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Extrapolative Bubbles and Trading Volume

Jingchi Liao
Shenzhen Stock Exchange

Cameron Peng
London School of Economics and Political Science

Ning Zhu
SAIF, Shanghai Jiaotong University

We propose an extrapolative model of bubbles to explain the sharp rise in prices *and* volume observed in historical financial bubbles. The model generates a novel mechanism for volume: because of the interaction between extrapolative beliefs and disposition effects, investors are quick to not only buy assets with positive past returns but also sell them if good returns continue. Using account-level transaction data on the 2014–2015 Chinese stock market bubble, we test and confirm the model's predictions about trading volume. We quantify the magnitude of the proposed mechanism and show that it can increase trading volume by another 30%. (*JEL* G11, G12, G41, G50)

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Up and down, up and down,
I will lead them up and down.
I am feared in field and town.
Goblin, lead them up and down.

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Puck, in William Shakespeare's *A Midsummer Nigh's Dream*,
Act 2, scene 1, lines 396–9

Asset bubbles span the history of modern finance, from the Dutch tulip mania in the seventeenth century to the recent U.S. housing bubble. For decades, explaining bubbles has been an intriguing yet challenging task under the traditional regime of rational expectations. To account for the dynamic patterns of prices and trading volume observed in historical bubbles is even more difficult. A 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 phase 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. Before dropping sharply in the crash, rising volume often manifests first in a trading frenzy. In some cases, the rise and fall in volume is even greater than the rise and fall in price.[1]

These empirical observations raise two fundamental questions. What drives prices to rise and fall? Why do investors trade so much? The answers not only shed light on the underlying mechanism of bubble formation but also have important welfare implications. In particular, households tend to be heavily invested in the underlying asset. They incur substantial financial losses, not just during the devastating market crash, but also due to the large amount of fees associated with their constant trading in the run-up (An et al. 2021; Liu et al. 2021).

To explain the price pattern of bubbles, recent research increasingly points to extrapolation—the idea that expectations about future price changes positively depend on past price changes—as a key driver (Glaeser and Nathanson 2017; Barberis et al. 2018; Chinco 2020; DeFusco, Nathanson, and Zwick 2020). Extrapolators tend to buy assets that have performed well recently, thereby pushing up their prices even further. However, a significant challenge facing the extrapolative framework is to also explain the high volume. To see why, imagine that a positive shock to asset fundamentals induces an initial price run-up. Although optimistic extrapolators can sustain the run-up by pushing prices well beyond the fundamental value, they will be similar in their beliefs—based on past price changes—and therefore trade little among themselves. One way out of this conundrum, suggested by Barberis et al. (2018), is when extrapolators' demand for the underlying asset becomes more volatile during the run-up, leading them to "flip-flop" in their asset holdings. Barberis et al. (2018) attribute this behavior to "wavering" beliefs—that is, paying attention to

[1] See DeFusco, Nathanson, and Zwick (2020) for a summary of the dynamic patterns of price and volume across four different bubbles: the U.S. internet bubble, the Japanese equities bubble in the late 1980s, the experimental bubble from Smith, Suchanek, and Williams (1988), and the bubble in the art market from 1985 to 1995.

different signals at different times—but there is also room for other, potentially more fundamental forces to generate such behavior.[2]

In this paper, we take up the challenge of explaining the high volume. We show that introducing the disposition effect into an otherwise standard extrapolative framework can micro-found the flip-flopping and is, in fact, empirically important in a recent bubble. The disposition effect refers to the tendency to sell assets trading at a gain and hold on to assets with losses, a phenomenon prevalent among both individuals and institutions across many markets (Odean 1998; Frazzini 2006; Barber and Odean 2013). If an investor tends to *buy* an asset with positive recent returns, but *sell* that asset if the good returns continue, one would characterize this behavior as extrapolation and the disposition effect. This trading pattern is consistent with extensive evidence (e.g., Odean 1998; Odean 1999; Barber and Odean 2013). While researchers have proposed a number of explanations for the disposition effect, a leading candidate is realization utility, that is, the idea that investors derive utility from realizing gains and losses from the assets they own (Barberis and Xiong 2009, 2012). In other words, our solution to the high-volume puzzle is to combine realization utility, a form of nonstandard *preference*, with extrapolation, a form of nonstandard *belief*.

The following example illustrates the intuition of our framework. Suppose there are two assets: cash and a stock. Investors A and B are prone to both extrapolation and the disposition effect, but 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 future returns. As a result, although there are no additional fundamental shocks on date 1, the stock's price rises even more. As the price goes up, B starts to accumulate a capital gain in his portfolio. Because of the disposition effect, B is eager to sell his stock position to lock up that gain. A, however, is not influenced by these positive gains, since she holds cash with zero returns. In equilibrium, A ends up buying the stock from B at a price higher than B's purchase price. On date 2, the same trade takes place, 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 than A's purchase price. They continue to swap each other's asset positions over the next few dates and, in doing so, push up both price and volume.

To structure our empirical exercise, we formalize the above intuition with a simple model of "disposition extrapolators"; that is, investors subject to both

[2] Another solution to the high-volume puzzle is offered by DeFusco, Nathanson, and Zwick (2020). They 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 the aggregate volume.

extrapolative beliefs and disposition effects. We model extrapolative beliefs through expectations about future prices and the disposition effect through realization utility.[3] The model confirms the earlier intuition by producing a bubble featuring large rises in prices and volume. While the mechanism for the price run-up is similar to other models of extrapolation, the mechanism for volume is new. 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 if she is already holding the asset, realization *utility* kicks in, prompting her to sell. As a result, investors switch between assets, generating high volume.

The model makes 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 marketwide bubble affected thousands of public companies and over 100 million investors. Both prices and volume first rose to record highs and then crashed. These dynamics 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 transactions for millions of retail investors. In addition to covering the 2014–2015 stock market bubble, the data include all the transactions made prior to the bubble, allowing us to measure extrapolation and disposition *ex ante*. Specifically, using prebubble transactions, we measure the degree of extrapolation by examining the past returns of the stocks an investor tends to buy. Systematic buying of stocks with higher recent returns suggests a higher degree of extrapolation. We measure an investor's degree of disposition as the difference in her propensities to sell winners and losers (Odean 1998; Dhar and Zhu 2006).

With these investor-level measures of extrapolation and disposition in hand, we examine the model's predictions about trading volume. The first prediction is that, during a run-up, disposition extrapolators increase their volume more than other investors do; we test this prediction at the market, investor, and stock levels. At the market level, by May 2015, when the bubble peaks, disposition extrapolators—defined by having above-median degrees of extrapolation and disposition—have increased their monthly volume by almost 800%. In comparison, pure extrapolators—defined by having an above-median degree of extrapolation but a below-median degree of disposition—have increased their monthly volume by only 500%. This contrast is a direct consequence of the disposition effect: although pure extrapolators are (even more) aggressively buying, they tend to buy-and-hold and don't reshuffle their portfolios nearly as much as disposition extrapolators do.

At the investor level, higher degrees of extrapolation and disposition both lead to more trading. Specifically, we regress each investor's change in volume

[3] In the remainder of this paper, we use the terms "disposition effect" and "realization utility" interchangeably, but we acknowledge that other mechanisms (e.g., nonstandard beliefs in Peng 2017 and cognitive dissonance in Chang, Solomon, and Westerfield 2016) could also explain the disp1osition effect.

at the peak of the bubble relative to the prebubble period on her degrees of extrapolation and disposition, while controlling for an exhaustive list of other account characteristics. In these regressions, degrees of extrapolation and disposition are both associated with higher volume at the investor level, but in different ways: consistent with the model, extrapolation ensures large stock holdings throughout the run-up, while disposition induces quick rebalancing of portfolio composition. In two additional placebo tests, extrapolation and disposition do not explain trading volume in normal market conditions, confirming that the two forces are particularly pertinent to the rising volume in the run-up.

At the stock level, in the cross-section of individual stocks, those traded more by disposition extrapolators have higher turnover. For 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 weekly stock-level degrees of extrapolation and disposition. 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 week. 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 high aggregate volume but also explain why some stocks are traded more than others.

