Price and Volume Dynamics in Bubbles*

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Abstract

We propose a model of "disposition extrapolators"—investors subject to both extrapolative beliefs and the disposition effect—to explain the sharp rise in both prices and volume observed in many financial bubbles. The model highlights a novel mechanism for volume, whereby disposition extrapolators are quick to buy a stock with positive past returns, but also quick to sell it if good returns continue. We test this model using account-level transaction data on the 2014–2015 Chinese stock market bubble and find that disposition extrapolators 1) sharply increase their volume, almost 300% more than pure extrapolators; 2) trade heavily on the extensive-margin; and 3) actively trade stocks they have never held before. Finally, we empirically show that extrapolators are responsible for driving up prices during the bubble.

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1 Introduction

Asset bubbles span the history of modern finance, from the Dutch tulip mania in the 17th century to the recent U.S. housing bubble. For decades, explaining the existence of bubbles has been a challenging task under the traditional regime of rational expectations. Moreover, during the course of a bubble, prices and trading volume evolve in such a dramatic way that their dynamic patterns largely remain a mystery. An asset bubble typically starts with a run-up, during which asset prices rise above the fundamental value and continue to increase for a substantial period. This period of rising prices eventually ends in a crash in which prices fall back to—or even drop below—the asset's fundamental value. Along with soaring prices, volume also rises significantly in the run-up—often manifested by a trading frenzy—but then drops sharply in the crash. In some cases, the rise and fall in volume is even greater than in prices.

These empirical observations raise two fundamental questions concerning bubbles. First, what drives prices to rise and fall? Second, why do investors trade so much? The answers to these questions not only shed light on the underlying mechanism behind bubble formation, but also have important welfare implications for policy-makers. In particular, households tend to be heavily invested in the underlying asset. They incur substantial financial losses, not just from the devastating market crash, but also from the large amount of fees due to their constant trading in the run-up.

Recent efforts to understand bubbles place extrapolation—the idea that investor expectations about future price changes depend positively on past price changes—at the center of the discussion.[1] According to these accounts, extrapolators tend to buy assets whose prices have recently gone up, thereby pushing up prices even further. However, as stressed by Barberis et al. (2018) and DeFusco et al. (2018), a significant challenge facing the extrapolation framework is to explain high prices and high volume together. To see the challenge, imagine that some positive shocks to asset fundamentals push up prices initially. Although extrapo-

[1]The idea that extrapolators drive up prices in a bubble dates back to Bagehot (1873) and several recent papers formalize this argument (Barberis et al. 2018; DeFusco et al. 2018; Glaeser and Nathanson 2017).

lators can generate a price run-up by pushing up prices beyond the fundamental value, their beliefs are similarly dependent on past price changes and would result in very little trading among themselves.[2] Recent experimental evidence further shows that owners of an asset tend to form more optimistic beliefs about the asset's future returns than non-owners, and this makes the observed high volume even more puzzling (Hartzmark et al. 2019).

In this paper, we propose a simple way out of this conundrum by introducing a second ingredient to a basic extrapolative framework—the disposition effect. Prevalent among both individuals and institutions across many markets (Barber and Odean 2013; Frazzini 2006), the disposition effect refers to the tendency to sell stocks trading at a gain and hold on to stocks with losses (Odean 1998; Shefrin and Statman 1985). Together, extrapolation and the disposition effect characterize an investor who tends to *buy* an asset the price of which has recently gone up, but *sell* that asset if its price rises further after purchase—a trading pattern consistent with extensive empirical evidence (e.g., Odean 1998, 1999; Barber and Odean 2013). A prominent explanation for the disposition effect is realization utility, the idea that investors derive utility from realizing gains and losses on assets that they own. In other words, our solution to this high volume puzzle is to combine realization utility, a form of non-standard *preference*, with extrapolation, a form of non-standard *beliefs*.

The following example illustrates the intuition of our framework. Suppose there are two assets: cash and a stock. Two investors, A and B, are prone to both extrapolation and the disposition effect, but they have different initial endowments: on date 0, A holds cash while B holds the stock. On the same date, we introduce a positive fundamental shock about the stock, which pushes its price up. On date 1, by extrapolating the positive stock return on date 0, A and B form optimistic views about its returns going forward. As a result, although there are no additional fundamental shocks on date 1, the stock's price rises even more.

[2] Both Barberis et al. (2018) and DeFusco et al. (2018) explicitly address the high volume in a bubble by coupling extrapolation with some additional ingredients. Barberis et al. (2018) assume that investors "waver" between an extrapolative signal and a value signal, which induces greater disagreement in a bubble. DeFusco et al. (2018) assume that extrapolators have different investment horizons and that short-term expectations are more sensitive than long-term expectations to past returns. In a bubble, positive past price changes disproportionately attract short-horizon investors, who then push up aggregate volume.

As the price goes up, B starts to accumulate a capital gain in his portfolio. Due to the disposition effect, B is eager to sell his stock position to lock up the gain. A, on the other hand, is not influenced by the disposition effect, because she holds cash with zero returns. In equilibrium, A ends up buying the stock from B, at a higher price. On date 2, the same trade happens, except that A and B have now switched their positions: A is now holding the stock and B is now holding cash. In equilibrium, B ends up buying the stock from A at a higher price. They continue to swap each other's asset positions over the new few dates and, in doing so, push up both price and volume.

To structure our empirical exercise, we formalize the example above with a simple model of *disposition extrapolators*, that is, investors subject to both extrapolative beliefs and the disposition effect. More specifically, we model extrapolative beliefs through expectations about future prices and the disposition effect using realization utility.[3] The model confirms our intuition that these two ingredients can generate a bubble episode featuring large rises in prices and volume. The mechanism for price is similar to other models of extrapolation, but the mechanism for *volume* is new. In particular, it arises from a conflict between *beliefs* and *preferences*. As prices rise in a bubble, extrapolative beliefs and realization utility take turns in dominating an investor's portfolio decisions: when not holding the asset, she is tempted to buy due to extrapolative *beliefs*, but when holding the asset, realization *utility* kicks in, prompting her to sell. As a result, investors switch between different assets, generating high volume.

The model makes a number of new predictions about trading volume during a bubble, which we test in the context of the Chinese stock market bubble from 2014 to 2015. This market-wide bubble affected thousands of public companies and over 100 million investors. Both prices and volume first rose to record highs and then crashed, which provide an ideal setting for investigating the sources of price and volume movements during a bubble. Our data, provided by one of the largest brokerage firms in China, contain account-level transac-

[3]In the remainder of this paper, we use the disposition effect and realization utility interchangeably, but acknowledge that other mechanisms (e.g., nonstandard beliefs in Peng (2017) and cognitive dissonance in Chang et al. (2016)) could also explain the disposition effect.

tions for more than one million retail investors. In addition to covering the 2014–2015 stock market bubble, they also include complete trading history prior to the bubble, allowing us to measure extrapolation and disposition *ex ante*. Specifically, using pre-bubble transactions, we measure the degree of extrapolation by examining the past returns of the stocks an investor tends to buy, and the degree of disposition by the difference in selling propensities between winners and losers (Odean 1998; Dhar and Zhu 2006).

With investor-level measures of extrapolation and disposition, we offer four sets of new facts about the composition of trading volume during a bubble. First, at the market level, disposition extrapolators as a group increase their volume much more than other investors. At peak, their trading volume increases by almost 800%. In comparison, pure extrapolators increase by 500%, implying a 300% difference. This contrast is a direct consequence of the disposition effect: although pure extrapolators are very aggressive at buying more shares, they tend to buy-and-hold and don't reshuffle their portfolios nearly as much as disposition extrapolators.

Second, at the investor level, higher degrees of extrapolation and disposition are both associated with more trading. Specifically, we regress each investor's change in volume at the peak of the bubble on her degrees of extrapolation and disposition while controlling for an exhaustive list of other account characteristics. Consistent with the market-level evidence, both extrapolation and disposition contribute to higher volume, but they work in different ways: extrapolation induces more buying and a large stock holding, whereas disposition urges an investor to rebalance her portfolio more frequently.

Third, in the cross-section of individual stocks, those traded more by disposition extrapolators experience higher turnover. In each week, we average the degrees of extrapolation and disposition at the stock level, using each investor's buying or selling volume of that stock as the weight. This gives us a panel of stock-level degrees of extrapolation and disposition at the weekly frequency. We then run a panel regression by regressing weekly turnover on degrees of extrapolation and disposition, controlling for stock fixed effects and clustering standard errors by weeks. Both extrapolation and disposition can significantly explain the cross-sectional variation of turnover with a positive sign. Therefore, extrapolation and disposition not only contribute to the overall high volume, but also shed light on why some stocks are traded more than others.

Fourth, we examine the model's more nuanced predictions about the composition of volume. First, more than half of the total volume comes from extensive-margin trading, which suggests that investors are very active at establishing new positions and liquidating existing positions. Disposition extrapolators, in particular, trade heavily on the extensive margin and "flip-flop" through various stocks. Second, investors venture are constantly entering into "new territories" by trading stocks they have never held before: almost 80% of the total volume comes from the trading of "new" stocks. Overall, these results not only provide further support to our model, but also document some new stylized facts about the sources of volume.

Lastly, we turn to the relationship between extrapolation and the rising prices during a bubble. Although this prediction is not unique to our model, direct empirical evidence of this kind has been scarce due to the lack of detailed data and a plausible empirical strategy. We take advantage of the granular feature of our data by constructing a panel of stock-level measures of extrapolation at the weekly frequency. While regressing *current* returns on *current* extrapolation is subject to the reverse causality concern—that positive returns cause more trading from extrapolation rather than the other way around—we address this issue through both predictive and IV regressions. In the predictive regressions, lagged extrapolation positively *predicts* current returns; in the IV regressions, instrumented current extrapolation (using lagged extrapolation) are associated with higher current returns. Both sets of regressions document a substantial impact extrapolators have on stock prices during the run-up. Furthermore, we show that they also contribute to the falling prices during the crash.

Whether bubbles are rational and whether crashes are predictable are the subjects of considerable ongoing debate (e.g., Fama 2014; Greenwood et al. 2019). In this paper, we define bubbles by their empirical characteristics—the rising prices, the talk of overvaluation, the high volume, and the subsequent crash—and try to make sense of these patterns. More broadly, our framework can be used to explain other financial phenomena concerning trading volume, such as the fact that rising markets are accompanied by higher volume than falling markets (Griffin et al. 2006; Statman et al. 2006; Stein 1995).

We make three main contributions to the literature. First, we propose a new framework for thinking about bubbles, and the key innovation is our volume mechanism. Previous models highlight disagreement in beliefs (Harrison and Kreps 1978; Scheinkman and Xiong 2003), wavering between signals (Barberis et al. 2018), overconfidence (Gervais and Odean 2001; Scheinkman and Xiong 2003), and short-term speculation (DeFusco et al. 2018) as possible drivers of volume. In comparison, our mechanism is based on the tension between extrapolation (*beliefs*) and the disposition effect (*preferences*). Fundamentally, this tension arises from differential asset holdings: while asset returns affect beliefs in the same way for all investors, they only affects the preferences of those holding the asset. This leads to some novel predictions about the composition of trading volume, which we empirically confirm.

Second, we document several novel facts about the composition of volume during a bubble. These results pinpoint disposition extrapolators as the main contributors of volume due to the joint effect of non-standard beliefs (extrapolation) and non-standard preferences (disposition effect). These results highlight the importance of behavioral biases in explaining bubble episodes and are hard to reconcile under existing models of bubbles. Moreover, some empirical results are new to the literature—for instance, the fact that a sizable fraction of total volume comes from extensive-margin trading and the trading of "new" assets—and may be of interest for future models of bubbles to explain.

Third, we empirically show that extrapolators are responsible for the rising prices during a bubble. Due to the granular feature of our data, we are able to isolate the arrival of extrapolators from the period of returns we examine to rule out the reverse causality concern. To the best of our knowledge, this is the first exercise that directly sheds light on how extrapolators effect price behavior during bubble run-ups.[4] In doing so, we provide empirical

[4]A few papers examine 2014–2015 market crash using account-level data from brokerage firms: Bian et al. (2018a) study leverage networks and market contagion Bian et al. (2018b) study the contribution of

support not only to our model, but also to other models of extrapolation in general.

