 3 and 6-month horizons, and at the 12-month horizon it is 16%. We do not know how the models perform beyond the 12-month horizon due to the short sample length.

We consider two macroeconomic variables that are popular predictors of housing return: the real interest rate and real stock return.[7] We use the 3-month Hang Seng Interbank Offered Rate (HIBOR) as the measure of nominal risk-free rate. To calculate a real interest rate, we subtract from the month $t-3$ HIBOR the annualized quarterly percentage change (from month $t-3$ to t) of the composite CPI in Hong Kong. Likewise, we calculate the annualized monthly change in the Hang Seng index from month $t-1$ to month t, and then subtract from it the annualized change in the CPI over the same period.

In Table 6 we add the two variables to the predictive regression. Price dispersion and volume seem to be orthogonal to the two macroeconomic variables in the predictive regression, as the magnitude and significance of price dispersion and volume do not change much with the inclusion of the two variables. Price dispersion and volume contain information that the two macroeconomic variables do not. In addition, the in-sample fit does not improve substantially with the presence of the two macroeconomic variables.

[7] We have also considered real best lending rate and HIBOR of other maturities. None of them forecasts better than the 3-month HIBOR. In addition, Ho and Wong (2008) show that exports can explain house prices in Hong Kong in a co-integration framework. We add the annual growth of real exports to the forecasting equation and do not find the variable to be significant, both in and out of sample. As a result we only consider the two macroeconomic variables.

4.1 Out-of-Sample Forecasts

So far we are looking at in-sample prediction results. To mimic forecasting in real time, we also carry out an out-of-sample forecasting exercise by recursively estimating our model over time, predicting housing return for the future. We compare our model that has price dispersion, volume and lagged return (the dispersion-volume model), with 1) a model with only lagged return (the AR(1) model), and 2) a model with real rate, real stock return and lagged return (the macro model). The window size is 60 months, though changing the window size does not affect the results much. Again, we forecast for 1, 3, 6 and 12-month horizons.

Table 7 shows the p-values of the Diebold-Mariano test. When the p-value is less than 0.10, it means that the dispersion-volume model forecasts better than the alternative model at the 10% level. The dispersion-volume model beats the AR(1) models at the 1, 3, and 6-month horizons, and it beats the macro model at the 1 and 6-month horizons. We interpret this as evidence that the dispersion-volume model has good out-sample predictive power, at least for horizons less than 1 year. Figures 4 to 7 plot our forecasts with the actual returns. Consistent with Table 8, the dispersion-volume model provides decent forecasts for short horizons, but at the 12-month horizon the dispersion-volume model's performance worsens.

4.2 Out-of-Sample Directional Forecasts

Table 8 answers a different question: does the model predict the direction of housing return correctly? First, we create a binary directional variable (it has a value of 1 if the housing return is positive, and a value of 0 otherwise), and we fit the three models on the binary variable recursively. The out-sample forecasts are then interpreted as follows: if the forecast is more than or equal to 0.5, we interpret the model as predicting a positive housing return. We then compare the number of times that the model predicts the direction of the market correctly in Table 8. First, the AR(1) model predicts incorrectly more often than correctly: of the 131 predictions made, only 44.5% of them are correct. The macro model performs better, with a correct prediction 55.5% of the time. The dispersion-volume model has an even better performance, with a correct prediction 56.3% of the time.

5. Conclusion

We argue that anchoring and loss aversion are important determinants of house price dynamics. When sellers have asymmetric preference on profit and loss, or when buyers attach a value to the previous purchase price of the housing unit, house price change becomes predictable. In particular, when both effects are present, housing return is predicted by price dispersion (standard deviation of the residuals from a hedonic regression) and transaction volume. Using a sample of housing transactions in Hong

Kong from 1992 to 2006, we show that the two variables can forecast house price, both in and out of sample, as well as conventional predictors like real interest rate and real stock return.

For monitoring or forecasting the property market return in the short run, we propose that price dispersion and transaction volume should be considered along with conventional macroeconomic fundamentals. The data requirement is minimal: in each month, with a representative sample of housing transactions, we can run a hedonic regression on the characteristics and calculate the price dispersion. Together with the number of transactions, we can improve upon forecasts using only macroeconomic fundamentals.