To quantify the importance of our proposed mechanism, we conduct the following counterfactual analysis. We start by estimating the degrees of extrapolation and disposition for the entire investor population. Consistent with the model, we assume that the initial buying decisions are primarily driven by extrapolative beliefs, while subsequent trading behaviors are jointly driven by extrapolative beliefs and realization utility. We then consider a counterfactual in which disposition extrapolators are absent from the market and reestimate the two parameters. Plugging these parameters back into the model, our results suggest that the addition of disposition extrapolators increases peak volume by another 30%.

Lastly, we provide evidence consistent with extrapolators contributing to the price run-up and crash. We take advantage of the granular nature of our data by constructing a panel of weekly stock-level measures of extrapolation. While regressing returns contemporaneously on extrapolation is subject to a reverse-causality concern—namely, that positive returns cause more trading due to extrapolation rather than the other way around—we address this issue through both predictive and IV regressions. In both, the entry of more extrapolators is associated with more positive stock returns. While it is difficult, absent plausible instruments for extrapolation, to establish causality, our evidence is nonetheless consistent with the model's prediction that extrapolators are responsible for driving prices up and down during the bubble.

Whether bubbles are rational and whether crashes are predictable are the subject of ongoing debate (e.g., Fama 2014; Greenwood, Shleifer, and You 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 involving volume, for example, the fact that rising markets are accompanied by higher volume than falling markets (Stein 1995; Statman, Thorley, and Vorkink 2006; Griffin, Nardari, and Stulz 2007). Although the model does not generate a positive correlation between past volatility and future volume (Karpoff 1987), we discuss potential extensions that can enable the model to do so. In our empirical exercise, we take a recent bubble in the Chinese stock market as given and provide evidence consistent with our proposed mechanism.

We make three main contributions to the literature. First, building on the existing framework of extrapolative bubbles, we propose a framework that integrates extrapolation with realization utility. This framework generates a novel volume mechanism, one that provides a micro-foundation for flip-flopping during financial bubbles. Previous models have highlighted 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, Nathanson, and Zwick 2020) as possible drivers of volume. In contrast, our mechanism is based on the tension between extrapolation, a feature of beliefs, and the disposition effect, a feature of preferences. More fundamentally, this tension arises from differential asset holdings: asset returns affect belief formation similarly for all investors but affect preferences differently depending on the investor's asset holdings.

Second, we document new empirical findings about the sources of high volume, a defining feature of a financial bubble. Most empirical studies of bubbles focus on understanding the patterns of prices and holdings (e.g., Brunnermeier and Nagel 2004; Griffin et al. 2011; Bian et al. 2018a,b) with limited attention devoted to volume. One notable exception is DeFusco, Nathanson, and Zwick (2020); they show that much of the volume is driven by short-term speculation. We confirm our model's predictions about how the interaction of extrapolation and the disposition effect contributes to rising volume. Moreover, we quantify the importance of our mechanism and show that it was responsible for an additional 30% increase in trading volume during the recent Chinese stock bubble.

Third, we empirically show that extrapolators are responsible for a bubble's price dynamics. While this intuition is behind most extrapolative models of bubbles (e.g., Glaeser and Nathanson 2017; Barberis et al. 2018), evidence has been scarce because of data limitations and the lack of a plausible empirical strategy. The granularity of our data allows us to examine the arrival of extrapolators at a high frequency and rule out common concerns, such as reverse causality. We thus provide empirical support not only to our own model but also to other models of extrapolation.

1. A Model of Bubbles

In this section, we present a dynamic model of bubbles based on extrapolation and the disposition effect. The goal is twofold. First, we formalize the intuition spelled out in the Introduction. Second, we use the model to derive additional testable predictions about the sources of volume. While the main intuition can be preserved in a two-period model, a dynamic model illustrates other key features of a bubble: (a) the intertemporal relationship between fundamentals and prices, (b) how crashes (endogenously) occur, (c) the time-series relationship between price and volume, and (d) the time lag between the peak and the trough.

1.1 The setup

1.1.1 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 asset (cash) with returns normalized to zero and a risky asset (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.[4] We assume they are prone to both extrapolation and the disposition effect and label them "disposition extrapolators." Below, we will 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.[5] Therefore, throughout this paper, we think of extrapolation as a feature of *beliefs* and the disposition effect as a feature of *preferences*.

1.1.2 Beliefs. Our modeling of extrapolative beliefs closely follows Barberis et al. (2018). Disposition extrapolators form their beliefs based on an

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[4] A short-selling constraint is a common assumption in models of bubbles (e.g., Harrison and Kreps 1978; Scheinkman and Xiong 2003) and realistically characterizes the Chinese stock market (see Gao et al. 2020 for recent evidence). A borrowing constraint is assumed for tractability. Otherwise, risk-neutral investors can take infinite leverage when expected stock returns are positive.

[5] Other mechanisms, such as nonstandard beliefs (e.g., Odean 1998 and Peng 2017) and cognitive dissonance (e.g., Chang, Solomon, and Westerfield 2016), could also explain the disposition effect. As we will show later, the key to our volume mechanism is the *behavior* of selling winners and holding on to losers. Therefore, although we do not show this explicitly, these other mechanisms should produce similar predictions.

extrapolative signal. The extrapolative signal on date t, denoted by X_t, is specified by

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

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, allows a sequence of positive dividend shocks to give an initial push to stock prices.[6]

Finally, given a continuum of investors, we assume that each investor's beliefs are subject to random noise, $\varepsilon_{i,t}$, distributed $N\left(0,\sigma_\varepsilon^2\right)$ and i.i.d. over time. $\varepsilon_{i,t}$ 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, which shuts down of the channel of rising volume due to greater dispersion in beliefs. In sum, disposition extrapolator i's expectation about the price change from dates t to $t+1$, denoted by $E_{i,t}\Delta P_{t+1}$, is given by

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

The *average* expectation across all investors, denoted by $E_t \Delta P_{t+1}$, is $\gamma X_t + (1-\gamma)(D_t - P_t)$, 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.

1.1.3 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 $E_t(W_{t+1})$, the expected wealth at the next date.[7] 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:

[6] 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 adding the value signal to extrapolators' expectations would not be necessary. The price and volume dynamics under this setting are similar, but we stick to our baseline setting for simplicity.

[7] Another assumption made 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 one who is myopic and simply maximizes the next period's wealth.

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

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.[8] N_t denotes the number of shares held by the end of date t, and, as a result, $\left(P_t-\overline{P}_t\right)(N_{t-1}-N_t)$ represents profits realized on the current date.[9] 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, which creates an incentive 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 that realization utility kicks in only in the act of selling.[10]

1.1.4 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 holdings. If she is holding cash, she 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 $\varepsilon_{i,t}$ is distributed $N\left(0,\sigma_\varepsilon^2\right)$ and i.i.d., the total demand from cash investors is $\Phi(E_t\Delta P_{t+1}/\sigma_\varepsilon)\left(W_{X,t-1}^C/P_t\right)$, where $\Phi(\cdot)$ denotes the cumulative probability function of the standard normal distribution. In this expression, $\Phi(E_t\Delta P_{t+1}/\sigma_\varepsilon)$ 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 $\Phi\left(\left(E_t\Delta P_{t+1}-\beta\left(P_t-\overline{P}_t\right)\right)/\sigma_\varepsilon\right)Q$. Therefore, the total share demand, denoted by H_t, is given by

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

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

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[8] Ideally, we would like to keep track of all possible trading paths to obtain an individual-specific reference price; that is, to have $\overline{P}_{i,t}$, rather than $\overline{P}_t$. Nonetheless, the large number of dates (100) makes keeping track of all possible paths (2^{100}) infeasible. Therefore, we assume a common reference price for all investors.

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

[10] One additional piece of evidence that supports this specification is provided by Frydman and Camerer (2016). Using neutral data collected from an experimental asset market, they show that exogenously increasing the salience of the stock's expected return reduces the disposition effect partially, but not fully, and they argue that this is consistent with a tension between extrapolation and realization utility.

1.1.5 Parameter values. We set $T = 100$, so we have 101 dates. The dividend shocks on dates 1 to 10 are set to zero. We then introduce four consecutive shocks—2, 4, 6, and 8—from dates 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 market-level estimates in Cassella and Gulen (2018) but larger than the stock-level estimates in Da, Huang, and Jin (2021). We assume that investors start with a wealth level of 100 and $Q = 1/2$, so that investors are split in half by their initial asset holdings.[11] We will provide evidence below to support the assumption of heterogeneous holdings. 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 1.3, we study the model's comparative statics by varying some key parameter values.