The rest of this paper proceeds as follows. In Section 2, we present the model and derive its new predictions. In Section 3, we describe the bubble episode and elaborate on the data. In Section 4, we empirically test model's predictions about trading volume. In Section 5, we show how extrapolators contribute to the price run-up. We conclude in Section 6.

2 A model of bubbles

In this section, we present a model of bubbles based on extrapolation and the disposition effect. The goal is twofold. First, we formalize the intuition delivered by the aforementioned example and show in a simple, stylized setting that extrapolation coupled with the disposition effect can lead to the rising prices and volume observed in a bubble. Second, we use this model to derive additional, testable predictions about trading volume.

2.1 The setup

Market. There are $T+1$ dates, denoted by $t = 0, 1, ..., T$. On date t, a risk-neutral investor allocates her wealth W_t between two assets: a risk-free option (cash) with returns normalized to zero and a risky option (stock) with a fixed supply of Q shares. There is no transaction cost. The stock, potentially subject to a bubble, is a claim to a dividend D_T paid on the final date T, where D_T is given by the process

$$D_T = D_0 + d_1 + ... + d_T. \tag{1}$$

The dividend shock on date t, d_t, is distributed $N\left(0, \sigma_D^2\right)$ and i.i.d. over time. D_0 is public information on date 0; d_t becomes public at the beginning of date t. On date t, investors are fully informed about the cumulative dividend D_t so far, where $D_t = D_0 + d_1 + ... + d_t$.

There is a continuum of investors, all subject to short-selling and borrowing constraints.[5]

leverage-induced fire sales to the market crash.

[5]Short-selling constraint is a common assumption in models of bubbles (e.g., Harrison and Kreps, 1978;

We assume they are prone to both extrapolation and the disposition effect and label them as *disposition extrapolators*. In what follows, we model extrapolation in the standard way by assuming that investors form their beliefs about future price changes based on past price changes. To model the disposition effect, we consider realization utility as the main driver.[6] Therefore, throughout this paper, we think of extrapolation as a feature of *beliefs* and the disposition effect as a feature of *preferences*.

Beliefs. Our modeling of extrapolative beliefs closely follows Barberis et al. (2018). Disposition extrapolators form their beliefs based on an *extrapolative* signal. The extrapolative signal on date t, denoted by X_t, is specified by

$$X_t \equiv (1-\theta) \sum_{k=1}^{t-1} \theta^{k-1} \left(P_{t-k} - P_{t-k-1} \right) + \theta^{t-1} X_1, \tag{2}$$

where $0 < \theta \leq 1$ and X_1 measures investor enthusiasm on date 1. X_t is an exponentially weighted average of past price changes, with more recent ones weighted more heavily. The degree of overweighting is determined by θ: as θ decreases, investors increasingly overweight recent periods. Thus, a lower θ corresponds to higher extrapolation. We follow Barberis et al. (2018) and assume that investors also incorporate a *value* signal, defined by $D_t - P_t$, into their belief formation. The value signal represents the expectation held by a rational investor, and, in the context of our model, it allows a sequence of positive dividend shocks to give an initial push to stock prices and trigger a bubble.[7]

Finally, given a continuum of investors, we assume that each investor's beliefs are subject

Scheinkman and Xiong, 2003), and it realistically characterizes the Chinese stock market: the government only legalized short-selling in 2010 and, to date, it has been exercised only on a small scale. The borrowing-constraint assumption is mainly for tractability: without it, risk-neutral investors will take infinite leverage when the stock's expected price change is positive.

[6] Other mechanisms, such as non-standard beliefs (e.g., Odean 1998 and Peng 2017) and cognitive dissonance (e.g., Chang et al. 2016), could also explain the disposition effect. Key to our bubble mechanism, as we show later, is the tendency to sell winners and losers in an existing portfolio. Therefore, using these other mechanisms should produce similar predictions, but we do not pursue this question in more detail.

[7] Alternatively, we can model the market as featuring both fundamental traders and disposition extrapolators. In this setting, dividend shocks affect prices via the expectations of fundamental traders and we don't need to add the value signal to extrapolators' expectations. The price and volume dynamics are similar, but we stick to our baseline setting for simplicity.

to a random noise, $\epsilon_{i,t}$, distributed $N\left(0, \sigma_\epsilon^2\right)$ and i.i.d. over time. $\epsilon_{i,t}$ generates some initial disagreement that leads investors to trade even before any dividend shocks are introduced. The baseline level of trading volume is determined by σ_ϵ^2. Importantly, σ_ϵ^2 is constant over time in our model, which means that rising volume *cannot* be due to greater dispersion in beliefs. In sum, for disposition extrapolator i, her expectation about the price change from date t to $t+1$, denoted by $E_{i,t}\Delta P_{t+1}$, is given by

$$E_{i,t}\Delta P_{t+1} = \gamma X_t + (1-\gamma)\left(D_t - P_t\right) + \epsilon_{i,t}. \tag{3}$$

The average expectation across all investors, denoted by $E_t \Delta P_{t+1}$, is $\gamma X_t + (1-\gamma)\left(D_t - P_t\right)$, a weighted average of the two signals. In the baseline case, we set $\gamma = 0.9$, so that disposition extrapolators' beliefs are mainly driven by the extrapolative signal.

Preferences. Under risk neutrality, an investor maximizes her expected final wealth. With zero transaction cost, the dynamic portfolio problem is reduced to two periods: on date t, she maximizes $E_t\left(W_{t+1}\right)$, the expected wealth by the next date.[8] We then introduce realization utility to this two-period problem by assuming a utility function that depends on not only the expected *wealth* by the *next* date, but also the *profits* realized on the *current* date. Specifically, she maximizes the following utility function:

$$E_t\left(W_{t+1}\right) + \beta\left(P_t - \overline{P}_t\right)\left(N_{t-1} - N_t\right)\mathbb{1}_{\{N_{t-1}>0 \text{ and } N_{t-1}>N_t\}}, \tag{4}$$

where $\overline{P}_t$ represents the reference price, proxied by the average purchase price, and $P_t - \overline{P}_t$ measures the price change since purchase.[9] N_t denotes the number of shares held by the end of date t, and as a result, $\left(P_t - \overline{P}_t\right)\left(N_{t-1} - N_t\right)$ represents profits realized on the current

[8] An additional assumption required for this simplification is that, on date t, the expected price changes for dates $t+2$ to T are all zero. Alternatively, we can think of this investor as myopic and simply maximizing the next period's wealth.

[9] Ideally, we would like to keep track of all possible trading paths to get an individual-specific reference price; that is, to have $\overline{P}_{i,t}$, rather than $\overline{P}_t$. Nonetheless, the large number of dates (101) makes it infeasible to keep track of all possible paths (2^{101}). Therefore, we assume a common reference price for all investors.

date.[10] The realization-utility term induces the disposition effect in the following way. When $P_t > \overline{P}_t$, the stock is trading at a gain and would increase utility by $\left(P_t - \overline{P}_t\right)(N_{t-1} - N_t)$ if sold. This creates an incentive for utility-maximizing investors to sell winners and hold on to losers. β is a parameter that measures the strength of realization utility: with a higher β, investors display a stronger disposition effect. The indicator function, $\mathbb{1}_{\{N_{t-1}>0 \text{ and } N_{t-1}>N_t\}}$, ensures realization utility kicks in only in the act of stock selling.

Share demand. We denote the values of cash and stock investment at the end of date t by W_t^C and W_t^S. An investor's specific portfolio problem depends on her asset holding. If she is holding cash, he maximizes $E_t(W_{t+1})$, subject to the belief-formation process in Equation (3). In this case, she switches to the stock if $E_{i,t}\Delta P_{t+1} > 0$ and sticks to cash otherwise. Given that $\epsilon_{i,t}$ is distributed $N(0, \sigma_\epsilon^2)$ and i.i.d., the total demand from cash investors is $\Phi(E_t\Delta P_{t+1}/\sigma_\epsilon)\left(W_{X,t-1}^C/P_t\right)$, where $\Phi(\cdot)$ denotes the cumulative probability function of the standard normal distribution. In this expression, $\Phi(E_t\Delta P_{t+1}/\sigma_\epsilon)$ represents the proportion of cash holders switching to the stock and $W_{X,t-1}^C/P_t$ represents their total wealth by the previous date, adjusted by the current stock price.

A stock investor instead maximizes the utility function in Equation (4). She holds on to the stock if $E_{i,t}\Delta P_{t+1} > \beta\left(P_t - \overline{P}_t\right)$ and switches to cash otherwise. The share demand from stock investors is similarly given by $\Phi\left(\left(E_t\Delta P_{t+1} - \beta\left(P_t - \overline{P}_t\right)\right)/\sigma_\epsilon\right)Q$. Therefore, the total share demand, denoted by H_t, is given by

$$H_t = \Phi(E_t\Delta P_{t+1}/\sigma_\epsilon)\left(W_{X,t-1}^C/P_t\right) + \Phi\left(\left(E_t\Delta P_{t+1} - \beta\left(P_t - \overline{P}_t\right)\right)/\sigma_\epsilon\right)Q. \tag{5}$$

With the market-clearing condition $H_t = Q$, we can solve for the equilibrium price P_t.

Parameter values. We set $T = 100$, so we have a total of 101 dates. For simplicity, the dividend shocks from date 1 to 10 are set to zero. We then introduce four consecutive

[10] The above specification models the disposition effect in reduced form. In the Appendix, by imposing some additional assumptions, we derive a similar two-period problem even for investors solving the full dynamic-portfolio problem.

shocks—2, 4, 6, and 8—from date 11 to 14; the dividend shocks are set at zero afterward. D_0 is initially set at 100, and X_1 at zero. σ_ϵ is fixed at 2, which generates a moderate degree of belief error. The value of θ is initially set at 0.8, consistent with the estimation by Cassella and Gulen (2018). We assume that investors start with a wealth level of 100 and $Q = 1/2$. For now, we hold constant the wealth distribution between cash and the stock; results are similar if we relax this assumption. Finally, we set $\beta = 1$. Later, in Section 2.3, we study the model's comparative statics by varying some key parameter values.

2.2 Baseline results

Prices. Figure 2a plots the evolution of prices and dividends for the baseline scenario: the solid line represents the price and the dashed line represents the dividend. From date 1 to 10, in the absence of any demand shocks or changes in beliefs, the price remains constant. Starting on date 11, with the introduction of four consecutive positive dividend shocks, the price begins to rise. However, it does not rise as much as the dividend: according to Equation (3), investors only put a weight of 0.1 on the value signal and initially underreact.

The subsequent price dynamics are directly tied to the evolution of investor beliefs, shown in Figure 2b. Although shocks end on date 15, the price continues to rise. Before the price reaches the dividend, the value and extrapolative signals collectively push it up: the value signal suggests the stock is undervalued, whereas the extrapolative signal suggests the upward trend will continue. In Figure 2b, both the solid and dashed lines, corresponding to the two signals, remain positive before date 20, the date when the price reaches the dividend.

After the price exceeds the dividend, the value signal turns negative, suggesting the stock is now overvalued. But the extrapolative signal remains positive due to the string of positive past returns, thereby pushing up the price even more despite the negative value signal. Towards the end of the run-up, the price does not rise as quickly as before, partly because the value signal becomes more negative and partly because the initial dividend shocks recede into the past and extrapolators become less excited. The value signal eventually turns so negative that it outweighs the extrapolative signal, triggering the price fall.

In Figure 2c, the solid line represents the evolution of $P_t - \overline{P}_t$, a measure of portfolio returns for stock investors. It rises together with the price run-up, indicating a stronger propensity to sell during a bubble. Intuitively, the disposition effect works to counteract the buying pressure from cash holders; in the model, this also ensures the existence of an equilibrium price. At this point, one might wonder: given that the disposition effect induces selling, would prices still go up with a stronger disposition effect? The answer is yes. Notice that the disposition effect induces selling *only when* $P_t > \overline{P}_t$; that is, when the stock price exceeds the purchase price. During the run-up, the average purchase price ($\overline{P}_t$) is very close to the previous stock price (P_{t-1}), as most current stock investors have just bought the stock on the previous date. Often, P_t has to exceed P_{t-1} to induce sufficient selling for the market to clear. Indeed, as we show later, this price result holds under various degrees of disposition.