References

Beggs, A. and K. Graddy (2009), "Anchoring Effects: Evidence from Art Auctions," *American Economic Review*, 99(3): 1027-39.

Black, R. and J. Diaz III (1996), "The Use of Information versus Asking Price in the Real Property Negotiation Process," *Journal of Property Research*, 13: 287-97.

Bokhari, S. and D. Geltner (2010), "Loss Aversion and Anchoring in Commercial Real Estate Pricing: Empirical Evidence and Price Index Implications," working paper.

Chapman, G. B. and E. J. Johnson (2002), "Incorporating the Irrelevant: Anchors in Judgments of Belief and Value," in T. Gilovich, D. Griffin and D. Kahneman, eds., *Heuristics and Biases: The Psychology of Intuitive Judgment* : 120-38, Cambridge University Press.

Davis, M. and J. Heathcote (2005), "Housing and the Business Cycle," *International Economic Review*, 46(3), 751-84.

Genesove, D. and C. Mayer (2001), "Loss Aversion and Seller Behavior: Evidence from the Housing Market," *Quarterly Journal of Economics*, 166: 1233-60.

Glindro, E. T., T. Subhanij, J. Szeto and H. Zhu (2007), "Are Asia-Pacific Housing Prices Too High For Comfort?" BIS working paper.

Grinblatt, M. and M. Keloharju (2001), "What Makes Investors Trade?" *Journal of Finance*, 56(2): 589-616.

Ho, Lok Sang and Gary Wong (2008), "Nexus between Housing and the Macro Economy: The Hong Kong Case," *Pacific Economic Review*, 13(2): 223-39.

Kahneman, D. and A. Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47: 263-91.

Kan, K., S. K. S. Kwong and C. K. Y. Leung (2004), "The Dynamics and Volatility of Commercial and Residential Property Prices: Theory and Evidence," *Journal of Regional Science*, 44(1): 95-123.

Leung, C. K. Y. (2007), "Equilibrium Correlations of Asset Price and Return," *Journal of Real Estate Finance and Economics*, 34: 233-56.

Leung, C. K. Y., G. C. Lau and Y. C. F. Leong (2002), "Testing Alternative Theories of the Property Price-Trading Volume Correlation," *Journal of Real Estate Research*, 23(3): 253-63.

Leung, C. K. Y., Y. C. F. Leong and S. K. Wong (2006), "Housing Price Dispersion: An Empirical Investigation," *Journal of Real Estate Finance and Economics*, 32(3): 357-85.

Leung, F., K. Chow and G. Han (2008), "Long-Term and Short-Term Determinants of Property Prices in Hong Kong," HKMA Working Paper No.15/2008, Hong Kong Monetary Authority.

Leung, T. C. and K. P. Tsang (2010), "Anchoring and Loss Aversion in the Housing Market: Can They Explain House Price Dynamics?" working paper.

McAlvanah, P. and C. C. Moul (2010), "The House Doesn't Always Win: Evidence of Anchoring among Australian Bookies," working paper.

Mei, J., M. A. Moses, Z. B. Shapira and L. J. White (2010), "Loss Aversion? What Loss Aversion? Some Suprising Evidence from the Art Market," working paper.

Northcraft, G. B. and M. A. Neale (1987), "Experts, Amateurs, and Real Estate: An Anchoring-and-Adjustment Perspective on Property Pricing Decisions," *Organizational Behavior and Human Decision Processes*, 39(1): 84-97.

Odean, T. (1998), "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance*, 53(5): 1775-98.

Peng, Wensheng (2002), "What Drives Property Prices in Hong Kong?" HKMA Quarterly Bulletin.

Shapira, Z. and I. Venezia (2001), "Patterns of Behavior of Professionally Managed and Independent Investors," *Journal of Banking and Finance*, 25(8): 1573-87.

Shefrin, H. and M. Statman (1985), "The Disposition to Sell Winners too Early and Ride Losers too Long: Theory and Evidence," *Journal of Finance*, XL: 777–90.

Tversky, A. and D. Kahneman (1982), "Judgements of and by Representativeness," in D. Kahneman, P. Slovic, and A. Tversky, eds., *Judgment under Uncertainty: Heuristics and Biases*: 84-98. Cambridge University Press.

Tversky, A. and D. Kahneman (1991), "Loss Aversion in Riskless Choice: A Reference-Dependent Model," *Quarterly Journal of Economics*, 106: 1039-61.