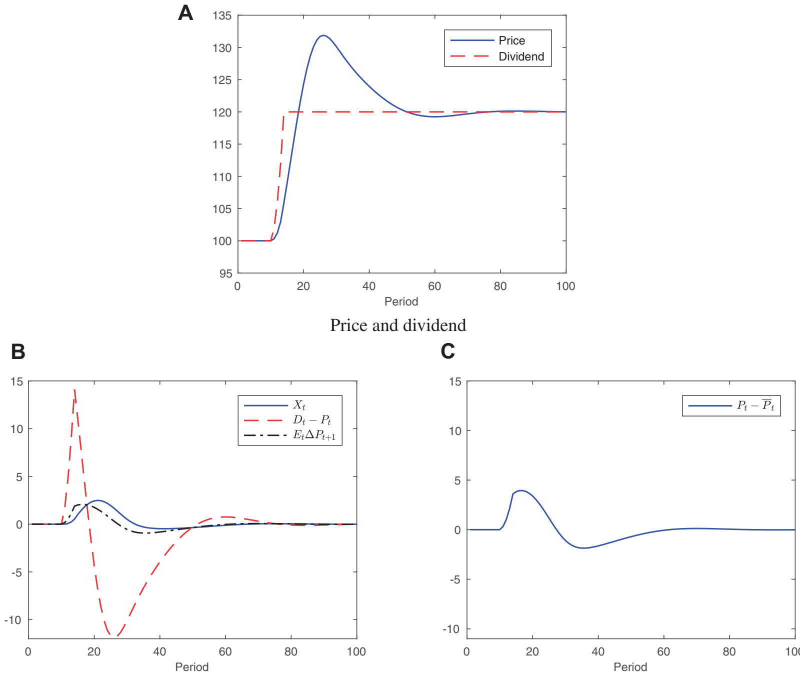
1.2 Baseline results

1.2.1 Prices. Figure 1, panel A, 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 dates 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 1, panel B. Although the shocks end on date 15, the price continues to rise. Before the price reaches the dividend, the value and extrapolative signals collectively push up the price. The value signal suggests that the stock is undervalued, whereas the extrapolative signal suggests that the upward trend will continue. In Figure 1, panel B, both the solid and dashed lines, corresponding to the two signals, remain positive before date 20, when the price reaches the dividend.

After the price exceeds the dividend, the value signal turns negative, suggesting that 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. Toward 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

11 A key ingredient is that different investors hold different assets right before the positive shocks hit. As a result, the assumption of different initial holdings is innocuous. We can instead assume that investors have homogeneous initial holdings, investing half in the stock and half in cash. In the next period, because investors are risk neutral and the stock has a zero return, half of the investors (those with a positive noise) will be completely invested in the stock, and the other half (those with a negative noise) will be holding cash. In the Internet Appendix, we show that, even without the assumption of risk neutrality, the model can generate price and volume dynamics under constant absolute risk aversion (CARA) preferences similar to the risk-neutral case.



Price and dividend

Extrapolative and value signals

$P_t - \overline{P}_t$

Figure 1
Prices and signals in the baseline case
In panel A, the dashed line represents the dividend, D_t, and the solid line represents the stock price, P_t. In panel B, 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 as $\gamma X_t + (1-\gamma)(D_t - P_t)$, where $\gamma = 0.9$. In panel C, the solid line represents the difference between the current stock price and the reference price, $P_t - \overline{P}_t$. There are 101 dates. The dividend shocks are set to zero, except for dates 11 to 14, when the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\varepsilon = 2$, $D_0 = 100$, $X_1 = 0$, and $Q = 1/2$.

into the past and extrapolators become less excited. The value signal eventually turns so negative that it outweighs the extrapolative signal, triggering the price to fall.

In Figure 1, panel C, 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 be wondering: 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. While normally $\overline{P}_t$ depends on past prices up to many periods ago, during the run-up it is very close to P_{t-1}; because of the high turnover, most stock investors have just bought the stock on the previous date. For the market to clear, P_t will need to exceed P_{t-1}. Indeed, as we will show later, this price result holds under various parametric values for β, the degree of disposition.

While we have specified the reference price as the volume-weighted average purchase price, the model's price and volume dynamics are robust to alternative specifications of the reference price. In the Internet Appendix, we model the reference price in two alternative ways: one backward-looking and the other forward-looking (Kőszegi and Rabin 2006; Kőszegi and Rabin 2007; Kőszegi and Rabin 2009; Meng and Weng 2018). We observe price and volume dynamics similar to the benchmark case. When the reference price is more forward-looking, as in the second specification, investors require a higher price to sell, resulting in a higher equilibrium price and more trading during the bubble.

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

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

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 have the same value. In Figure 2, panel A, the solid line, which represents V_t, is hump shaped: it rises substantially after the dividend shocks, continues to increase afterward, 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 becomes neutral; that is, when $E_t \Delta P_{t+1}$ approaches zero. As a result, volume peaks ahead of price; in Figure 2, panel A, volume peaks on date 17 and prices peak on date 27. This pattern is consistent with the evidence in DeFusco, Nathanson, and Zwick (2020), 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 2, panel B, the solid line, which represents the expected future price change, increases from 0 to 2. However, these optimistic beliefs would 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. The two forces therefore simultaneously drive investors' decisions: extrapolative beliefs say "hold," while realization utility says "sell." The tipping point comes when the utility gain from selling winners outweighs the utility loss from optimistic beliefs. For the market to clear, the price must rise enough for *preferences* to dominate *beliefs* for some investors; in Figure 2, panel B, $\beta\left(P_t - \overline{P}_t\right)$ 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.

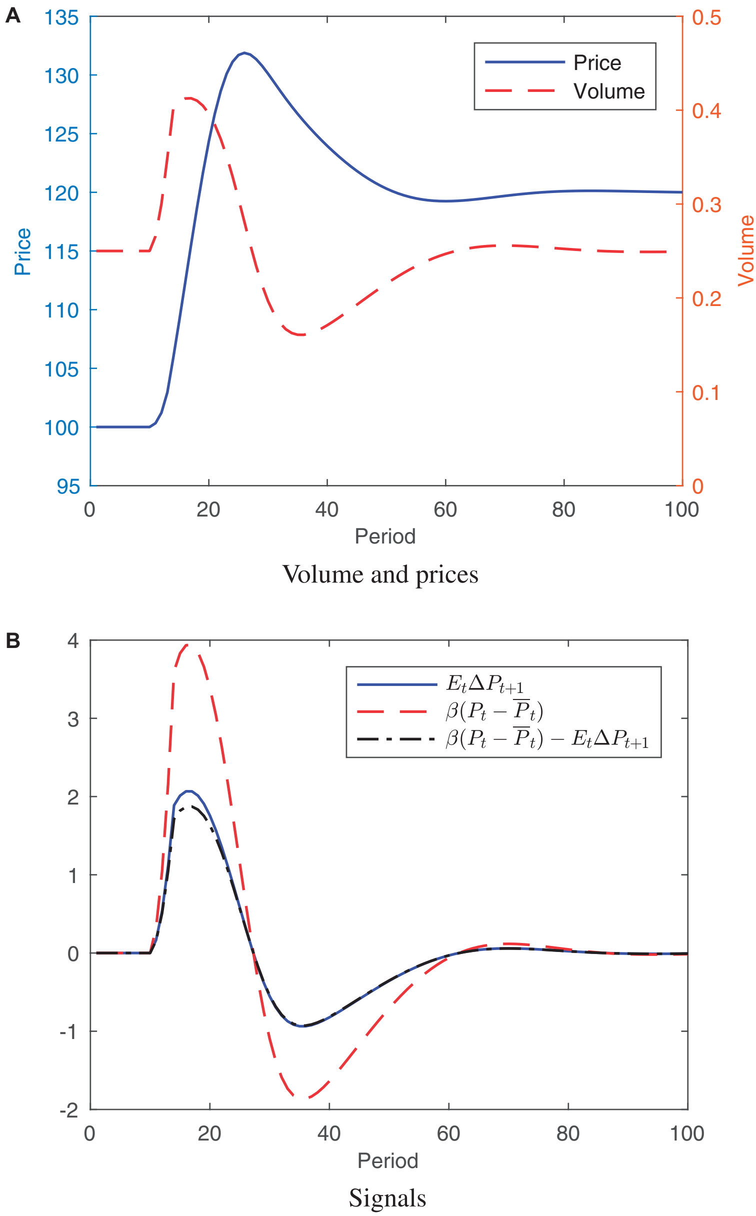


Figure 2
Trading volume in the baseline case
In panel A, the solid line represents total trading volume, and the dashed line represents the stock price. In panel B, the solid line represents $E_t \Delta P_{t+1}$; the dashed line represents $\beta\left(P_t - \overline{P}_t\right)$; and the dash-dot line represents $\beta\left(P_t - \overline{P}_t\right) - E_t \Delta P_{t+1}$. There are 101 dates. The dividend shocks are set to zero, except for dates 11 to 14, when the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\varepsilon = 2$, $D_0 = 100$, $X_1 = 0$, and $Q = 1/2$.