Trading volume. The total trading volume on date t, denoted by V_t, is given by

$$V_t = \frac{1}{2}\left(\Phi\left(E_t \Delta P_{t+1}/\sigma_\epsilon\right)\left(W^C_{X,t-1}/P_t\right) + \Phi\left(\left(\beta\left(P_t - \overline{P}_t\right) - E_t\Delta P_{t+1}\right)/\sigma_\epsilon\right)Q\right). \qquad (6)$$

In the model, volume comes from two sources: cash holders buying and stock investors selling, represented by the two terms on the right-hand side of Equation (6). Because a buy matches a sell, the two terms always carry the same value. In Figure 3a, the solid line, which represents V_t, is hump-shaped: it rises substantially after the dividend shocks, continues to increase afterwards, and, notably, begins to drop while the price is still rising. Intuitively, volume peaks when investor beliefs are most optimistic, that is, when $E_t\Delta P_{t+1}$ peaks. In comparison, prices peak when investor enthusiasm turns to neutral; that is, when $E_t\Delta P_{t+1}$ approaches zero. As a result, volume peaks ahead of price: in Figure 3a, volume peaks on date 17 and prices peak on date 27. This pattern is consistent with the empirical evidence in DeFusco et al. (2018), in which they first document this lead-lag relationship.

Our previous reasoning for rising prices also explains the stronger propensity to buy the stock. Indeed, in Figure 3b, the solid line, which represents the expected future price change, increases from 0 to 2. However, these optimistic beliefs effectively discourage stock investors from selling, so what makes them sell? The disposition effect. As $P_t - \overline{P}_t$ rises sharply in the run-up, the stock is associated with more gains. As such, two forces simultaneously drive their decisions: extrapolative beliefs say "hold" while realization utility says "sell." In equilibrium, the price rises so much that *preferences* dominate *beliefs*: in Figure 3b, $\beta\left(P_t - \overline{P}_t\right)$ increases more than $E_t \Delta P_{t+1}$ and $\beta\left(P_t - \overline{P}_t\right) - E_t \Delta P_{t+1}$ remains positive for much of the bubble.

2.3 Comparative statics

The model's main result—the high prices and volume in a bubble—holds under a range of parameter values. Figure 4 shows the maximum prices and volumes when the value of a particular parameter changes; the solid line represents peak prices and the dashed line represents peak volumes. Each graph corresponds to one key parameter in the model: θ, the degree of extrapolation; β, the degree of disposition; σ_ϵ, the standard deviation of beliefs among investors; and γ, the weight placed on the extrapolative signal. For each graph, we generate the maximum price and volume by varying the corresponding parameter values along the horizontal axis while holding other parameter values fixed to their baseline levels.

In Figure 4a, consistent with other models of extrapolation, the peak price monotonically decreases in θ. As θ decreases, the extrapolative signal becomes more sensitive to recent price changes, and the same dividend shocks generate greater price increases. This feeds back into more optimistic beliefs via the extrapolative signal, resulting in a higher peak price. We empirically confirm this result in Section 5. Figure 4b shows the price at peak decreases in the degree of disposition (β), because a higher β generates greater selling pressure in the run-up. However, as discussed above, a stronger disposition effect does not completely erase the bubble, because investors update their reference price more frequently to the recent price and demand a positive return to sell.

The patterns in Figures 4c and 4d shed light on some conceptual issues about the model. In Figure 4c, both peak price and volume *decrease* in σ_ϵ, the initial dispersion of beliefs. With a higher σ_ϵ, investor share demand becomes less sensitive to *changes* in beliefs and preferences—in Equation (5), changes in $E_t\Delta P_{t+1}$ and $P_t - \overline{P}_t$ are discounted by σ_ϵ—and leads to a *smaller* bubble. This again highlights the difference between our model and models of disagreement, where greater dispersion in beliefs leads to a greater bubble. Finally, in Figure 4d, the price at peak increases in γ, the weight placed on the extrapolative signal. The intuition is similar to Figure 4a: as investors pay more attention to the extrapolative signal, they can push up prices even more.

2.4 Predictions about volume

The model features a single investor type, but empirically other types of investors may also be present in a bubble. Our model immediately suggests that disposition extrapolators are the ones who trade the most during a bubble. In the Appendix, we study a heterogeneous-agent extension with two additional investor types—extrapolation-only and disposition-only—and confirm the above intuition. Indeed, because most of the volume comes from disposition extrapolators switching back and forth between cash and the stock, both ingredients are needed to get high volume. This leads to the following prediction about the composition of volume during a bubble:

Prediction 1 *During a bubble, disposition extrapolators increase their volume more than other investors do.*

Moreover, our model implies that disposition extrapolators trade more aggressively on the *extensive* margin; that is, they tend to liquidate existing positions and initiate new positions, as opposed to trading back and forth with the same set of assets via additional buys and partial sells. Indeed, realization utility urges them to quickly "conclude a successful investment episode", and extrapolation subsequently directs them to "move on to the next episode". Notice that our baseline setting does not make this prediction directly: due to risk neutrality, there is only extensive-margin. To allow for intensive-margin trading, in the Appendix, we examine a setting under constant absolute risk aversion (CARA) preferences and show that indeed most of disposition extrapolators' volume comes from extensive-margin trading.[11]

Prediction 2 *During a bubble, a greater fraction of total volume comes from extensive-margin trading as opposed to intensive-margin trading.*

A related, yet different prediction that comes out from a multi-asset extension of the model suggests that after liquidating an existing position, a disposition extrapolator would like to venture into a new stock—one that has done very well in the past and caught her attention. This also suggests that volume in a bubble would come from trading stocks they have not held before.

Prediction 3 *During a bubble, a greater fraction of total volume comes from trading stocks investors have not held before.*

Discussion. Our volume mechanism stems from the tension between extrapolation and the disposition effect. In particular, each investor constantly faces a conflict between these two forces: when out of the market, he is tempted to enter due to extrapolation, but as soon as he is back in the market, the disposition effect kicks in and prompts him to sell. As a result, investors switch back and forth between cash and the stock; hence the volume. This mechanism is novel in that it is based on the interaction between extrapolation—a feature of *beliefs*—and the disposition effect—a feature of *preferences*. In contrast, in Scheinkman and Xiong (2003) and Barberis et al. (2018), volume rises due to greater dispersion in beliefs, and, in DeFusco et al. (2018), volume rises due to the entry of short-horizon buyers into the market.[12] To our knowledge, this is the first paper that combines non-standard beliefs and preferences to shed light on asset prices and volume.

[11] When the model contains only one stock, investors tend to "exit and reenter" the entire market, a behavior echoed by Newton's experience in the South Sea Bubble. In a multi-stock setting, extensive-margin trading involves liquidating existing holdings and simultaneously reinvesting the proceeds in some new stocks.

[12] In Scheinkman and Xiong (2003), investors are overconfident about their own private signals and form different expectations about future returns based on their own signals; in Barberis et al. (2018), investors waver between two signals whose values differ more during a bubble, leading to more dispersed beliefs. DeFusco et al. (2018) contains a detailed discussion of these different theories of bubbles.

In addition to the conceptual differences, our model also differs in being directly testable: both elements are well-documented phenomena and can be plausibly measured using transaction data. This feature allows our empirical design to closely match the predictions. In this regard, DeFusco et al. (2018) share a similar feature: they are able to measure home buyers' horizon and link short-term buyers to the rise of volume. In Section 4, we closely examine the predictions listed above, and, in doing so, we highlight the unique features about our model's mechanism for volume.

3 Background and data

3.1 Overview of the bubble

The Chinese financial market, well known for its speculative nature, is a fertile ground for bubbles. In the past, researchers have examined bubble episodes in the stock and warrants markets (e.g., Mei et al. 2009; Xiong and Yu 2011). An ongoing debate focuses on whether the current Chinese real estate boom is a bubble and is likely to reverse (e.g., Fang et al. 2016; Glaeser et al. 2017). In this paper, we examine a bubble episode that occurred in the Chinese stock market from 2014 to 2015. As we show below, this episode clearly demonstrated some of the classic features of a financial bubble: an initial boom prompted by good fundamental news, a prolonged period of overvaluation, a heightened level of trading volume, and an abrupt crash in which prices fell faster even more quickly than they rose.[13]

Like many historical bubbles, this one was triggered in part by new information about the economy. Around July 2014, the media began to speculate on the market's performance going forward. The next four months witnessed the emergence of numerous arguments in support of

[13]Financial media and commentators almost unanimously call the episode a bubble. For example, a *Wall Street Journal* article (https://www.wsj.com/articles/china-market-bubble-still-taking-on-air-1433500241) suggests that there were ample indications of a bubble, including "unprecedented amounts of margin lending, massive numbers of people rushing to open new brokerage accounts and a crush of companies launching IPOs, raising fresh equity and selling insider shares as fast as they can." Several Chinese government officials also described the episode as a bubble. For example, an official document compiled by a group of researchers led by the former vice chairwoman of the People's Bank of China declared this episode a financial bubble.

a bullish market. Popular accounts emphasized the so-called "reform dividend theory," which stresses privatizing state-owned enterprises and promoting internet finance companies as the keys to a successful economic transition. Under the new economic model, the government would give these firms a bigger role to play, thereby boosting their share prices. At that time, it was unclear how credible the theory was, as very few policies had been enacted. Nonetheless, many investors bought the theory with no hesitation and their conviction was reinforced by prominent media such as the *People's Daily* (the official mouthpiece of the Chinese Communist Party), whose front-page articles strongly urged investors to trust the stock market. Before long, speculation turned into reality: the market experienced a run-up spanning six months, during which time most Chinese stocks doubled in value.

Figure 1 shows the evolution of prices and trading volume from 2014 to 2015. The solid line (in blue) represents the daily closing price of the Shenzhen Component Index (SZCI), a value-weighted index consisting of 500 stocks listed on the Shenzhen Stock Exchange (SZSE). During the run-up (the blue shaded area), the index increased from 8,332 to 18,098, reaching its highest level since 2008. The thin line (in red) represents the total number of shares traded on the SZSE, with the scale on the right axis. Volume rose more than prices did, increasing four times relative to its pre-bubble level.

Facing these dramatic market movements, the China Securities Regulatory Commission (CSRC) became increasingly wary of the mounting leverage investors were taking on. It was particularly concerned about the prevalence of outside-market leverage (or shadow leverage), a type of leverage financed by trust companies rather than broker-dealers, making it difficult for the CSRC to monitor and regulate its usage. In mid-June 2015, after conducting a preliminary investigation, the CSRC pulled the plug on outside-market leverage, which triggered the subsequent market crash. Following an initial slump, many leverage accounts faced margin calls, forcing investors to liquidate their entire positions; selling pressure from these fire sales dragged prices down even further and forced more accounts into liquidation, thereby creating a negative price spiral. Indeed, during the crash, prices fell much more quickly than they had risen: SZCI dropped by almost 40% in just one month. Although the government responded immediately with various measures to prop up the market, the recovery was short-lived; the market plummeted again in mid-August and continued to fall until September.

Given the discussion above, we adopt the following timeline to study this bubble: (1) 2014:01 to 2014:11 is the pre-bubble period, because price reactions in the market were muted; (2) 2014:12 to 2015:05 is the run-up, manifested by intensive media coverage and strong market reactions; and (3) 2015:06 to 2015:08 is the crash.

3.2 The data

We use account-level transaction data provided by one of the largest brokerage firms in China to study this bubble episode. The company has branches in almost all of China's provincial-districts and are market leaders in several regions. We choose 2005 as the starting point of our analysis because several reforms at the beginning of 2005 significantly broadened household access to the stock market. Furthermore, we focus on individual investors because they make up the largest category of investors in the Chinese stock market. Individuals hold approximately 45% of all tradable shares and their trading accounts for 85% of total volume. During this bubble, they became even more active, responsible for over 90% of total volume right before the bubble burst. An individual can have two types of account: a *regular* account for standard transactions and a *margin* account for leveraged trading and short-selling. In this study, we focus on regular accounts and abstract away from the effect of leverage on prices and volume. We acknowledge that the behavior of institutions is equally interesting and leave such exploration for future research.