Table 1. Summary Statistics of the Economic Property Research Center (EPRC) Data (Jan 1992 – Dec 2006)

	Mean	Standard Deviation	Min	Max	1^{st}-order Autocorrelation	12^{th}-order Autocorrelation	Augmented Dickey-Fuller Test p-value
Price per Squared Foot	$3367.913	1066.525	2033.550	6748.301	0.976	0.590	0.481
Annualized Monthly Price Change	2.953%	79.506	-319.837	250.321	-0.167	0.142	0.000
Price Dispersion	$582.427	176.486	207.781	1017.205	0.915	0.434	0.120
Number of Transactions	4072.767	2014.573	754.000	14444.000	0.615	0.116	0.001

Table 2. Simulation Results from the Myopic Model

	No Loss Aversion No Anchoring	No Loss Aversion Anchoring	Loss Aversion No Anchoring	Loss Aversion Anchoring
Corr between Price and Dispersion	**-0.002**	**-0.1342**	**-0.7783**	**0.1303**
Corr between Price and Transaction	**0.000**	**-0.002**	**0.8341**	**0.6862**
Corr between Dispersion and Transaction	**0.000**	**0.005**	**-0.8112**	**0.5684**
Return Predicted by Dispersion?	**No**	**No**	**No**	**Yes**
Return Predicted by Transaction?	**No**	**No**	**Yes**	**Yes**
First-order Autocorrelation of Return	**-0.03**	**-0.319**	**-0.513**	**-0.452**

Note: The results are based on 500 simulations of a sample of 1,000 housing units and 200 periods. Correlations are from the average of the simulations. Predictability is determined by whether the mean of the 500 betas from the predictive regression is significantly different from zero. Autocorrelation of return is calculated using the average of the 500 returns.

Table 3. Simulation Results from the Myopic Model with Both Cognitive Biases

	Strong Anchoring	Weak Anchoring	Strong Anchoring	Weak Anchoring
	$\gamma = 1$	$\gamma = 0.6$	$\gamma = 1$	$\gamma = 0.6$
	Strong Loss Aversion	Weak Loss Aversion	Weak Loss Aversion	Strong Loss Aversion
	$\pi_h = 0.9, \pi_l = 0.1$	$\pi_h = 0.6, \pi_l = 0.4$	$\pi_h = 0.6, \pi_l = 0.4$	$\pi_h = 0.9, \pi_l = 0.1$
Corr between Price and Dispersion	**0.0861**	**0.1412**	**0.1060**	**0.0641**
Corr between Price and Transaction	**0.8496**	**0.7881**	**0.7473**	**0.8572**
Corr between Dispersion and Transaction	**0.3868**	**0.2183**	**0.2948**	**0.2846**
Return Predicted by Dispersion?	**Yes**	**No**	**No**	**Yes**
Return Predicted by Transaction?	**Yes**	**Yes**	**Yes**	**Yes**
First-order Autocorrelation of Return	**-0.521**	**-0.457**	**-0.466**	**-0.507**

Note: The results are based on 500 simulations of a sample of 1,000 housing units and 200 periods. Correlations are from the average of the simulations. Predictability is determined by whether the mean of the 500 betas from the predictive regression is significantly different from zero. Autocorrelation of return is calculated using the average of the 500 returns.

Table 4. Regressing Housing Return on Dispersion and Volume for Jan 1992 to Dec 2006

$$R_t^{(k)} = \beta_0 + \beta_1 D_t + \beta_2 N_t + \beta_3 R_{t-k}^{(k)} + \epsilon_t$$

Horizon	1 Month Ahead	3 Months Ahead	6 Months Ahead	12 Months Ahead
Log Price Dispersion D_t	-0.804 (0.175)***	-0.586 (0.122)***	-0.534 (0.106)***	-0.575 (0.101)***
Log Transactions N_t	0.669 (0.133)***	0.362 (0.092)***	0.244 (0.059)***	0.113 (0.049)**
Lagged Return $R_{t-k}^{(k)}$	-0.243 (0.080)***	-0.056 (0.090)	0.082 (0.085)	0.113 (0.095)
Constant	-37.386 (94.362)	76.053 (79.366)	139.795 (64.761)**	273.072 (59.300)***
Adjusted R^2	0.187	0.221	0.297	0.436
# of Observations	178	174	168	156