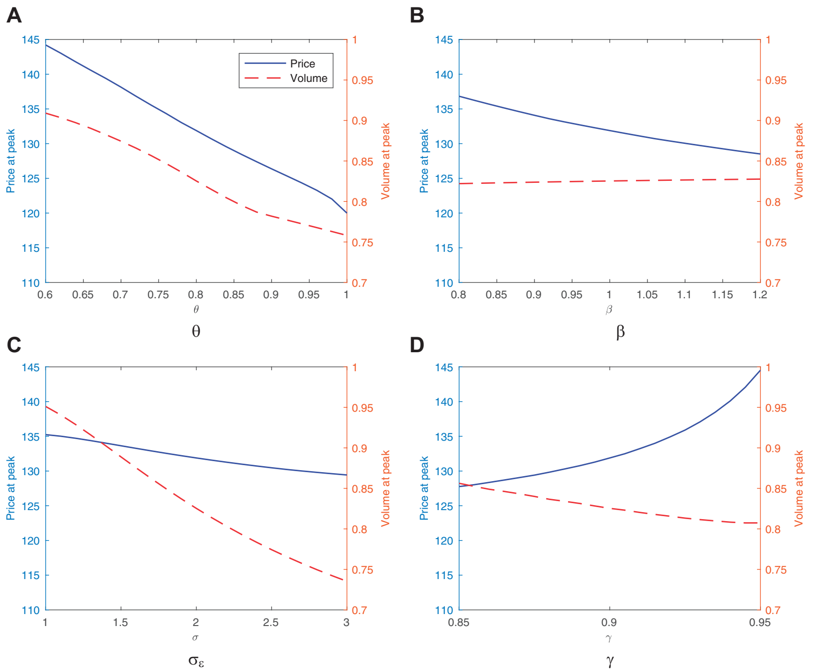


Figure 3
Comparative statics
This figure presents the price and volume at peak under parameters that are different from those of the baseline scenario. There are 101 dates. The dividend shocks are set to zero, except for dates 11 to 14, when the dividend shocks are 2, 4, 6, and 8, respectively. In the baseline scenario, the parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\varepsilon = 2$, and $\gamma = 0.9$. The title of each subfigure is the parameter concerned.

1.3 Comparative statics

The model's main result—the high prices and volume in a bubble—holds under a range of parameter values. Figure 3 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 3, panel A, the peak price monotonically decreases in θ, consistent with other models of extrapolation. 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, raising peak price. We empirically confirm this result in Section 4. Figure 3, panel B, shows that the price at the 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 Figure 3, panels C and D, shed light on some of the model's conceptual issues. In Figure 3, panel C, 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, in which greater dispersion in beliefs leads to a larger bubble. Finally, in Figure 3, panel D, the price at peak increases in γ, the weight placed on the extrapolative signal. The intuition is similar to that in Figure 3, panel A: as investors pay more attention to the extrapolative signal, they can push up prices even more.

1.4 Trading volume

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

Trading volume. During a bubble, disposition extrapolators increase their trading 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 ones, 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 one. Notice that our baseline setting does not make this prediction directly; because of risk neutrality, there is only extensive-margin trading. To allow for intensive-margin trading, we examine, in the Internet Appendix, a setting under CARA preferences and confirm this prediction.[12] A related prediction from a multiasset 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

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

done very well in the past and has caught her attention. This also suggests that volume in a bubble would come from investors trading stocks they have never traded before.

1.4.2 Volume during the crash. After the stock has experienced a series of negative returns, volume would also fall according to our model. In Figure 2, panel A, this is reflected by total volume dropping well below 0.25, the benchmark level, during the crash. This low volume is consistent with the empirical evidence that falling markets are generally associated with lower volume than that of rising markets. For example, Stein (1995) documents a strong positive correlation between changes in price and changes in volume in the U.S. housing market; Statman, Thorley, and Vorkink (2006) show that past returns positively predict future turnover at both the market and stock levels; and Griffin, Nardari, and Stulz (2007) provide similar evidence at the market level from 46 countries. Using data on four bubbles—the U.S. stock market in 1929, technology stocks in 1998–2000, U.S. housing in 2004–2006, and commodities in 2007–2008 Barberis et al. (2018) show a positive correlation between past returns and future volume. Our model provides an explanation for this asymmetry: because disposition-prone investors are reluctant to sell at a loss during a crash, investors as a group trade less than before.

Another strand of the literature shows a positive correlation between past volatility and future volume (for a review, see, e.g., Karpoff 1987). This suggests that volume falls in the crash but still remains above the prebubble level; as we will show later, this was also the case during the Chinese stock market bubble we examine. Our model, in its current form, does not generate such a pattern, but natural extensions, such as incorporating investor attention and introducing richer investor heterogeneity, should enable it to do so.[13] We leave these extensions to future research. We also note that, in the Internet Appendix, we examine trading volume in January 2016 when the market crashed *without* first experiencing a run-up. Consistent with the model, disposition extrapolators decreased their trading volume to a greater extent than the other investors did.

1.4.3 Discussion. Our volume mechanism stems from the tension between extrapolation and the disposition effect. 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

[13] One modification is to incorporate time-varying investor attention. Indeed, financial bubbles are typically associated with intensive media coverage and make investors more active. "Activated" investors may continue to trade during the market crash and help sustain higher volume than usual. However, one force that may challenge this explanation is the "ostrich" effect: for example, Sicherman et al. (2016) show bad performance reduces investor attention, potentially offsetting media-induced attention. The second modification is to deviate from the homogeneous setting by introducing fundamental investors, who are willing to enter the market during the crash when assets are undervalued (Barberis et al. 2018).

in beliefs and, in DeFusco, Nathanson, and Zwick (2020), due to the entry of short-horizon buyers into the market; DeFusco, Nathanson, and Zwick (2020) discuss the differences among these theories of bubbles. To the best of our knowledge, ours is the first paper that combines nonstandard beliefs and preferences to shed light on asset prices and volume at the same time.

In addition to these conceptual differences, our model also differs in its testability: both elements are well-documented phenomena and can be plausibly inferred from transaction data. This feature allows our empirical design to closely match the predictions. In this regard, DeFusco, Nathanson, and Zwick (2020) share a similar feature: they are able to measure home buyers' horizon and link short-term buyers to the rise of volume. In Section 3, we examine the predictions listed above to provide empirical support for the model's volume mechanism.

We note that the switching behavior generated by our model appears to be different from the endowment effect, according to which people already endowed with a risky bet are more willing to take risks than those endowed with a certain amount (Sprenger 2015; Anagol, Balasubramaniam, and Ramadorai 2018). Recent evidence suggests that the endowment effect and the disposition effect are two distinct phenomena in that, conditional on the endowment effect, investors also exhibit a disposition effect (Anagol, Balasubramaniam, and Ramadorai 2018; Hartzmark, Hirshman, and Imas 2021). Conceptually, the disposition effect characterizes trading responses to past returns and holding-period returns. This is particularly relevant during a bubble as asset prices experience dramatic changes in a short period of time. In contrast, the endowment effect is deeply rooted in people's assessment of risk when the referent changes. If we incorporate the endowment effect into the current model, it would lead to great increases in prices and volume in equilibrium.[14] Therefore, our model is robust to the consideration of the endowment effect.