We further restrict the sample to individuals with non-trivial yet relatively small holdings, defined by having a maximum balance between 0.01 and 1 million RMB by the end of 2013. We also limit the sample to investors who own an account before 2014 and have been actively trading, making ex-ante estimation possible given that the bubble started in 2014.[14] In doing

[14]Specifically, we limit to investors who have made at least 14 buys and 10 sells before 2014. The two cutoff numbers correspond to the 10th-percentiles in their distributions in the entire investor population.

so, we effectively exclude large individual accounts, a significant proportion of which were defacto managed by institutions that provide shadow leverage to these accounts. Representing over 80% of the investor population, these small individual accounts in our sample were mostly owned by typical Chinese mom-and-pop investors. Although, on average, they only held a low balance in their accounts, together they remained the largest force in the market, accounting for more than 20% of stock ownership and 50% of volume in the entire market. Given these criteria, our main sample consists the detailed transactions of around 600,000 retail investors from 2005 to 2016.

Our data have a structure similar to those used by Odean (1998): each observation specifies the buyer, seller, date, time, price, quantity, and security code. The time stamp specifies the order of intraday transactions, allowing us to precisely infer the nature of each transaction (e.g., whether an investor is opening a new position or buying additional shares for an existing position) and to uncover some new facts about the composition of volume. We complement our analysis with a number of additional datasets. The first is investor characteristic data: demographic information collected from brokerage firms and trading characteristics based on past transactions. The second one, called "the survey data", contains responses to a number of questions asked when an investor opens an account for the first time. These survey questions include expected returns and risks, self reported wealth, income, and sophistication, investment horizon, experience, and objectives, and both short-term and long-term tolerances for losses. Not all investors take these surveys: on average, we are able to merge half of the full-sample with the survey data. All the price and return data are from CSMAR.

3.3 Measuring extrapolation and disposition

To bring the model's predictions to the data, we devise a systematic way to measure investor types based on their transactions. Specifically, we assign each investor a degree of extrapolation (DOX) and a degree of disposition (DOD). In the context of our model, DOX is similar to $1-\theta$, one minus the extrapolation horizon; DOD represents β, the weight placed on the disposition signal. Empirically, disposition extrapolators are characterized by having a high DOX and a high DOD.

We start with the estimation of DOX. Technically, as DOX increases, investors become more sensitive to recent price changes, resulting in a greater propensity to purchase stocks with positive recent returns. This observation motivates us to look at buying behavior and measure DOX as the weighted-average past returns based on all the transactions classified as initial buys. More specifically,

$$DOX_i = \frac{\sum (Buy_{i,t} * PastRet_t)}{\sum Buy_{i,t}}, \tag{7}$$

where $Buy_{i,t}$ denotes the total transaction value for investor i and transaction t and $PastRet_t$ denotes the past return over a certain horizon prior to the transaction. Another way to interpret DOX is that it is a measure for positive feedback trading (e.g., DeLong et al. 1990) and we take the stand that the underlying mechanism for positive feedback trading is extrapolation. We are aware that buying behavior may capture factors beyond extrapolative beliefs and we aim to address the related issues as below.

First, the calculation of past returns depends on the horizon and it is not obvious from previous studies what horizon Chinese retail investors use.[15] To determine the extrapolation horizon, we examine the relationship between future trading flows (both buys and sells) and past stock returns. Like Barber et al. (2009), we regress trading flows on lagged returns using a panel of individual stocks (see the Appendix). Results from Fama-MacBeth regressions show that trading flows respond to returns up to 10 weeks ago and most strongly to the most recent month/week. Measures of DOX under different horizons are highly correlated, but for simplicity, we use DOX based on past monthly returns throughout the paper.

Second, the act of buying winners could be driven by extrapolative beliefs, but could also be associated with rational motives such as a momentum trading strategy. In this regard, existing studies do not find momentum in the cross-section of Chinese stocks across various

[15] In the United States, prior research suggests that the extrapolation horizon may extend up to three years back (Barber et al. 2009) and several authors also use the return over the last 12 months to identify extrapolators (Barberis et al. 2018).

horizons (e.g., Gao et al. 2014; Pan and Xu 2011), which suggests that the motive behind buying winners is more speculative than rational.

Third, we need to determine the set of transactions for estimation—*initial* buys only or both *initial* and *additional* buys.[16] The main concern with additional buys is that they may be associated with mechanisms other than beliefs, such as realization utility (Barberis and Xiong 2012) and cognitive dissonance (Chang et al. 2016).[17] More plausible is the notion that the main mechanism underlying investors' initial buying behavior is beliefs.[18] Therefore, to measure DOX more accurately, we use initial buys only.

We estimate DOX using all the initial buys from 2005 to 2013. The first two columns in Table 1 reports the summary statistics for DOX, where $DOXM$ represents our main measure based on past monthly returns and $DOXW$ represents an alternative one based on past weekly returns. Overall, Chinese investors are extrapolative: the 75-percentiles are positive for both measures, suggesting that more than 75% of the investors tend to buy things have gone up recently. Results are robust to both raw returns and market-adjusted returns.

The estimation of DOD follows the methodology employed by Odean (1998) and Dhar and Zhu (2006). We examine all the positions on days of sales and calculate two metrics measuring the propensities of selling winners and losers separately: PGR (Proportion of Gains Realized), defined by

$$\text{PGR} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}}, \tag{8}$$

and PLR (Proportion of Losses Realized), defined by

$$\text{PLR} = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}}, \tag{9}$$

[16]Purchasing a stock that is not in the current portfolio is considered an initial buy. Purchasing a stock that is in the current portfolio is considered an additional buy.

[17]Odean (1998) finds investors tend to buy stocks additionally after their prices have gone down from the purchase price, which is rather different from the trend-chasing behavior they display in initial buys.

[18]Another factor affecting initial buys is attention: stocks with extreme returns are more attention-grabbing (Barber and Odean 2008). In the Chinese stock market, the most attention-grabbing stocks are those hitting daily price limits. After hitting price limits, however, these stocks typically have zero liquidity. Therefore, it is unlikely that initial buys capture attention in our setting.

where gains and losses are calculated based on the average purchase price and labeled as realized or paper depending on whether they are sold or not. The degree of disposition is the measured either as the difference between the two metrics, denoted by *DODD*, or the ratio between the two, denoted by *DODR*. While prior literature has raised some concerns about using these measures to capture the disposition effect at the individual level, especially when investors infrequently trade, the large sample size we work with makes is impossible to follow an alternative approach such as a hazard-rate model (Feng and Seasholes 2005). Nonetheless, the fact that Chinese retail investors trade very frequently largely mitigates such concerns.

Column (3) and (4) in Table 1 report the summary statistics for *DODD* and *DODR*. Consistent with existing evidence, the disposition effect is prevalent among Chinese investors: the 75-percentile for *DODD* is positive and the 75-percentile for *DODR* is greater than one, suggesting that more than 75% of Chinese retail investors are prone to the disposition effect. Throughout the paper, we will primarily employ *DODR*, the ratio-based degree of disposition, as our main measure. Results are robust to the use of *DODD*.

It is worth noting that extrapolation and the disposition effect are very persistent characteristics. If we split the estimation period equally into two halves and then construct two measures separately, they are highly correlated. This provides further justification for using *ex-ante* measures to study trading behavior in the bubble: the disposition extrapolators identified *prior to* the bubble are likely to be ones who behave as disposition extrapolators *during* the bubble.

In addition to *DOX* and *DOD*, we also construct a variety of other account-level characteristics, many of which will serve as control variables in subsequent analysis. Their summary statistics are reported in Column (5) to (11) in Table 1. Many of these variables have extreme outliers (e.g., return rate), so we winsorize all variables at the 1% and 99% levels. Panel B of Table 1 further reports the correlation matrix across all the key account characteristics and highlights a number of observations. First, extrapolation and disposition effect appear to be independent investor attributes: the correlation coefficients remain very small across all specifications. Second, *DOX* is highly correlated with measures for volatility-seeking (*VOL*) and gambling preference (*SKEW*) while *DOD* is highly correlated with the measure for diversification (*HHI*, the Herfindahl–Hirschman Index). Therefore, it is important to put these variables in as controls in subsequent analysis.

Finally, in Table 2, we report the average *DOX* and *DOD* across various demographic groups. Prior literature shows that (a) the disposition effect is correlated with investor sophistication (Dhar and Zhu 2006), (b) the disposition effect can be mitigated by trading experience (Feng and Seasholes 2005), and (c) men and women trade differently (Barber and Odean 2001). For extrapolation, we find that it is weakly correlated with age and education, but more pronounced among women. For the disposition effect, we find that it is weakly correlated with education, but stronger among older investors and among women. We control for demographic variables whenever possible.

4 Volume Dynamics in the Bubble

In this section, we present four pieces of evidence that support our mechanism for trading volume in a bubble. Section 4.1 shows that, at the market-level, disposition extrapolators as a group are largely responsible for the rise in total volume. Section 4.2 confirms this result at the investor level using a regression framework that controls for an exhaustive list of other variables. Section 4.3 further examines the cross-section of individual stocks and shows that stocks traded more by disposition extrapolators experience a higher increase in turnover. Section 4.4 tests the model's more nuanced predictions by showing that much of the volume comes from extensive-margin trading and the trading of new stocks. Finally, in Section 4.5, we discuss some alternative explanations for our results and the implications they have for theories of bubbles.

4.1 Market-level evidence

We sort investors into three different groups based on their ex-ante measures of extrapolation and disposition: disposition extrapolators, pure extrapolators, and others. Specifically, disposition extrapolators have both DOX and DOD above the median, pure extrapolators have DOX above the median and DOD below, and the rest are classified as other investors. We then compare their trading volumes throughout the bubble.

In Figure 5a, each line represents the evolution of a group's volume, defined as the total value of shares traded and normalized to 1 at the beginning of 2014. Group-level volumes were very similar prior to the bubble: hovering around the value of 1, the three lines are almost indistinguishable in the pre-bubble period. However, in the run-up, disposition extrapolators increased their volume much more than other investors did: at peak, their trading volume increased by almost 800%; in comparison, pure extrapolators increased by 500% and other investors by 600%. The comparison between disposition extrapolators and pure extrapolators highlights the importance of the disposition effect in explaining volume: its addition generates an additional 300% increase in trading volume. Therefore, without the presence of disposition extrapolators, the rise of volume would have been on a much smaller scale.

Figure 5b and 5c further decompose trading volume into two different sources: turnover, which measures the speed at which investors rebalance their portfolios, and balance, the size of the portfolio. The different dynamics between the two figures paint a more vivid picture about how disposition extrapolators traded: not only were they most active in reshuffling their holdings, they were also very aggressive in increasing their overall exposure to the underlying assets. In comparison, pure extrapolators were more aggressive in buying more shares—the value of their holdings increased by more than 150%—but their turnover only went up by less than 150%, compared to an 300% increase by disposition extrapolators; other (non-extrapolative) investors exhibited a turnover similar to disposition extrapolators, but their holdings merely went up by around 100%. In short, both extrapolation and the disposition effect play separate, yet complement roles in driving up volume—the exact intuition delivered by the model.

In Figure 6, the two lines plot the fractions of total volume made up by disposition extrapolators and pure extrapolators, respectively. Consistent with before, as the bubble progressed, disposition extrapolators accounted for an increasing fraction of total volume: their trading constituted around 25% of total volume prior to the bubble, but reached 34% at the peak. In comparison, pure extrapolators increasingly accounted for a small fraction of total volume, from an initial 25% to almost 20%.

Finally, in both Figures 5 and 6, we see group-level differences in volume begin to disappear in the crash. In Figure 5, disposition extrapolators substantially decreased their volume as soon as the crash started and, by the end of September 2015, their volume had already returned to a level similar to that of other investors. A similar pattern is evident in Figure 6, where the fraction of total volume accounted for by disposition extrapolators dropped significantly in the crash. That is a direct result of the disposition effect: as positions turn into losses, investors tend to hold on to these losers and trade less.