Note: Newey-West standard errors in parenthesis; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5. Regressing Housing Return on Dispersion and Volume (Non-Overlapping Observations) for Jan 1992 to Dec 2006

$$R_t^{(k)} = \beta_0 + \beta_1 D_t + \beta_2 N_t + \beta_3 R_{t-k}^{(k)} + \epsilon_t$$

Horizon	**3 Months Ahead**	**6 Months Ahead**	**12 Months Ahead**
Log Price Dispersion D_t	-0.742 (0.157)***	-0.366 (0.134)**	-0.403 (0.221)*
Log Transactions N_t	0.447 (0.108)***	0.041 (0.109)	0.065 (0.100)
Lagged Return $R_{t-k}^{(k)}$	-0.255 (0.106)**	0.393 (0.124)**	0.186 (0.243)
Constant	107.241 (97.485)	201.756 (106.642)*	206.614 (152.056)
Adjusted R^2	0.359	0.316	0.158
Number of Observations	58	28	13

Note: Newey-West standard errors in parenthesis; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6. Regressing Housing Return on Dispersion and Volume with Macroeconomic Variables for Jan 1992 to Dec 2006:

$$R_t^{(k)} = \beta_0 + \beta_1 D_t + \beta_2 N_t + \beta_3 R_{t-k}^{(k)} + \beta_4 rr_t + \beta_5 sr_t + \epsilon_t$$

Horizon	1 Month Ahead	3 Months Ahead	6 Months Ahead	12 Months Ahead
Log Price Dispersion D_t	-0.638 (0.182)***	-0.454 (0.122)***	-0.440 (0.111)***	-0.477 (0.095)***
Log Transactions N_t	0.661 (0.136)***	0.380 (0.085)***	0.263 (0.053)***	0.131 (0.047)***
Lagged Return $R_{t-k}^{(k)}$	-0.263 (0.083)***	-0.179 (0.089)**	-0.063 (0.122)	-0.080 (0.132)
Real Interest Rate rr_t	-1.885 (0.714)**	-1.990 (0.502)***	-1.478 (0.579)***	-1.336 (0.373)***
Real Stock Return sr_t	0.111 (0.075)	0.071 (0.023)***	0.062 (0.017)***	0.027 (0.016)
Constant	-132.104 (87.059)	-17.482 (78.877)	68.339 (70.816)	199.709 (62.245)***
Adjusted R^2	0.210	0.295	0.379	0.489
# of Observations	178	174	168	156

Note: Newey-West standard errors in parenthesis; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7. Out-Sample Forecasting RMSE for AR(1) Model, Macro Model and Dispersion-Volume Model (Window Size = 60 months)

Horizon	1 Month Ahead	3 Months Ahead	6 Months Ahead	12 Months Ahead
D-M p-value: Dispersion-Volume over AR(1)?	0.081*	0.039*	0.021**	0.207
D-M p-value: Dispersion-Volume over Macro?	0.172	0.130	0.050**	0.468
# of Forecasts	131	127	121	109

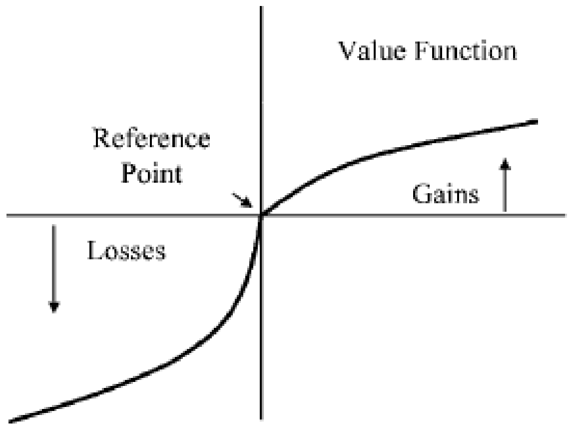
Note: We recursively estimate the models using a window length of 60 months. Based on the estimates in each month we forecast housing returns 1, 3, 6 and 12 months ahead. We then use the Diebold and Mariano test to see if one model significantly forecasts better than another model.