2. Background and Data

2.1 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 bubbles in the stock and warrants markets (e.g., Mei, Scheinkman, and Xiong 2009; Xiong and Yu 2011; Pearson, Yang, and Zhang 2021; Li, Subrahmanyam, and Yang 2021). 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

[14] One way to model the endowment effect is to assume that stock investors have more optimistic views than cash holders about the stock's future returns. Put differently, we can assume that the certain equivalence of a risky bet is higher for stock investors because of their greater risk-bearing capacity. Under this model specification, stock investors will demand a higher price for them to sell, resulting in higher price and volume in equilibrium.

from 2014 to 2015. As we will show below, this episode clearly demonstrates some of the classic features of a financial bubble: an initial boom prompted by good fundamental news, a prolonged period of overvaluation, a heightened trading volume, and an abrupt crash in which prices fell even more quickly than they had risen.[15]

Like many historical bubbles, this one was triggered in part by new information about the economy, a stage often referred to as "displacement" (Barberis et al. 2018; Chinco 2020). Around July 2014, the media began to make bullish speculations about the 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 into it with no hesitation. Their conviction was reinforced by state 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 6 months, during which time most Chinese stocks doubled in value.

Figure 4 shows the evolution of prices and trading volume from 2014 to 2015. The solid line 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 shaded area), the index increased from 8,332 to 18,098, reaching its highest level since 2008. The thin line represents the number of shares traded on the SZSE, with the scale on the right axis. Volume rose more than prices did, increasing to four times its prebubble 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. During the crash, prices fell much more quickly than they had risen: SZCI dropped by almost 40% in just 1 month.

15 Financial media and commentators have almost unanimously called the episode a bubble. For example, a *Wall Street Journal* article (Frangos 2015) 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.

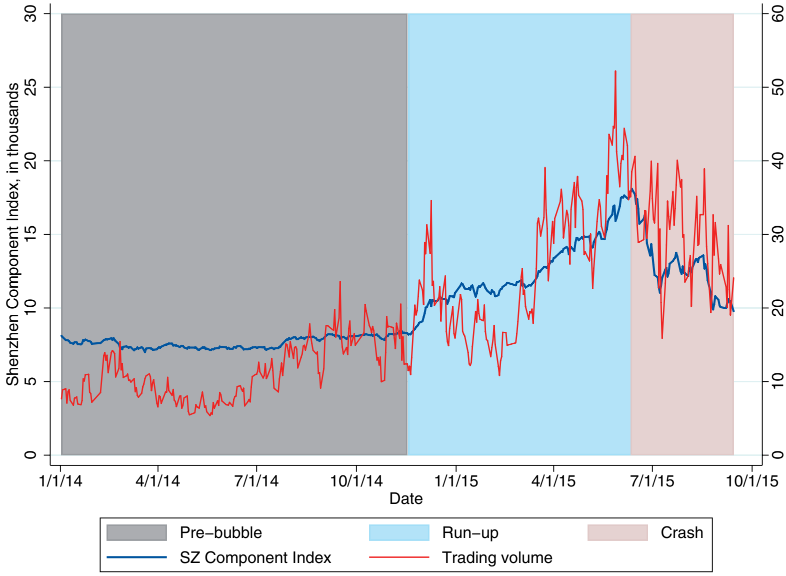


Figure 4
Prices and trading volume at SZSE
The thick line plots the closing price of the Shenzhen Component Index (SZCI; in thousands), and the thin line plots the number of shares traded on the SZSE (in billions; scale on the right axis). The time frame is from January 1, 2014, to September 15, 2015. The shaded areas represent the three stages of the bubble: the prebubble 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.

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 prebubble 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.

2.2 The data

We use account-level transaction data provided by one of the largest brokerage firms in China to study this bubble. The company has branches in almost all of China's provinces and is a market leader in several regions. Before applying any filters, the data include the complete transaction records of all exchange-traded assets for almost three million accounts, covering around 5% of the entire investor population around that time. Many of these accounts never trade and, after dropping these "zombie" accounts, the sample size is reduced to 1.2 million. In the Internet Appendix, we show that our sample is representative of the investor population. 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.[16] 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 nontrivial 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 owned an account before 2014 and had been actively trading, making the estimation of prebubble behavior possible given that the bubble started in 2014.[17] In doing so, we exclude large individual accounts, a significant proportion of which were de facto managed by institutions that provided them shadow leverage. Representing over 80% of the investor population, the small individual accounts in our sample were mostly owned by typical Chinese mom-and-pop investors. Although, on average, such investors held only a low balance in their accounts, collectively they remained the largest force in the market, accounting for around 20% of stock ownership and 50% of volume in the entire market. Given these criteria, our main sample consists of the detailed transactions of around 583,859 investors from 2005 to 2016.

Table 1 reports the summary statistics of the investors in our main sample. The median investor is 48 years old, has an account balance of 130K RMB and 8 years of investment experience, makes a total of 85 buys and 71 sells during these 8 years, reshuffles his or her portfolio almost once every month, and earns a negative monthly return of -1.4%. Table 1 also demonstrates several other features about these investors. First, the sample is balanced in gender. Second, as discussed above, the ownership of margin accounts is low: only 2% of the sample have a margin account. Third, investors have trading experience not only with stocks but also with warrants and structured funds, although stocks are by far their most popular financial asset.

We complement our analysis with additional data sets. The first is investor characteristic data: demographic information collected from brokerage firms and trading characteristics based on past transactions. The second data set, 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, sophistication,

[16] Individuals hold approximately 45% of all tradable shares and their trading accounts for 85% of volume. During this bubble, they became even more active and responsible for over 90% of volume right before the bubble burst.

[17] Specifically, we limit the sample to investors who have made at least 14 buys and 10 sells, the values of which correspond to the 10th percentiles in their distributions by the end of 2013 among all investors.

Table 1
Summary statistics of sample characteristics

	Min	P5	P25	P50	P75	P95	Max	Mean	SD
AGE	18	28	36	43	51	65	75	44	11
BAL	0.01	0.02	0.06	0.13	0.30	0.72	0.99	0.22	0.22
EXP	1.08	2.83	5.33	7.25	7.92	8.92	8.92	6.63	1.90
COUNT_BUY	14	19	40	85	194	636	3,502	178	289
COUNT_SELL	10	14	32	71	169	574	3,299	157	267
TN	0.0	0.1	0.4	0.8	2.1	8.9	781.4	3.9	31.0
RET	−35.0%	−7.4%	−2.9%	−1.4%	−0.3%	1.7%	18.8%	−1.9%	3.5%
FEMALE	0	0	0	0	1	1	1	0.48	0.50
DUMMY_MARGIN	0	0	0	0	0	0	1	0.02	0.15
DUMMY_CALLS	0	0	0	0	0	1	1	0.15	0.36
DUMMY_PUTS	0	0	0	0	0	1	1	0.11	0.32
DUMMY_A	0	0	0	0	0	0	1	0.02	0.16
DUMMY_B	0	0	0	0	0	1	1	0.13	0.34

This table reports the summary statistics of the main sample of investors. Only accounts opened prior to 2014 are included in the main sample. We also drop accounts that have made fewer than 14 buys or 10 sells. *BAL* is the average RMB holding in millions. *EXP* is the number of years since account open date. *COUNT_BUY* (*COUNT_SELL*) is the number of buys (sells). *TN* is turnover and is calculated by dividing total trading volume by average account balance. *RET* is the average monthly return rate, calculated by dividing total *RMB* return by average RMB holding. *DUMMY_MARGIN*, *DUMMY_CALLS*, *DUMMY_PUTS*, *DUMMY_A*, and *DUMMY_B* are dummy variables indicating having a margin account, having traded call warrants, having traded put warrants, having traded A funds, and having traded B funds, respectively. P5, P25, P50, P75, and P95 correspond to the 5th, 25th, 50th, 75th, and 95th percentiles in the distribution.

investment horizon, experience, 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 the China Stock Market & Accounting Research Database.

2.3 Measuring extrapolation and disposition

To bring the model's predictions to the data, we start by devising 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 our model, *DOX* is similar to $1-\theta$, 1 minus the extrapolation horizon, while *DOD* represents β, the weight placed on the disposition signal. Empirically, disposition extrapolators have a high *DOX* and a high *DOD*. The approach taken so far is largely reduced-form; later, we use a more structural approach to estimate θ and β in order to quantify the effect of our proposed mechanism.