4.2 Investor-level evidence

In the previous section, we sorted investors into groups and compared their trading volumes. One concern with the sorting approach is that *DOX* and *DOD* may simultaneously capture other investor characteristics, as we have demonstrated in Table 1 and 2. We therefore run investor-level regressions by regressing change in volume on *DOX*, *DOD*, as well as the interaction between *DOX* and *DOD*, while also controlling for various investor characteristics. Change in volume is measured by the ratio between monthly volume at peak (2015:05) to the average monthly volume in the pre-bubble period.

Regression results are reported in Table 3. To help interpret the coefficients, we normalize *DOX* and *DOD* by their respective standard deviations while keeping the other variables unchanged. Column (1) reports the baseline result without adding any controls: both coefficients for *DOX* and *DOD* are significantly positive with large magnitude. In particular, a one-standard-deviation increase in *DOX* is associated with a 402% increase in trading volume while a one-standard-deviation increase in DOD is associated with a 460% increase. The interaction term is also significant, which suggests that the effect of the disposition effect on volume is more pronounced among investors who are more extrapolative, and vice versa.

Column (2) to (4) each add an additional set of controls on the previous specification. Column (2) controls for trading characteristics such as account size (BAL), experience (EXP), portfolio diversification (HHI), volatility seeking (VOL), skewness seeking ($SKEW$), and past returns (RET). While many of these variables are significantly—for instance, investors with a larger account size increase their trading volume less—the significance of DOX and DOD is robust to their inclusion. Column (3) additionally adds demographic variables including gender, age, and education, and the results are essentially unchanged.

Column (4) represents our full specification by adding 1) a dummy variable for having a margin account, 2) a dummy variable for having traded warrants before to control for prior experience in bubbles (Xiong and Yu 2011), and 3) a set of survey-based characteristics. More specifically, survey-based characteristics include self-reported wealth, income, sophistication, investment horizon, as well as measures for risk tolerance in the short-term and in the long-term. Because only a fraction of the sample have answered the survey, the number of observations drops substantially, but the coefficients for DOX, DOD, and their interaction remain significantly with a slight smaller magnitude. Therefore, consistent with the market-level evidence, we show at the individual level that the combination of extrapolation and the disposition effect leads to higher volume.

Finally, in Column (5) and (6), we rerun the same regression in Column (4) but replace the left-hand variable by changes in turnover and balance, respectively. This is the regression version of the exercise in Figures 5b and 5c. Consistent with the market-level evidence, we find that the disposition effect is key to explaining the rise in turnover while extrapolation is responsible for the increase in holdings. Together, they contribute to the significance of disposition extrapolators in driving up volume.

4.3 Stock-level evidence

In this section, we examine the cross-section of individual stocks and try to link cross-sectional differences in trading volume to the behavior of disposition extrapolators. For each stock, we calculate its "exposure" to extrapolation in a given week as the buy-volume-weighted average degree of extrapolation, defined as

$$\overline{DOX}_{j,t} = \sum_{i=1}^{N} \left(\frac{Buy_{i,j,t}}{\sum_{i=1}^{N} Buy_{i,j,t}} \right) DOX_i, \tag{10}$$

where $Buy_{i,j,t}$ is the number of j shares bought by investor i in week t. Similarly, we calculate its "exposure" to disposition as the sell-volume-weighted average degree of disposition, defined as

$$\overline{DOD}_{j,t} = \sum_{i=1}^{N} \left(\frac{Sell_{i,j,t}}{\sum_{i=1}^{N} Sell_{i,j,t}} \right) DOD_i, \tag{11}$$

where $Sell_{i,j,t}$ is the number of j shares sold by investor i in week t. As a result, a higher $\overline{DOX}_{j,t}$ corresponds to more buying from extrapolators while a higher $\overline{DOD}_{j,t}$ corresponds to more selling from disposition-prone investors. This gives us a panel of stock-level degrees of extrapolation and disposition at the weekly frequency.

Next, we regress each stock's turnover, calculated by dividing total RMB volume to market capitalization, *contemporaneously* on its $\overline{DOX}$ and $\overline{DOD}$. The resulting coefficients show whether more trading from disposition extrapolators in a given week contributes to higher turnover in the same week. Unlike returns, turnover is much more persistent at the stock level, so we include a stock fixed effect in these regressions while clustering standard errors by time periods to control for common exposure to unobserved factors across stocks.[19] The stock fixed effect also means that we cannot include other stock-level controls such as beta, size, or B/M into the same regressions, because the run-up only lasted six months and these variables exhibited very little change.

Table 4 reports the panel regression results in the run-up, where $\overline{DOX}$ and $\overline{DOD}$ are

[19] These results are robust to adding a time fixed effect, double-clustering standard errors by stocks and time periods, and various combinations of different fixed effects and standard error clustering.

normalized using their standard deviations for easier interpretation. Column (1) reports the baseline result, where both coefficients are positive and highly significantly. In particular, a one-standard-deviation increase in $\overline{DOX}$ is associated with a 0.04 increase in weekly turnover while a one-standard-deviation increase in $\overline{DOD}$ is associated with a 0.02 increase in weekly turnover. Given that the average monthly turnover is around 0.2 during this period of time, these coefficients represent rather substantial explanatory power. We add additional sets of controls to the baseline regression from Column (2) to (4): contemporaneous weekly returns, lagged weekly returns, and lagged weekly turnover, respectively. Overall, while these additional controls reduce the t-stat for $\overline{DOX}$, both coefficients remain highly significant with large magnitude, even in the full specification in Column (4). Therefore, extrapolation and disposition not only shed light on aggregate volume, but also help explain why some stocks experience higher turnover than others.

4.4 Additional evidence about volume

So far, we have been primarily concerned with Prediction 1, which highlights the role of disposition extrapolators in driving up trading volume during a bubble. We now test the model's other predictions about trading volume.

Trading on the extensive-margin. Prediction 2 suggests that much of the trading volume during the bubble comes from extensive-margin trading as investors quickly exits one position and jump onto the next one. To test this prediction, we decompose total volume into extensive-margin and intensive-margin and compare their magnitudes. As a benchmark, Panel A of 5 reports the distribution of buy volume, sell volume, and total trading volume across three different periods from 2014:01 to 2015:12: run-up, crash, and quiet, defined as any period outside the run-up and crash. In addition to total transaction amount in RMB, we also report the total number of transactions as a robustness check.

Panel B of 5 shows the fraction of total volume accounted for by extensive-margin trades, where a purchase is considered extensive-margin if the starting position is zero (initial purchase) and a sale is considered extensive-margin if the end position is zero (liquidation). Overall, we find that, almost 55% of the total trading volume in the run-up comes from extensive-margin trading, compared to 46% in the crash and 52% in the quiet period. In particular, around 60% of sales are complete liquidations, and around 50% of all purchases are initial purchases. The same patterns hold if we instead measure volume by the total number of transactions.

Panel C of Table 5 further breaks down the fraction of extensive-margin trades by groups. Consistent with our model, extensive-margin trading is particularly prevalent among disposition extrapolators: almost 60% of their volume during the run-up is contributed by extensive-margin trades. In comparison, other groups of investors trade less on the extensive margin. Extensive-margin trading from disposition extrapolators dropped sharply in the crash by more than 10%. This is primarily driven by disposition extrapolators "doubling down" as they positions turn into losses during the crash.

Trading new stocks. Prediction 3 suggests that, during a bubble, as disposition extrapolators liquidate their winning positions, they tend to venture into new territories by putting the proceeds into stocks they have never traded before. We classify a stock as "new" if an investor has never held it in her monthly portfolios before. Panel D of 5 reports the fraction of total volume contributed by "new" stocks across different stages of the bubble. Indeed, almost 70% the total volume in the run-up comes from trading stocks they have never held before. In comparison, during the "quiet" period, the fraction is only 55%, and during the crash, it is merely 53%. In short, disposition extrapolators don't monotonically increase or decrease their stock holdings; rather, they alternately increase and decrease their exposure over time and across different stocks.

4.5 Discussion

Alternative explanations. Our results are robust to a number of alternative mechanisms for volume. It is easiest to understand the robustness of our results using Table 3.

Table 3 includes an exhaustive list of control variables: account size, experience, diversification, volatility seeking as a proxy for risk preference, skewness seeking as a proxy for gambling preference, past returns as a proxy for skills, demographic variables such as gender, age, and education, leverage constraints (dummy variable for having a margin account), prior trading experience with warrants, and survey-based characteristics (self-reported income, wealth, investment horizon, risk tolerance, investment objective, asset allocation, etc.). The wealth of control variables we include in these regressions validates the robustness of extrapolation and disposition in explaining volume.

We further address two alternative explanations beyond the control variables we have included. First, there is a concern that the rising leverage investors took during the bubble episode contributed to the high volume. Because we only use regular accounts, as opposed to leverage accounts, our volume results are not driven by the use of *regulated* leverage. We also controlled for the ownership of a leverage account in investor-level regressions. However, since we do not observe the *shadow* leverage investors took during this period (Bian et al. 2018a; Bian et al. 2018b), we cannot speak to the effect of shadow leverage on volume.

Second, many historical anecdotes of bubbles highlight the entry of new investors or short-term speculators as a plausible source of volume (e.g., DeFusco et al. 2018). Given the nature of our empirical design, we are not able to include new investors in our analysis. However, we find that even at the peak of the bubble, investors who entered the market after the run-up was already underway only accounted for less than 20% of total volume. Therefore, it is unlikely that the entry of new/other investors can fully explain the total volume.

Implications for theory. Our volume results cannot be easily reconciled by other theories of bubbles. First, existing theories based on extrapolation (e.g., Barberis et al. 2018; DeFusco et al. 2018) do not differentiate disposition extrapolators from pure extrapolators and are therefore silent on their difference during the bubble. Our results clearly show that the addition of the disposition effect makes a big difference to their trading behavior. One way to reconcile this discrepancy—in the language of Barberis et al. (2018)—is that disposition extrapolators are the "wavering" extrapolators who randomly switch between two signals pointing to different directions. This interpretation, however, suggests a different source for "wavering": instead of "wavering" between different signals in forming beliefs, disposition extrapolators "waver" between beliefs and preferences .

Our results are broadly consistent with the notion that the high volume is driven by short-term speculation (e.g., DeFusco et al. (2018)): disposition extrapolators behave as speculators by selling shares after immediate gains. However, our results also show that the same investor may change her investment horizon during a bubble. In DeFusco et al. (2018), positive past price changes disproportionately attract *ex-ante* short-horizon speculators. In our model, positive past price *endogenously* shortens the investment horizon for disposition-prone investors and makes them trade more.

Finally, it is also hard to reconcile our results under theories of overconfidence. On the one hand, static versions of overconfidence-based theories (e.g., Scheinkman and Xiong 2003) need to explain not only the aggregate rise in volume, but also the differential rises in volume across investor groups. It is not obvious why disposition extrapolators would become more overconfident in a bubble than other investors. On the other hand, dynamic versions of overconfidence-based theories (e.g., Gervais and Odean 2001) often posit good past portfolio returns as a source of overconfidence, but according to this theory, pure extrapolators—who ride the bubble more aggressively and make more profits in the run-up—should trade more than disposition extrapolators.

5 Extrapolators and prices

Many models of extrapolation—including ours—highlight extrapolative expectations as a primary driver of rising prices during a financial bubble. While this argument is intuitive and has a long tradition in the theoretical literature, empirical evidence in support of this argument has been scarce. Empirically identifying extrapolators is not an easy task without detailed transaction or survey data. Teasing out causality between behavior and prices is even harder: observing both rising prices and greater participation from extrapolators is consistent with extrapolators driving up prices, but is also consistent with the reverse argument that prices go up first and the rising prices subsequently attract more trading from extrapolators. In this section, we take advantage of the granular features of our data to examine the role of extrapolators in driving up stock prices during the 2014-15 Chinese stock market bubble.

To get more statistical power and facilitate our empirical strategy, we construct a panel of stock returns and characteristics at the weekly frequency, where the stock-level degree of extrapolation is constructed as in Equation (10). We then run various panel regressions by regressing weekly returns during the run-up on measures of extrapolation. In these regressions, we cluster standard errors by time period to control for correlated residuals in the cross-section and control for many other stock characteristics (e.g., size, B/M, beta, and past returns). The regression results are reported in Panel A of Table 6. As a benchmark, in Column (1), we first run the "wrong" regression by regressing returns *contemporaneously* on $\overline{DOX}$. The resulting coefficient is significantly positive, but as discussed above, the interpretation is unclear.