Table 8. 1-Month Ahead Directional Forecast for AR(1) Model, Macro Model and Dispersion-Volume Model

	AR(1) Model	Real Rate + Real Stock Return	Price Dispersion + Volume	Number of Forecasts
% of Directions Correctly Predicted	44.5%	55.5%	56.3%	119

Note: The setting is the same as the out-of-sample forecasting exercise in Table 8, except that we are predicting a binary variable of positive or negative change in house price.

Figure 1. Prospect Theory



Note: The figure is from Genesove and Mayer (2001).

Figure 2. Average Price Per Squared Feet (Left axis) and Price Dispersion (Right axis) at 2006 HKD Value (correlation = 0.681)

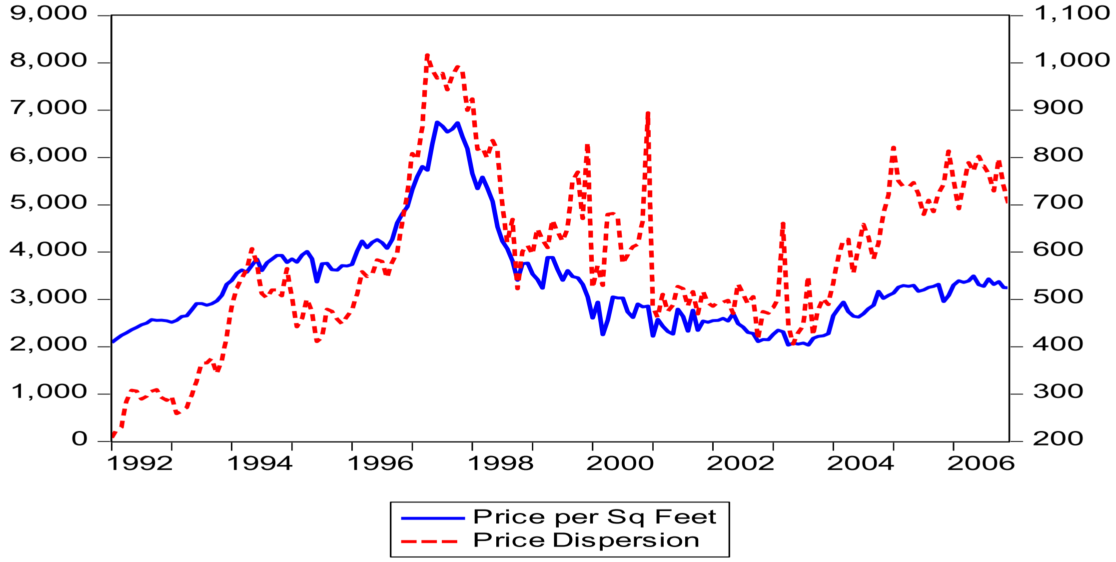


Figure 3. Average Price Per Squared Feet (Left axis) and Number of Transactions (Right axis) at 2006 HKD Value (correlation = 0.342)