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 return based on all the transactions classified as initial buys. More specifically,

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

where $Buy_{i,t}$ denotes the transaction value for investor i and transaction t and $PastRet_t$ denotes the past return prior to transaction t. Another way to interpret

DOX is as a measure of positive feedback trading (e.g., DeLong et al. 1990), for which we assume that the underlying mechanism is extrapolation. We are aware that buying behavior may capture factors beyond extrapolative beliefs, and we address this concern 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.[18] To determine the extrapolation horizon, we examine the relationship between trading flows and past stock returns. Like Barber, Odean, and Zhu (2009), we regress trading flows on lagged returns using a panel of individual stocks (see the Internet Appendix). Results from Fama-MacBeth regressions show that buying and selling 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 1-month return throughout the paper.

Second, the act of buying winners could be driven by extrapolative beliefs, but also could be associated with rational motives, such as a momentum trading strategy. In this regard, studies have not found momentum in the cross-section of Chinese stocks across various horizons (e.g., Pan and Xu 2011; Gao, Hu, and Yan 2014), 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?[19] 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, Solomon, and Westerfield 2016).[20] More plausible is the notion that the main mechanism underlying investors' initial buying behavior is beliefs.[21] 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 2 report the summary statistics for *DOX*, where *DOXM* is our main measure based on past 1-month return and *DOXW* is an alternative one based on past 1-week return. Overall, Chinese investors are extrapolative: the 25th percentiles are positive for both measures, suggesting that more than

[18] In the United States, prior research suggests that the extrapolation horizon may reach 3 years back (Barber, Odean, and Zhu 2009), and several authors use the return over the last 12 months to identify extrapolators (Barberis et al. 2018).

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

[20] Odean (1998) finds that 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 displayed in initial buys.

[21] 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.

Table 2
Summary statistics for account characteristics

A. Summary statistics

	(1) *DOXW*	(2) *DOXM*	(3) *DODD*	(4) *DODR*	(5) *HHI*	(6) *VOL*	(7) *SKEW*	(8)	(9)	(10)	(11)
Min	−0.07	−0.11	−0.45	0.33	0.08	0.02	−0.28				
P5	−0.02	−0.02	−0.08	0.81	0.24	0.02	0.00				
P25	0.01	0.04	0.07	1.19	0.43	0.03	0.15				
P50	0.02	0.08	0.16	1.56	0.59	0.03	0.30				
P75	0.04	0.13	0.27	2.18	0.75	0.04	0.56				
P95	0.08	0.23	0.47	4.34	0.93	0.05	1.35				
Max	0.25	0.60	0.81	19.30	1.00	0.20	3.82				
Mean	0.03	0.09	0.17	1.96	0.59	0.03	0.44				
SD	0.03	0.08	0.17	1.52	0.21	0.01	0.47				

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	

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, respectively, between PGR and PLR, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners by 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. *SKEW* is calculated as volume-weighted past skewness. *TN* is turnover and is calculated by dividing total trading volume by average account balance. *RET* is the average monthly return rate, calculated by dividing total *RMB* return by average RMB holding. *BAL* is the average RMB holding in millions. *EXP* is the number of years since account open date. All variables are constructed based on transactions from 2005 to 2013. P5, P25, P50, P75, and P95 correspond to the 5th, 25th, 50th, 75th, and 95th percentiles in the distribution.

75% of the investors tend to buy stocks that have gone up recently. Results are robust to both raw returns and market-adjusted returns.

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

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

and PLR (Proportion of Losses Realized), defined by

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

where gains and losses are calculated based on the average purchase price and labeled as realized or paper depending on whether or not they are sold. The degree of disposition is then measured either as the difference between the two metrics, denoted by *DODD*, or as the ratio between the two, denoted by *DODR*.[22]

Columns 3 and 4 in Table 2 report the summary statistics for *DODD* and *DODR*. Consistent with existing evidence, the disposition effect is prevalent among Chinese investors: the 75th percentile for *DODD* is positive and the 75th percentile for *DODR* is greater than one, suggesting that more than 75% of Chinese retail investors are prone to the disposition effect. For simplicity, throughout the paper, we will primarily use *DODR*, the ratio-based degree of disposition, as our main measure. Results are robust, however, 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 into halves and then construct our measures separately in each subperiod, they are highly correlated; the Internet Appendix includes detailed analysis. This further justifies using ex ante measures to study trading behavior in the bubble: the disposition extrapolators identified *prior to* the bubble are likely to be the 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 the subsequent analysis. Columns 5 to 11 in Table 2 report their summary statistics. Many have extreme outliers (e.g., return rate), so we winsorize all variables at the 1% and 99% levels. Panel B of Table 2 reports the correlation matrix across all key account characteristics and highlights a number of observations. First, extrapolation and the disposition effect appear to be independent investor attributes: the correlation coefficients remain very small across all specifications. Second, *DOX* is highly correlated with measures of volatility-seeking (*VOL*, calculated as the volume-weighted average past volatility for stocks bought) and gambling preference (*SKEW*, calculated as the volume-weighted average past skewness for stocks bought), while *DOD* is highly correlated with the measure of diversification (*HHI*, the Herfindahl-Hirschman index). Therefore, it is important to put these variables in as controls in subsequent analysis.

Finally, in Table 3, 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),

22 While prior literature has raised concerns about using these measures when investors trade infrequently, our large sample size 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.

Table 3
Extrapolation and disposition effect across investor groups

	DOXW	*DOXM*	*DODD*	*DODR*	Obs.
A. Age					
30 or younger	0.027	0.078	0.162	1.804	19,612
30–39	0.026	0.081	0.170	1.891	78,485
40–49	0.026	0.085	0.172	1.945	85,165
50–59	0.027	0.091	0.176	2.056	51,940
60–69	0.027	0.093	0.161	2.040	24,514
70 or older	0.029	0.097	0.154	2.008	5,485
B. Education					
Doctoral	0.028	0.093	0.183	2.002	6,521
Master's	0.025	0.079	0.152	1.891	5,395
Bachelor's	0.027	0.086	0.164	1.909	75,969
3-year college	0.027	0.087	0.175	1.981	83,793
Professional school	0.026	0.084	0.174	1.977	21,841
High school	0.026	0.086	0.173	1.953	46,357
Middle school	0.026	0.086	0.170	1.955	25,469
Others	0.025	0.083	0.177	2.008	10,760
C. Gender					
Male	0.027	0.085	0.161	1.832	303,530
Female	0.028	0.093	0.187	2.100	280,329

This table reports the average degrees of extrapolation and disposition across 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, respectively, between PGR and PLR, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners by the total number of winners on days of sales and PLR (Proportion of Losses Realized) is similarly calculated. All variables are constructed based on transactions from 2005 to 2013.

and (c) men and women trade differently (Barber and Odean 2001). We find extrapolation weakly correlated with age and education but more pronounced among women and find the disposition effect weakly correlated with education but stronger among older investors and among women. We control for demographic variables whenever possible.

2.4 Evidence of heterogeneous holdings

Our model assumes that investors start with heterogeneous holdings. Table 4 shows, for each month from 2014 to 2015, the average ownership breadth—that is, the number of investors holding that stock divided by the total number of investors—of an individual stock. Overall, ownership breadth is low, ranging between 0.01% and 3.26% with a median of 0.07%. Furthermore, although thousands of stocks are traded on the exchange, an investor on average holds fewer than five in his or her portfolio, suggesting a portfolio composition that is highly concentrated. Therefore, investors hold quite different and largely underdiversified portfolios, lending empirical support to the assumption of heterogenous initial holdings.

Table 4
Distribution of ownership breadth in the cross-section of individual stocks, 2014–2015

Date	Min	P5	P25	P50	P75	P95	Max
Jan. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.50%
Feb. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.48%
Mar. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.42%	2.47%
Apr. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.47%
May 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.46%
Jun. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.45%
Jul. 2014	0.01%	0.02%	0.05%	0.08%	0.14%	0.41%	2.44%
Aug. 2014	0.01%	0.02%	0.05%	0.08%	0.14%	0.41%	2.43%
Sep. 2014	0.01%	0.02%	0.05%	0.08%	0.14%	0.41%	2.41%
Oct. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.40%
Nov. 2014	0.01%	0.02%	0.04%	0.08%	0.14%	0.41%	2.37%
Dec. 2014	0.01%	0.02%	0.04%	0.07%	0.14%	0.41%	2.26%
Jan. 2015	0.01%	0.02%	0.04%	0.07%	0.14%	0.41%	2.73%
Feb. 2015	0.01%	0.02%	0.04%	0.07%	0.14%	0.41%	2.92%
Mar. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.42%	2.87%
Apr. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.42%	2.78%
May 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.41%	2.81%
Jun. 2015	0.01%	0.02%	0.04%	0.07%	0.12%	0.40%	3.26%
Jul. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.39%	2.94%
Aug. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.38%	2.76%
Sep. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.37%	2.73%
Oct. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.38%	2.58%
Nov. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.38%	2.44%
Dec. 2015	0.01%	0.02%	0.04%	0.07%	0.13%	0.38%	2.40%

In each month in 2014–2015, we calculate each stock's ownership breadth, defined by dividing the number of investors holding that stock by the number of investors in the population.