To rule out the reverse causality concern, we employ two alternative specifications: predictive regressions and instrumental variable (IV) regressions. In Column (2), we run a predictive regression by regressing *future* stock return on *past* extrapolation. The underlying idea is that stock-level extrapolation is persistent at the weekly level: stocks traded more by extrapolators in a given week are more likely to be traded by extrapolators in the following week. Indeed, $\overline{DOX}$ exhibits strong autocorrelation, with a AR(1) coefficient of 0.45 at the weekly frequency. In Column (2), the coefficient for $\overline{DOX}$ is positive and significant at the 5% level. In terms of economic significance, a one-standard-deviation increase in $\overline{DOX}$ in the current week predicts 50-basis-point higher returns in the following week, which amounts to roughly 13% for the entire run-up. While the t-stat is not huge, it is still sizable given the short sample period we examine. In comparison, almost none of the standard asset pricing factors appear to have any predictive power for future returns. Column (3) confirms the results in Column (2) by controlling for size and value non-linearly with size and value bins.

In Column (4), we run an IV regression by instrumenting current $\overline{DOX}$ using lagged $\overline{DOX}$. This allows us to study the contemporaneous effect of extrapolation on stock prices while ruling out the reverse causality concern. Consistent with the results from predictive regressions, $\overline{DOX}$ is positive and significant. A one-standard-deviation increase in the instrumented $\overline{DOX}$ is associated with a 1% increase in weekly returns in the same week, which amounts to 26% during the run-up. Given that the entire market almost doubled during this period of time, the explanatory power of extrapolation for returns is rather substantial.

Panel B repeats the same set of regressions in Panel A, but for the crash instead. While the contemporaneous regression still produces a positive coefficient, the predictive regressions and the IV regression instead produce a *negative* coefficient. This contrast highlights the main appeal of our empirical approach: by isolating the arrival of extrapolators from the period we use to measure returns, we are able to avoid spurious results in as Column (1) and (5). According to the IV regression, a one-standard-deviation increase in the instrumented $\overline{DOX}$ is associated with a 4% decrease in returns in the same week, suggesting a substantial negative impact extrapolators have on prices during the crash. Overall, we find strong support for extrapolation driving the market to go up and down during the bubble.

6 Conclusion

We examine a recent bubble episode in the Chinese stock market, using detailed account-level data from a large brokerage firm in China. The dataset covers a long panel of account-level transaction data for over one million Chinese retail investors. To make sense of the joint dynamics of price and volume in a bubble, we first present a model of bubbles based on extrapolation and the disposition effect. The model highlights a novel mechanism for volume based on the interplay between extrapolation and the disposition effect. Empirical evidence supports the model's mechanisms for volume and price. Disposition extrapolators are quick to buy a stock with good past performance, but also quick to sell it if its price continues to rise. They increase their trading volume much more than others, trade aggressively on the extensive-margin, and trade a lot of stocks they have never been exposed to before. We find evidence in support of extrapolators driving up prices during the run-up. Taken together, these results provide empirical support for our novel framework for thinking about bubbles.

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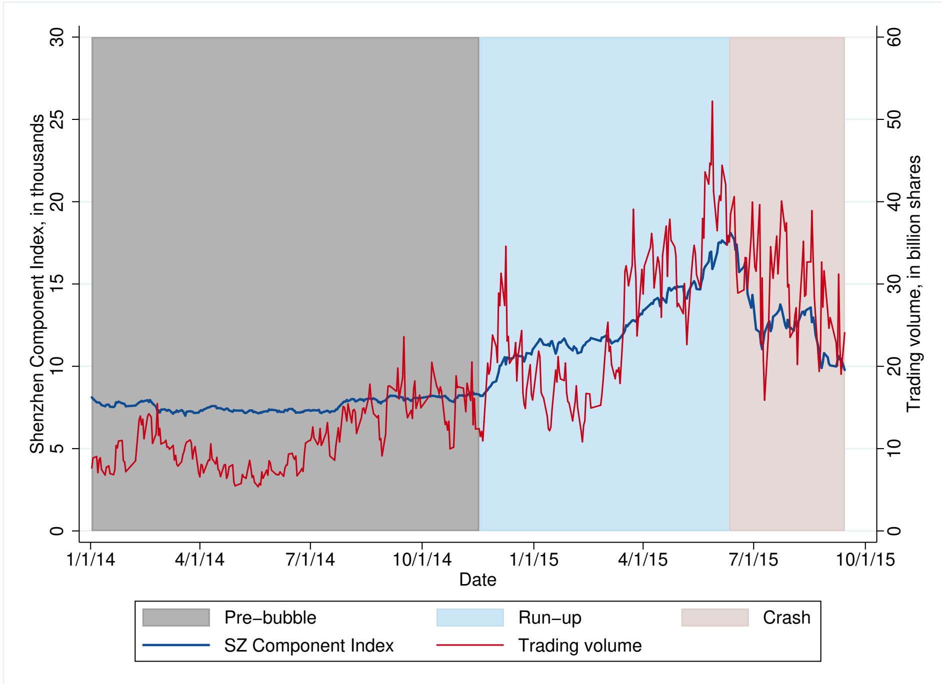
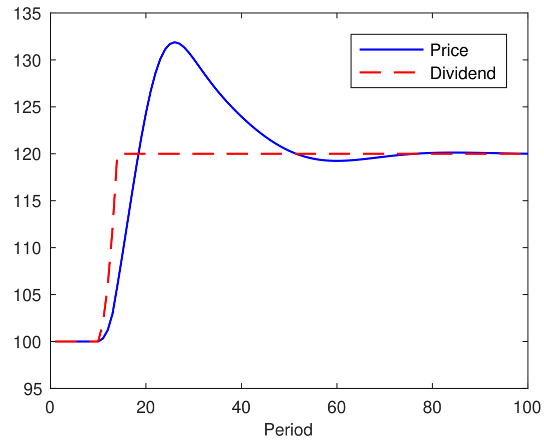
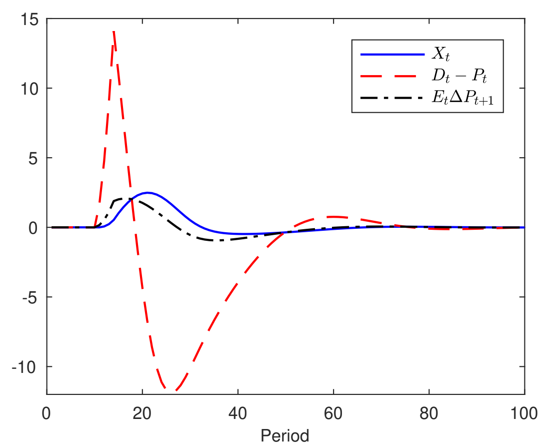


Figure 1: Prices and trading volume at SZSE

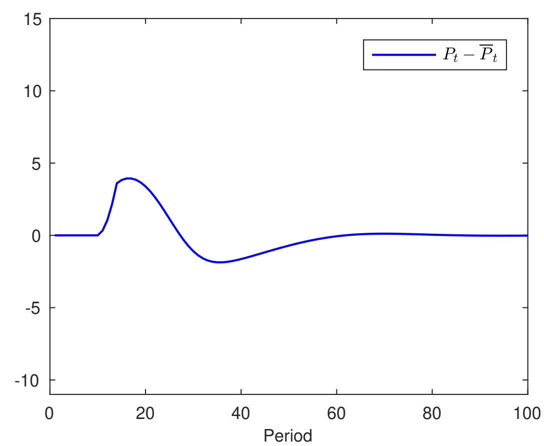
Note: The thick blue line plots the closing price of the Shenzhen Component Index (SZCI; in thousands) and the thin red line plots the total number of shares traded at SZSE (in billions; scale on the right axis). The time frame is from January 1, 2014, to September 15, 2015. The shaded areas represent three stages of the bubble: the pre-bubble stage, from January 1, 2014, to November 17, 2014; the run-up stage, from November 18, 2014, to June 12, 2015; and the crash stage, from June 13, 2015, to September 15, 2015.



(a) Price and dividend



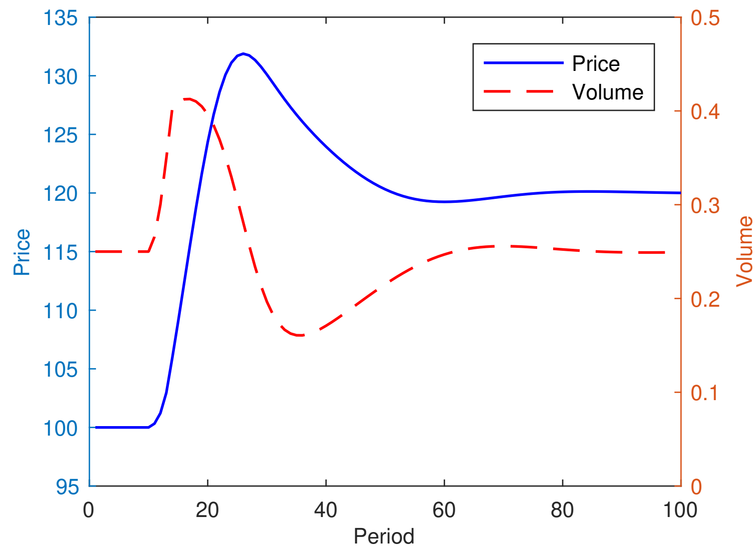
(b) Extrapolative and value signals



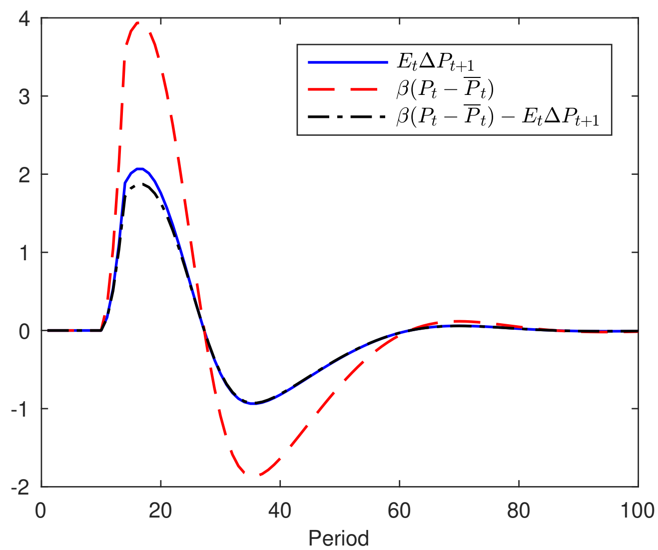
(c) $P_t - \overline{P}_t$

Figure 2: Prices and signals in the baseline case

Note: In Figure 2a, the dashed line represents dividend D_t and the solid line represents stock price P_t. In Figure 2b, the solid line represents X_t, the dashed line represents $D_t - P_t$, and the dash-dot line represents $E_t\Delta P_{t+1}$, defined by $E_t\Delta P_{t+1} = \gamma X_t + (1-\gamma)(D_t - P_t)$, where $\gamma = 0.9$. In Figure 2c, the solid line represents the difference between the current stock price and the reference price, $P_t - \overline{P}_t$. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\epsilon = 2$, $D_0 = 100$, $X_1 = 0$, and $Q = 1/2$.



(a) Volume and prices



(b) Signals

Figure 3: Trading volume in the baseline case

Note: In Figure 3a, the solid line represents total trading volume, and the dashed line represents the stock price. In Figure 3b, the solid line represents $E_t \Delta P_{t+1}$, the dashed line represents $\beta\left(P_t - \overline{P}_t\right)$, and the dash-dot line represents $\beta\left(P_t - \overline{P}_t\right) - E_t \Delta P_{t+1}$. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\epsilon = 2$, $D_0 = 100$, $X_1 = 0$, and $Q = 1/2$.