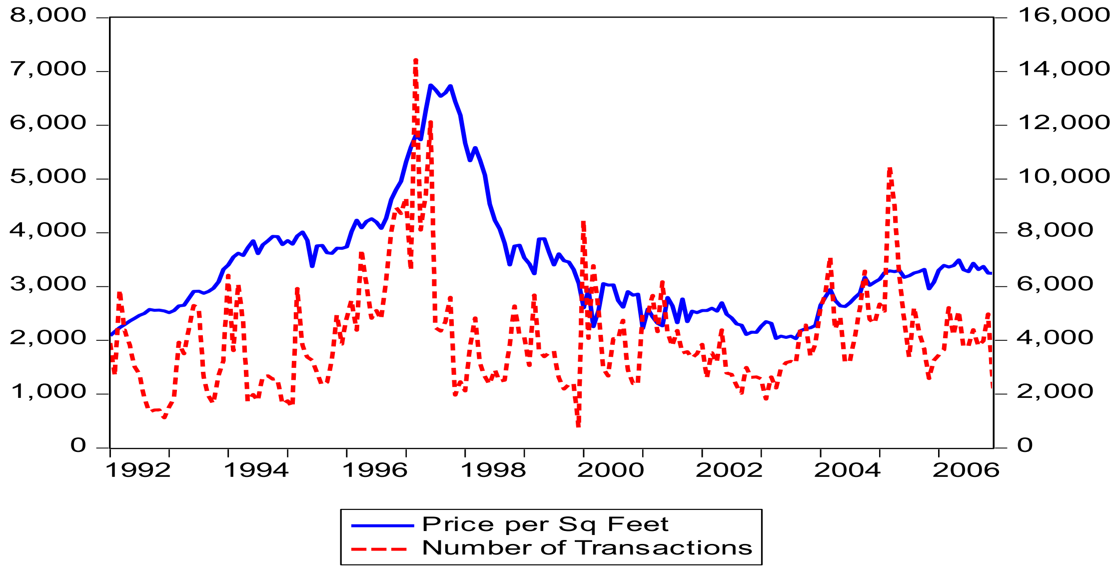
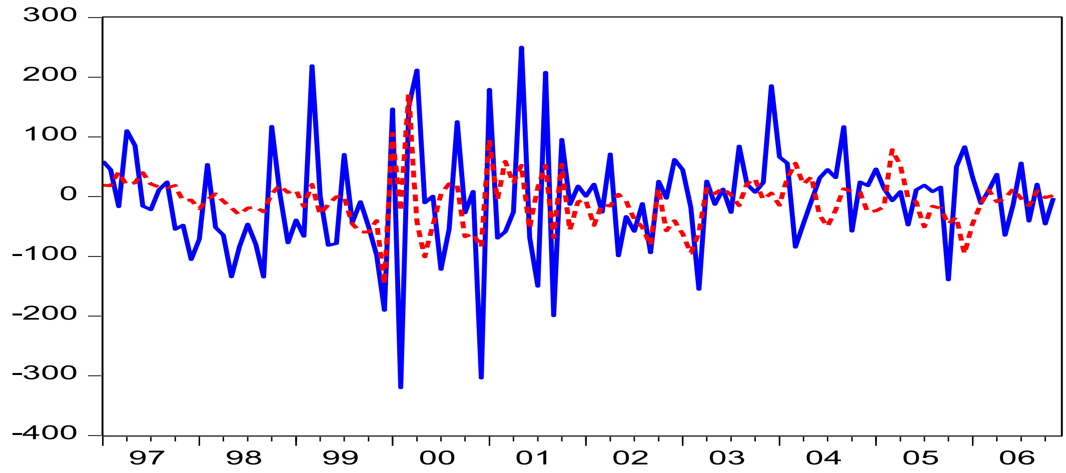
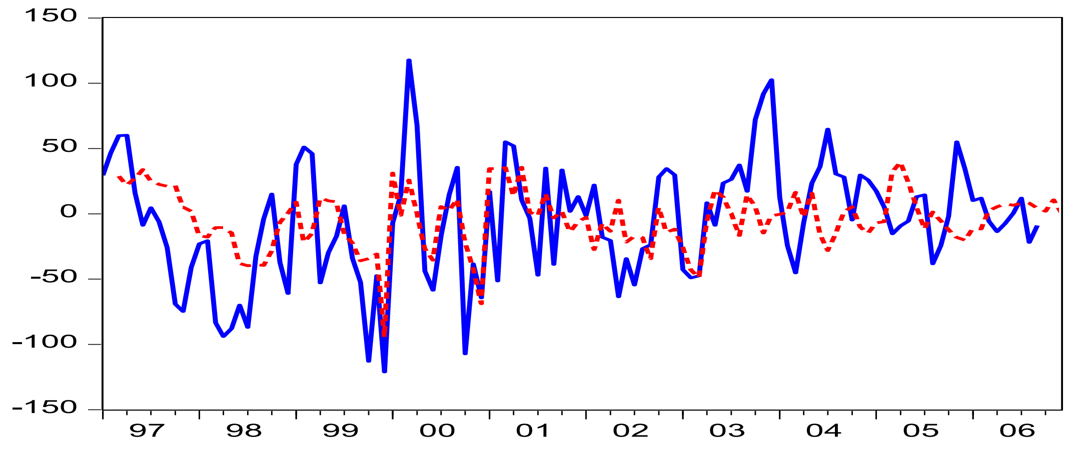


Figure 4. Out-Sample Forecasting with Price Dispersion and Volume (1-Month Ahead)