3. Volume Dynamics in the Bubble

In this section, we present four pieces of evidence in support of our mechanism for volume. Section 3.1 shows that, at the market level, disposition extrapolators as a group are largely responsible for the rise in total volume. Section 3.2 confirms this result at the investor level, using a regression framework that controls for other variables. Section 3.3 further examines the cross-section of individual stocks and shows that stocks traded more by disposition extrapolators have a higher increase in turnover. Section 3.4 quantifies the contribution of our proposed mechanism to the rise in trading volume. In Section 3.5, we discuss some alternative explanations for our results and the implications of our results for theories of bubbles.

3.1 Market-level evidence

We sort investors into three groups based on their ex ante measures of extrapolation and disposition: disposition extrapolators, pure extrapolators, and others. 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 (which includes mostly pure disposition investors). We then compare their trading volumes throughout the bubble.

In Figure 5, panel A, each line represents the evolution of a group's volume, defined as the value of shares traded and normalized to one at the beginning of

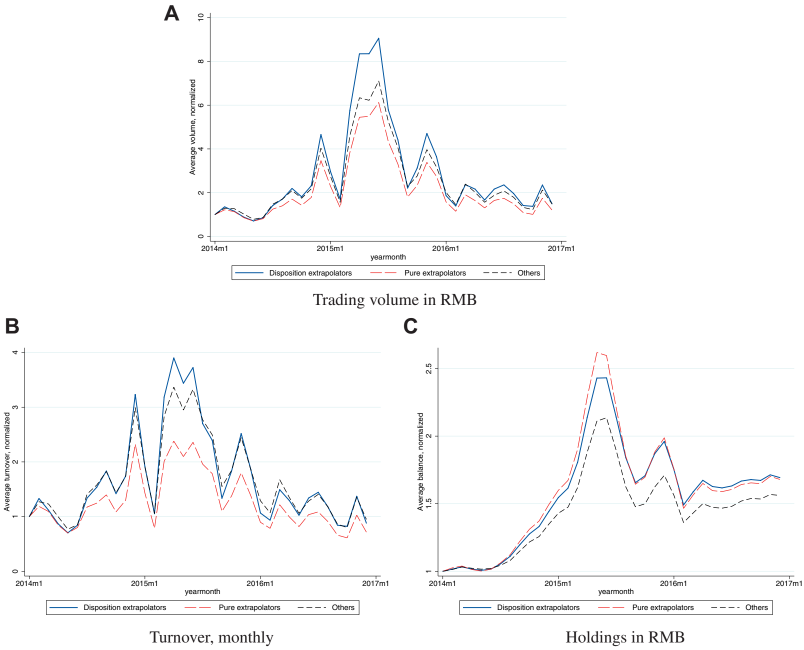


Figure 5
Evolution of volume by group
The three lines represent the evolution of volume for three investor groups: disposition extrapolators, pure extrapolators, and other investors. Disposition extrapolators have both *DOX* and *DOD* above the median; pure extrapolators have *DOX* above the median and *DOD* below; and the rest are classified as other investors. For all groups, volume, turnover, and balance are normalized to one at the beginning of 2014.

2014. Group-level volumes were very similar prior to the bubble; hovering around the value of one, the three lines are almost indistinguishable from one another. However, in the run-up, disposition extrapolators increased their volume much more than other investors did; at peak, their volume increased by almost 800%, while pure extrapolators increased their volume by 500% and other investors by 600%. The comparison between disposition and pure extrapolators directly highlights the importance of the disposition effect in explaining volume: its addition generates an additional 300% increase in volume. Without disposition extrapolators, the increase in volume would have been much smaller.

Figure 5, panels B and C, decompose volume into two sources: turnover, which measures the speed of portfolio rebalancing, and balance, which measures portfolio size. An investor may increase her trading volume either by holding more assets (balance) or by reshuffling portfolio composition more quickly (turnover). The different dynamics of the two figures paint a vivid picture of how disposition extrapolators traded: they were not only active in reshuffling their holdings but also very aggressive in increasing their overall

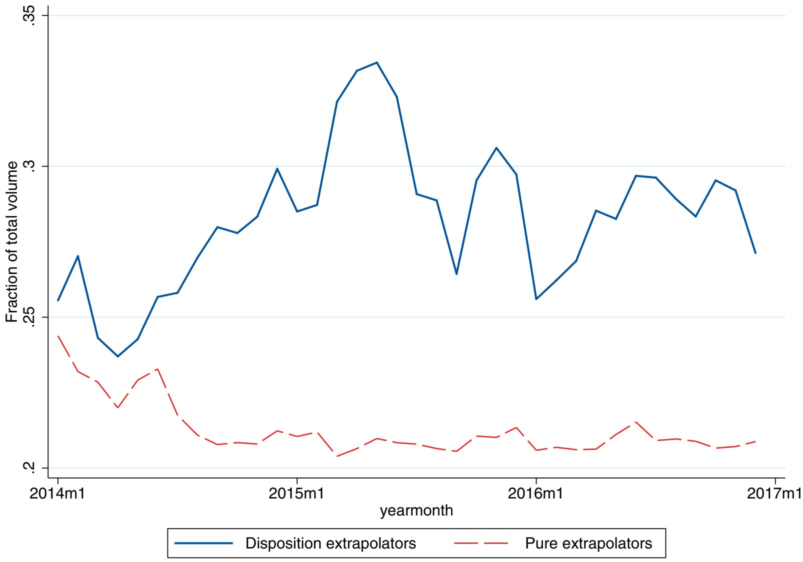


Figure 6
Decomposition of total volume by group
This plots the composition of total volume. The solid line represents the fraction of volume from disposition extrapolators, and the dashed line represents the fraction from pure extrapolators. Disposition extrapolators have both *DOX* and *DOD* above the median and pure extrapolators have *DOX* above the median and *DOD* below.

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 went up by less than 150%, compared to a 300% increase for disposition extrapolators. Other (nonextrapolative) investors exhibited a turnover similar to that of disposition extrapolators, but their holdings went up only around 100%. In short, extrapolation and the disposition effect play separate but complementary roles in driving up volume. This finding is exactly the 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. As before, disposition extrapolators accounted for an increasing fraction of total volume as the bubble progressed: their trading constituted around 25% of total volume prior to the bubble, but reached 34% at the peak. In comparison, pure extrapolators accounted for an ever smaller fraction of total volume, dropping from 25% to almost 20%.

Finally, in Figures 5 and 6, we see group-level differences in volume begin to disappear in the crash; investor-level regressions below further support this observation. 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 shown in Figure 6, with the fraction of total volume accounted for by disposition extrapolators dropping 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.

3.2 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 Tables 2 and 3. We therefore run investor-level regressions by regressing change in volume on *DOX*, *DOD*, and the interaction between them, while also controlling for various investor characteristics. Change in volume is measured by the ratio of monthly volume at peak (2015:05) to the average monthly volume in the prebubble period.

Table 5 reports regression results.[23] 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 results without adding any controls; the 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 volume, while a one-standard-deviation increase in *DOD* is associated with a 460% increase in volume. 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.

Columns 2 to 4 each add an additional set of controls to 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 significant, for instance, investors with a larger account size increase their volume less, the significance of *DOX* and *DOD* is robust to their inclusion. Column 3 adds demographic variables, including gender, age, and education, and the coefficients are essentially unchanged.