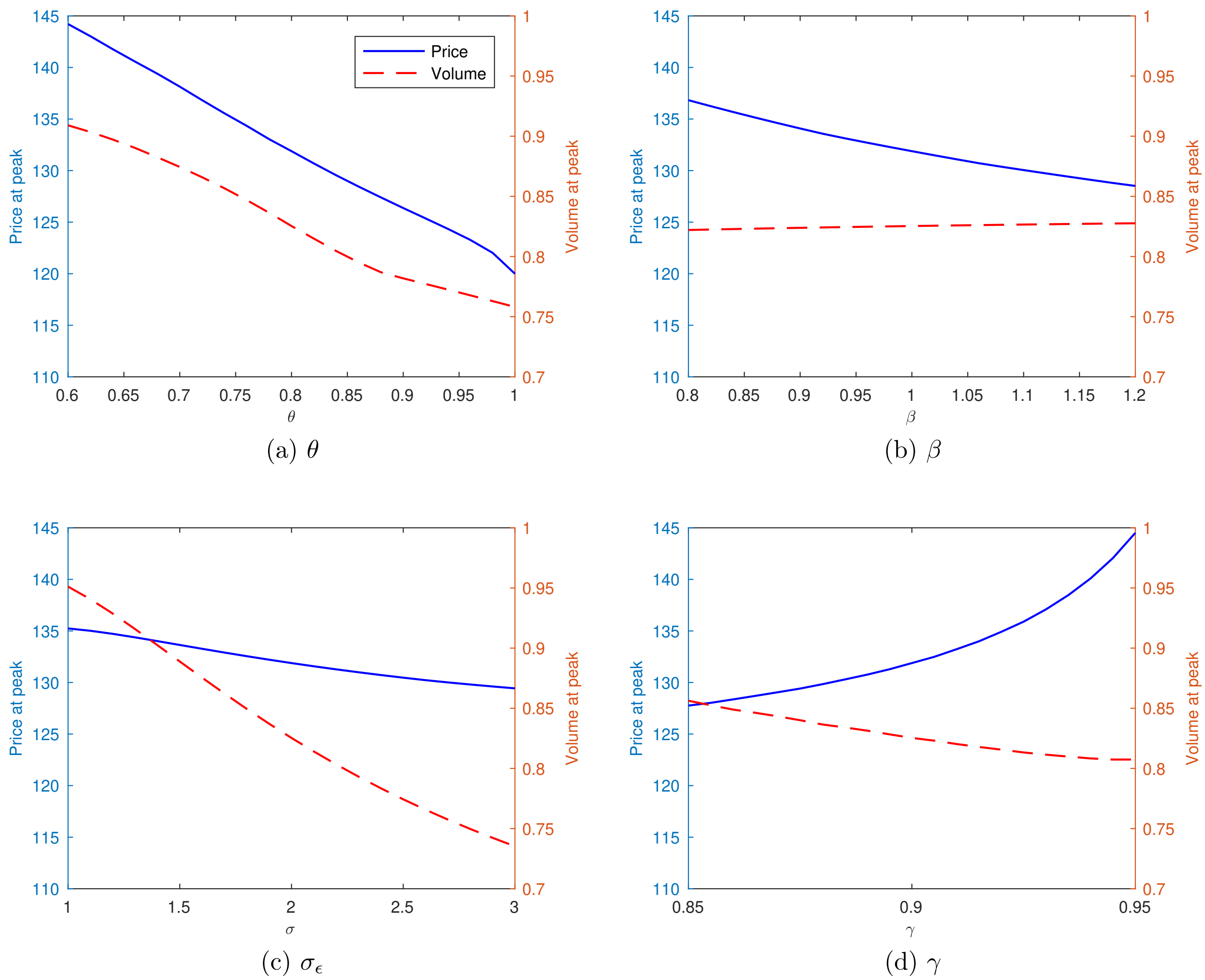
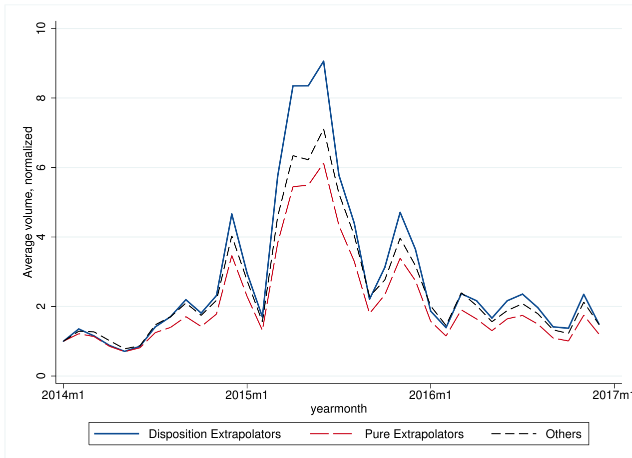
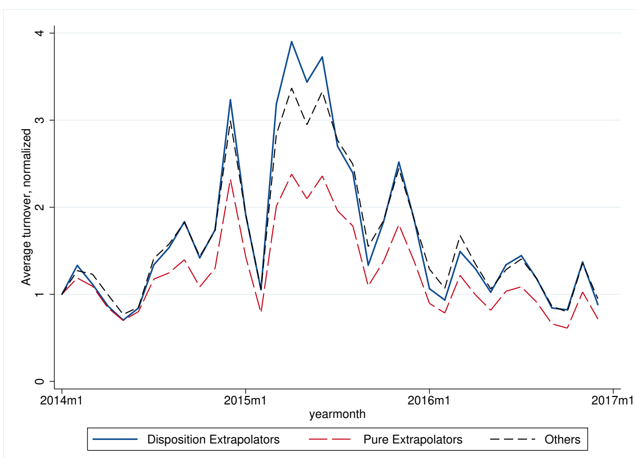


Figure 4: Comparative statics

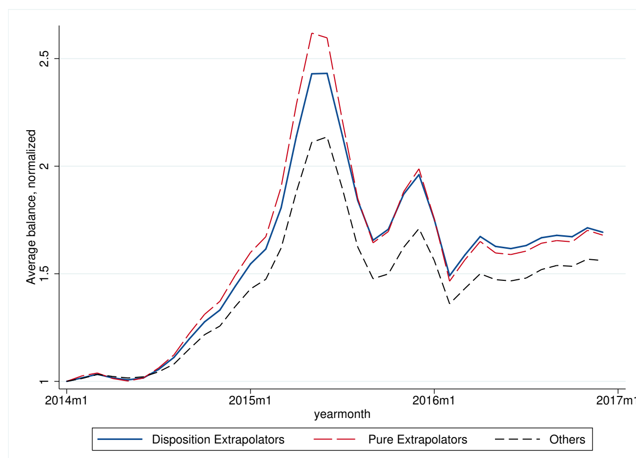
Note: This figure presents the price and volume at peak under parameters that are different from the baseline scenario. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. In the baseline scenario, the parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\epsilon = 2$, and $\gamma = 0.9$. The title of each sub-figure represents the parameter concerned.



(a) Trading volume in RMB



(b) Turnover, monthly



(c) Holdings in RMB

Figure 5: Evolution of volume by group

Note: The three lines in Figure 5a represent the evolution of volume for three investor groups: disposition extrapolators, pure extrapolators, and other investors. Disposition extrapolators have both DOX and DOD above the median, pure extrapolators have DOX above the median and DOD below, and the rest are classified as other investors. For all groups, volume/turnover/balance is normalized to 1 at the beginning of 2014.

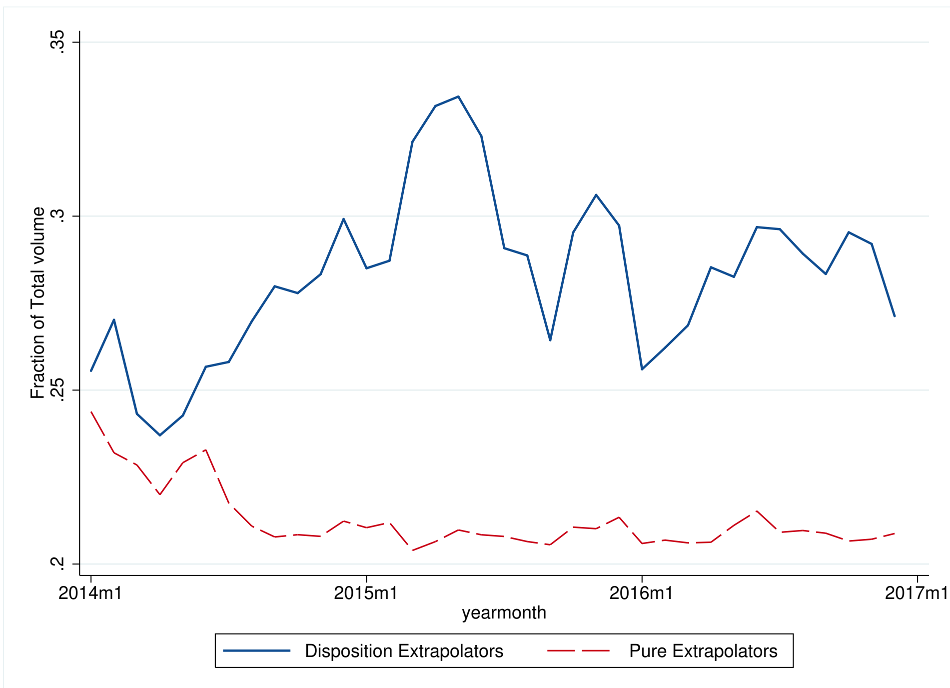


Figure 6: Decomposition of total volume by group

Note: This plots the composition of total volume. The solid line represents the fraction of volume from disposition extrapolators, and the dashed line represents the fraction from pure extrapolators. Disposition extrapolators have both DOX and DOD above the median, and pure extrapolators have DOX above the median and DOD below.

	Panel A: Summary statistics										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	DOXW	*DOXM*	*DODD*	*DODR*	*HHI*	*VOL*	*SKEW*	*TN*	*RET*	*BAL*	*EXP*
Min	-0.07	-0.11	-0.45	0.33	0.08	0.02	-0.28	0.02	-0.34	0.01	2.08
P5	-0.02	-0.02	-0.08	0.81	0.24	0.02	0.00	0.12	-0.07	0.02	3.83
P25	0.01	0.04	0.07	1.19	0.43	0.03	0.15	0.37	-0.03	0.06	6.33
P50	0.02	0.08	0.16	1.56	0.59	0.03	0.30	0.84	-0.01	0.13	8.25
P75	0.04	0.13	0.27	2.18	0.75	0.04	0.56	2.09	0.00	0.30	8.92
P95	0.08	0.23	0.47	4.34	0.93	0.05	1.35	8.92	0.02	0.72	9.92
Max	0.25	0.60	0.81	19.30	1.00	0.20	3.82	781.38	0.13	0.99	9.92
Mean	0.03	0.09	0.17	1.96	0.59	0.03	0.44	3.86	-0.02	0.22	7.63
Std. Dev.	0.03	0.08	0.17	1.52	0.21	0.01	0.47	30.97	0.03	0.22	1.90

	Panel B: Correlation matrix										
	DOXW	*DOXM*	*DODD*	*DODR*	*HHI*	*VOL*	*SKEW*	*TN*	*RET*	*BAL*	*EXP*
DOXW											
DOXM	0.78										
DODD	-0.03	-0.02									
DODR	-0.05	-0.02	0.64								
HHI	0.04	0.00	-0.11	-0.33							
VOL	0.20	0.22	-0.08	-0.09	0.07						
SKEW	0.08	0.08	-0.03	-0.04	0.04	0.55					
TN	0.00	-0.02	-0.04	-0.04	0.05	0.03	0.02				
RET	-0.02	0.05	0.09	0.11	-0.05	-0.11	-0.11	-0.09			
BAL	0.00	0.01	-0.10	-0.03	-0.14	0.07	0.04	0.04	0.00		
EXP	0.10	0.21	0.04	0.05	-0.11	0.11	0.00	-0.02	0.12	0.11	

Table 1: Summary statistics for account characteristics

Note: This table reports the summary statistics for account characteristics. *DOXW* and *DOXM* are degrees of extrapolation based on past weekly returns and monthly returns, respectively, and are calculated as volume-weighted past returns based on all initial buys. *DODD* and *DODR* are degrees of disposition based on the difference and ratio between PGR and PLR, respectively, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners to the total number of winners on days of sales and PLR (Proportion of Losses Realized) is similarly calculated. *HHI* is the Herfindahl–Hirschman Index based on monthly holdings. *VOL* is calculated as volume-weighted past volatility, and *SKEW* is calculated as volume-weighted past skewness. *TN* is turnover and is calculated by dividing total trading volume to average account balance. *RET* is the average monthly return rate, calculated by dividing total *RMB* return to average RMB holding. *BAL* is the average RMB holding in millions. *EXP* is the number of years since account open date.