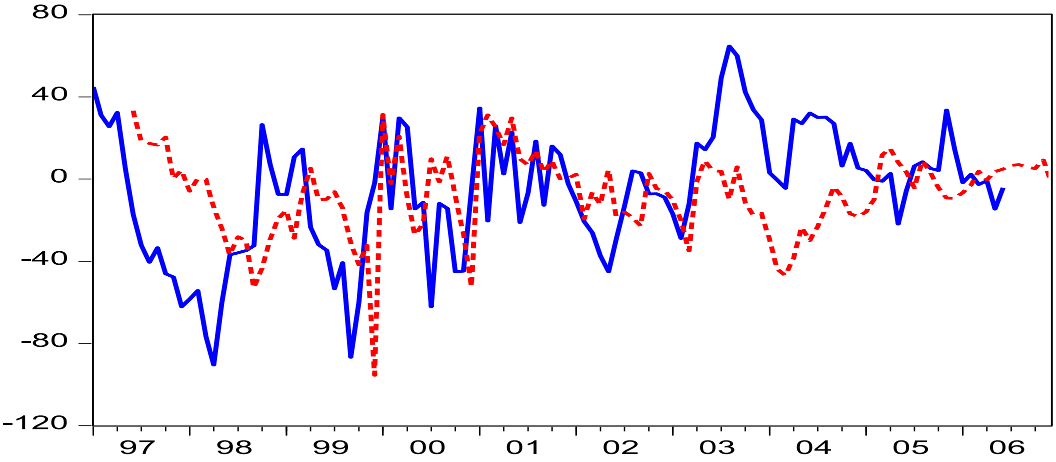
Note: Actual return is in blue (solid) and predicted return is in red (dotted). We recursively estimate the model with price dispersion, transaction volume and lagged return using a window length of 60 months. Based on the estimates in each month we forecast housing returns 1, 3, 6 and 12 months ahead.

Figure 5. Out-Sample Forecasting with Price Dispersion and Volume (3-Month Ahead)



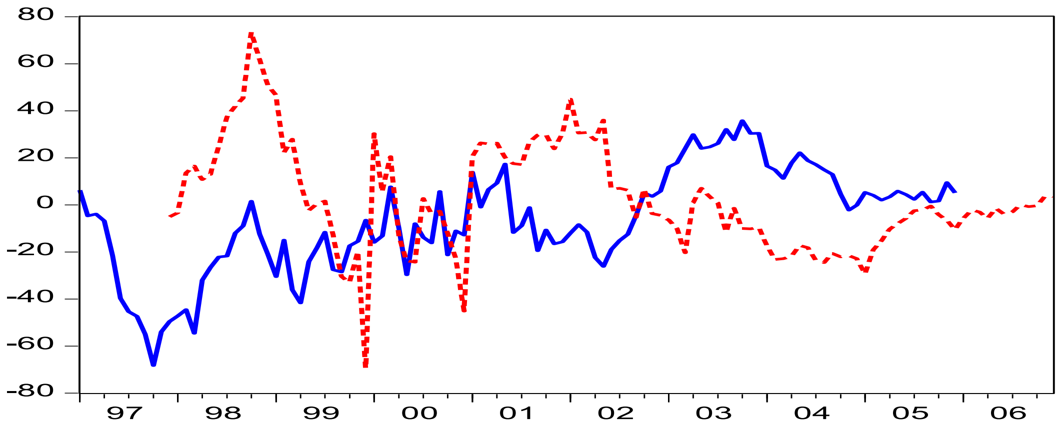
Note: Actual return is in blue (solid) and predicted return is in red (dotted). We recursively estimate the model with price dispersion, transaction volume and lagged return using a window length of 60 months. Based on the estimates in each month we forecast housing returns 1, 3, 6 and 12 months ahead.

Figure 6. Out-Sample Forecasting with Price Dispersion and Volume (6-Month Ahead)



Note: Actual return is in blue (solid) and predicted return is in red (dotted). We recursively estimate the model with price dispersion, transaction volume and lagged return using a window length of 60 months. Based on the estimates in each month we forecast housing returns 1, 3, 6 and 12 months ahead.

Figure 7. Out-Sample Forecasting with Price Dispersion and Volume (12-Month Ahead)



Note: Actual return is in blue (solid) and predicted return is in red (dotted). We recursively estimate the model with price dispersion, transaction volume and lagged return using a window length of 60 months. Based on the estimates in each month we forecast housing returns 1, 3, 6 and 12 months ahead.