	DOXW	*DOXM*	*DODD*	*DODR*	Obs.
Panel A: Age					
40 or below	0.167	1.850	0.026	0.079	56,078
40-49	0.170	1.908	0.026	0.083	89,353
50-59	0.175	2.016	0.027	0.089	68,380
60-69	0.170	2.057	0.027	0.093	37,316
70 or above	0.155	2.015	0.029	0.096	14,085
Panel B: Education					
Doctoral	0.183	2.002	0.028	0.093	6,521
Masters	0.152	1.891	0.025	0.079	5,395
Bachelor	0.164	1.909	0.027	0.086	75,969
3-year college	0.175	1.981	0.027	0.087	83,793
Professional school	0.174	1.977	0.026	0.084	21,841
High school	0.173	1.953	0.026	0.086	46,357
Middle school	0.170	1.955	0.026	0.086	25,469
Others	0.177	2.008	0.025	0.083	10,760
Panel C: Gender					
Male	0.161	1.832	0.027	0.085	303,530
Female	0.187	2.100	0.028	0.093	280,329

Table 2: Extrapolation and disposition effect across investor groups

Note: This table reports the average degrees of extrapolation and disposition across different demographic groups. *DOXW* and *DOXM* are degrees of extrapolation based on past weekly returns and monthly returns, respectively, and are calculated as volume-weighted past returns based on all initial buys. *DODD* and *DODR* are degrees of disposition based on the difference and ratio between PGR and PLR, respectively, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners to the total number of winers on days of sales and PLR (Proportion of Losses Realized) is similarly calculated.

	ΔVolume				ΔTurnover	ΔBalance
	(1)	(2)	(3)	(4)	(5)	(6)
DOX	4.02***	3.69***	3.64***	2.64***	-0.02	0.32***
	(10.31)	(9.56)	(9.44)	(5.56)	(-0.10)	(17.33)
DOD	4.60***	4.32***	4.14***	3.65***	1.96***	-0.05***
	(13.31)	(12.27)	(11.81)	(7.84)	(11.24)	(-4.04)
*DOX*DOD*	0.84***	0.72***	0.71***	0.76**	0.27**	-0.04***
	(2.94)	(2.63)	(2.59)	(2.15)	(1.99)	(-4.61)
BAL		-19.60***	-18.77***	-14.96***	-0.60	-1.39***
		(-22.44)	(-21.08)	(-13.61)	(-1.45)	(-32.24)
EXP		2.69***	2.84***	3.25***	1.33***	0.04***
		(31.98)	(32.83)	(30.55)	(34.34)	(9.14)
HHI		0.80	-0.18	2.70**	-3.67***	1.03***
		(0.75)	(-0.17)	(2.08)	(-7.74)	(20.71)
VOL		-122.23***	-118.97***	-80.00***	-69.62***	6.15***
		(-7.35)	(-7.16)	(-3.91)	(-10.10)	(7.09)
SKEW		1.20**	1.31**	1.14*	0.63***	-0.02
		(2.20)	(2.42)	(1.70)	(2.96)	(-0.56)
RET		-13.35***	-12.85***	4.75	6.69***	-2.18***
		(-3.22)	(-3.10)	(1.11)	(4.45)	(-7.07)
Other Controls						
Demographics	NO	NO	YES	YES	YES	YES
Margin account, dummy	NO	NO	NO	YES	YES	YES
Traded warrants before, dummy	NO	NO	NO	YES	YES	YES
Survey-based characteristics	NO	NO	NO	YES	YES	YES
Constant	26.59***	14.81***	12.52***	3.34	4.70***	1.52***
	(55.20)	(12.71)	(10.31)	(1.14)	(4.53)	(11.79)
N	439,853	439,798	439,798	252,907	252,907	252,907
R^2	0.003	0.005	0.006	0.010	0.013	0.016

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Explaining account-level trading volume using extrapolation and the disposition effect

Note: This table reports the results from regressing changes in trading volume, turnover, and balance on degrees of extrapolation and disposition. *DOX* is the degree of extrapolation, calculated as volume-weighted past monthly returns based on all initial buys. *DOD* is the degree of disposition, calculated as the ratio between PGR and PLR, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners to the total number of winners on days of sales and PLR (Proportion of Losses Realized) is similarly calculated. *BAL* is the average RMB holding in millions. *EXP* is the number of years since account open date. *HHI* is the Herfindahl–Hirschman Index based on monthly holdings. *VOL* is calculated as volume-weighted past volatility, and *SKEW* is calculated as volume-weighted past skewness. *RET* is the average monthly return rate, calculated by dividing total *RMB* return to average RMB holding. Demographic variables include gender, age, and education. Survey-based characteristics include answers to questions related to expected returns and risks, self reported wealth, income, and sophistication, investment horizon, experience, and objectives, and both short-term and long-term tolerances for losses. ΔVolume is calculated as the ratio between monthly volume at peak (2015:05) to the average monthly volume in the pre-bubble period from 2014:01 to 2014:11. ΔTurnover and ΔBalance are similarly calculated.

	Turnover (t)			
	(1)	(2)	(3)	(4)
$\overline{DOX}$ (t)	0.04***	0.04***	0.01***	0.01***
	(14.30)	(9.34)	(2.89)	(2.92)
$\overline{DOD}$ (t)	0.02***	0.01***	0.01***	0.01***
	(7.76)	(6.32)	(5.13)	(5.53)
Return (t)		0.28***	0.38***	0.40***
		(3.97)	(6.44)	(7.31)
Return ($t-1$)			0.38***	0.25***
			(10.09)	(6.70)
Return ($t-2$)			0.28***	0.10**
			(6.54)	(2.37)
Return ($t-3$)			0.18***	0.00
			(4.37)	(0.10)
Return ($t-4$)			0.12***	0.02
			(2.86)	(0.44)
Turnover ($t-1$)				0.37***
				(7.76)
Turnover ($t-2$)				0.09***
				(4.84)
Turnover ($t-3$)				0.05
				(1.48)
Turnover ($t-4$)				-0.05
				(-1.05)
Return ($t-5$) to ($t-12$)	NO	NO	YES	YES
Turnover ($t-5$) to ($t-12$)	NO	NO	NO	YES
Stock FE	YES	YES	YES	YES
Time-clustered SE	YES	YES	YES	YES
N	63,639	63,639	63,307	63,307
R^2	0.50	0.52	0.62	0.70

Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Explaining stock-level turnover using extrapolation and the disposition effect

Note: This table reports panel regression results by regressing stock-level turnover on stock-level measures of extrapolation and disposition at the weekly frequency. A stock's turnover in a given week is calculated by dividing the total RMB trading amount to its market capitalization. Stock-level degree of extrapolation is calculated as the buy-volume-weighted average degree of extrapolation in a given week, and stock-level degree of disposition is calculated as the sell-volume-weighted average degree of disposition in a given week. The sample period is from 2014:12 to 2015:05.

	Volume (in billion RMB)			Trades (in millions)		
	Run-up	Crash	Quiet	Run-up	Crash	Quiet
Panel A: Total volume, the full-sample						
Buy	692	281	637	23	9	27
Sell	687	286	633	28	12	32
Total	1,380	567	1,269	51	22	59
Panel B: fraction of extensive-margin trades, the full sample						
Buy	51.5%	42.0%	49.3%	41.3%	30.9%	38.5%
Sell	58.4%	50.2%	54.9%	49.4%	40.6%	46.3%
Total	55.0%	46.0%	52.2%	45.0%	35.1%	42.1%
Panel C: fraction of extensive-margin trades, by groups						
Disposition extrapolators	58.9%	48.3%	55.6%	49.3%	37.0%	46.0%
Pure extrapolators	56.3%	49.2%	54.5%	46.4%	38.3%	44.6%
Others	52.9%	43.8%	49.9%	42.7%	33.1%	39.6%
Panel D: fraction of new stocks, the full sample						
"New" stocks	68.3%	52.9%	54.9%	63.7%	50.5%	49.8%

Table 5: Decomposition of total volume

Note: This table reports the distribution of trading volume across different stages of the bubble. The run-up corresponds to 2014:12 to 2015:05, the crash corresponds to 2015:06 to 2016:08. In Panel A to C, the quiet period corresponds to 2014:01 to 2014:11 and 2015:09 to 2015:12; in Panel D, to make it comparable to the run-up, we limit the quiet period to 2014:01 to 2014:06. A buy is considered extensive-margin if the starting position is zero and a sell is considered extensive-margin if the end position is zero. Disposition extrapolators have both *DOX* and *DOD* above the median, pure extrapolators have *DOX* above the median and *DOD* below, and the rest are classified as other investors. A stock is considered "new" if it has occurred in an investor's monthly portfolio holdings before and "old" otherwise.

	Panel A: Return $(t+1)$, run-up (%)				Panel B: Return $(t+1)$, crash (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{DOX}$ $(t+1)$	3.09***			0.98**	3.94***			-4.12**
	(7.65)			(2.09)	(3.87)			(-2.89)
$\overline{DOX}$ (t)		0.48**	0.47**			-1.68**	-1.70**	
		(2.29)	(2.22)			(-2.60)	(-2.74)	
Return (t)	-0.10*	-0.05	-0.05	-0.07	0.03	0.05	0.05	0.06
	(-1.75)	(-0.87)	(-0.84)	(-1.05)	(0.18)	(0.29)	(0.29)	(0.36)
BETA (t)	0.08	-0.16	-0.01	-0.07	-0.10	-1.03	-0.90	-1.08
	(0.29)	(-0.51)	(-0.04)	(-0.20)	(-0.11)	(-1.16)	(-0.85)	(-0.98)
SIZE (t)	-0.00	-0.00**			0.01	0.00		
	(-0.28)	(-2.13)			(1.07)	(0.06)		
B/M (t)	0.14	-0.05			0.46**	0.11		
	(1.54)	(-0.52)			(3.00)	(0.64)		
Turnover (t)	-2.16	1.19	0.47	0.58	-11.63	-5.92	-6.03	-5.38
	(-1.03)	(0.51)	(0.19)	(0.24)	(-1.63)	(-0.78)	(-0.71)	(-0.61)
FLOAT (t)	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.96)	(1.40)	(-0.07)	(0.15)	(-0.05)	(0.13)	(0.18)	(-0.09)
VOL (t)	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.30)	(-0.43)	(0.38)	(0.33)	(0.48)	(0.24)	(0.32)	(0.55)
Constant	-0.06***	0.02**	0.02**		-0.15***	0.03	0.03	
	(-4.47)	(2.28)	(2.19)		(-3.22)	(0.76)	(0.78)	
Size bins	NO	NO	YES	YES	NO	NO	YES	YES
B/M bins	NO	NO	YES	YES	NO	NO	YES	YES
Time-clustered SE	YES	YES	YES	YES	YES	YES	YES	YES
N	59,287	59,277	59,277	59,062	22,939	22,944	22,944	22,785
R^2	0.11	0.01	0.01	0.06	0.05	0.01	0.01	0.03

Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Regressing stock returns on stock-level measures of extrapolation and disposition

Note: This table reports panel regression results by regressing future returns on stock-level exposure to extrapolation at the weekly frequency. Stock-level exposure to extrapolation is calculated as the buy-volume-weighted average degree of extrapolation in a given week. *BETA* is the market beta. *SIZE* is the market capitalization in RMB. B/M is the ratio of book value to market value. Turnover is calculated by dividing total trading amount to total market capitalization. *FLOAT* is the total number of tradable shares. *VOL* is the total number of shares traded.