Column 4 represents our full specification by adding (a) a dummy variable for having a margin account, (b) a dummy variable for having previously traded warrants to control for prior experience in bubbles (Xiong and Yu 2011), and (c) a set of survey-based characteristics, including self-reported wealth, income, sophistication, and investment horizon and measures of short- and long-term risk tolerance. Because only a fraction of the sample has answered the survey, the number of observations drops substantially, but the coefficients for *DOX*, *DOD*, and their interaction remain significant, though with slightly smaller magnitude. Therefore, consistent with the market-level evidence, the

[23] We drop observations in which investors do not trade at all during 2014 and 2015. This reduces the sample size in Table 5 to around 440,000.

Table 5
Explaining account-level trading volume using extrapolation and the disposition effect

	ΔVolume$_i$				ΔTurnover$_i$	ΔBalance$_i$	ΔCrashVolume$_i$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DOX$_i$	4.02***	3.69***	3.64***	2.64***	−0.02	0.32***	−0.075
	(10.31)	(9.56)	(9.44)	(5.56)	(−0.10)	(17.33)	(−0.683)
DOD$_i$	4.60***	4.32***	4.14***	3.65***	1.96***	−0.05***	0.012
	(13.31)	(12.27)	(11.81)	(7.84)	(11.24)	(−4.04)	(0.124)
*DOX$_i$ *DOD$_i$*	0.84***	0.72***	0.71***	0.76**	0.27**	−0.04***	−0.105*
	(2.94)	(2.63)	(2.59)	(2.15)	(1.99)	(−4.61)	(−1.664)
BAL$_i$		−19.60***	−18.77***	−14.96***	−0.60	−1.39***	−3.687***
		(−22.44)	(−21.08)	(−13.61)	(−1.45)	(−32.24)	(−13.261)
EXP$_i$		2.69***	2.84***	3.25***	1.33***	0.04***	0.690***
		(31.98)	(32.83)	(30.55)	(34.34)	(9.14)	(12.303)
HHI$_i$		0.80	−0.18	2.70**	−3.67***	1.03***	4.352***
		(0.75)	(−0.17)	(2.08)	(−7.74)	(20.71)	(13.277)
VOL$_i$		−122.23***	−118.97***	−80.00***	−69.62***	6.15***	−1.888
		(−7.35)	(−7.16)	(−3.91)	(−10.10)	(7.09)	(−0.326)
SKEW$_i$		1.20**	1.31**	1.14*	0.63***	−0.02	0.620***
		(2.20)	(2.42)	(1.70)	(2.96)	(−0.56)	(3.431)
RET$_i$		−13.35***	−12.85***	4.75	6.69***	−2.18***	−5.487***
		(−3.22)	(−3.10)	(1.11)	(4.45)	(−7.07)	(−3.577)
Other controls							
Demographics	No	No	Yes	Yes	Yes	Yes	Yes
Margin account, dummy	No	No	No	Yes	Yes	Yes	Yes
Traded warrants before, dummy	No	No	No	Yes	Yes	Yes	Yes
Survey-based characteristics	No	No	No	Yes	Yes	Yes	Yes
Constant	26.59***	14.81***	12.52***	3.34	4.70***	1.52***	1.453*
	(55.20)	(12.71)	(10.31)	(1.14)	(4.53)	(11.79)	(1.800)
N	439,853	439,798	439,798	252,907	252,907	252,907	215,146
R^2	.003	.005	.006	.010	.013	.016	.007

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 of PGR to PLR, where PGR (Proportion of Gains Realized) is calculated by dividing the number of realized winners by 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. *SKEW* is calculated as volume-weighted past skewness. *RET* is the average monthly return rate, calculated by dividing total *RMB* return by average RMB holding. *DOX* to *RET* are constructed based on transactions from 2005 to 2013. 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 short-term and long-term tolerances for losses. ΔVolume is calculated as the ratio of monthly volume at peak (2015:05) to the average monthly volume in the prebubble period from 2014:01 to 2014:11. ΔTurnover and ΔBalance are similarly calculated. ΔCrashVolume is calculated as the ratio of monthly volume at trough (2015:09) to the average monthly volume in the prebubble period from 2014:01 to 2014:11. Robust t-statistics appear in parentheses. *** p<.01; ** p<.05; * p<.1.

combination of extrapolation and the disposition effect leads to higher volume at the investor level.

In columns 5 and 6, we rerun the same regression as in column 4 but replace the left-hand-side variable by changes in turnover and balance in the same period, respectively. This is effectively the regression version of the exercise conducted in Figure 5, panels B and C. Consistent with the market-level evidence, we find that extrapolation leads to greater holdings in the run-up but does not change turnover, whereas disposition induces higher turnover but has little impact on holdings. Together, they explain why disposition extrapolators increase their volume so much in the bubble.

Finally, column 7 repeats the same regression as in column 4 but replaces the dependent variable with trading volume during the crash. If omitted variables are driving the relationships documented in columns 1 to 4, then the same relationships should persist into the crash. However, in column 7, neither $\overline{DOX}$ nor $\overline{DOD}$ is significantly associated with the trading volume during the crash, which rules out the concern that omitted variables are driving the results in columns 1 to 4. In the Internet Appendix, we extend the analysis to 2016, a relatively quiet year, and again find that neither extrapolation nor disposition can significant explain volume. Therefore, consistent with the model's prediction, the interplay between extrapolation and disposition effects is particularly pertinent to the rise in volume in the run-up.[24]

3.3 Stock-level evidence

In this section, we examine the cross-section of individual stocks and try to link cross-sectional differences in 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 shares of stock j bought by investor i in week t. Similarly, we calculate the stock's "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 shares of stock j 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 weekly stock-level degrees of extrapolation and disposition.

Next, we regress each stock's turnover—calculated by dividing total RMB volume by market capitalization—contemporaneously on its $\overline{DOX}$ and $\overline{DOD}$. The resultant coefficients show whether more trading from disposition

[24] In the Internet Appendix, we further consider trading volume in January 2016, when the stock market crashed because of the introduction of circuit breakers. The crash occurred without first experiencing a run-up, thereby providing a test of our model under negative shocks. Consistent with the model, both extrapolation and disposition explain trading volume with a negative sign, suggesting that in a market disposition extrapolators decrease their trading volume more so than other investors do.

extrapolators in a given week contributes to higher turnover in the same week. Turnover is much more persistent than returns 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.[25] The stock fixed effect also means that we cannot include other stock-level controls, such as beta, size, and B/M, into the same regressions, because these variables changed very little during the 6-month run-up.

Table 6 reports the panel regression results, where $\overline{DOX}$ and $\overline{DOD}$ are normalized, using their standard deviations, for easier interpretation. Column 1 reports the baseline results, in which both coefficients are positive and highly significant. 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 median (average) weekly turnover is around 0.16 (0.19) during this period, these coefficients represent rather substantial explanatory power. We add additional sets of controls to the baseline regression in columns 2 to 4: contemporaneous weekly returns, lagged weekly returns, and lagged weekly turnover, respectively. Overall, while these additional controls reduce the t-statistics for $\overline{DOX}$, both coefficients remain highly significant with large magnitudes, 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.

3.4 Magnitude

To quantify the mechanism's magnitude, we estimate the two key parameters from the model, θ and β, which represent the degree of extrapolation and of disposition, respectively. Following a method similar to that in Cassella and Gulen (2018) and Da, Huang, and Jin (2021), we fit the belief formation process in Equation (3) with actual retail flows into stocks. Our identifying assumption is that initial buys are primarily driven by expectations rather than preferences, such as realization utility (Da, Huang, and Jin 2021). This assumption allows us to directly estimate θ.[26] We then use the trading flows of investors with a positive position to back out β; as the model implies, these decisions are jointly driven by expectations and realization utility. In summary, we estimate

[25] 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.

[26] Even if some preference considerations enter into initial buying decisions, they would not affect our estimation as long as investors do not treat recent returns and distant returns differently in their utility function. Indeed, as will be shown later, the key identification comes from the speed of decay: how investors use more recent returns relative to more distant returns in their initial buying decisions. The more they rely on the recent returns, the more extrapolative they are. This is a key implication of the standard formulation of extrapolative expectations. In contrast, most preference specifications are silent on the relationship between more recent returns and more distant return and treat all past returns equally.

Table 6
Explaining stock-level turnover using extrapolation and the disposition effect

	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	.50	.52	.62	.70

This table reports panel regression results by regressing weekly stock-level turnover on weekly stock-level measures of extrapolation and disposition. A stock's turnover in a given week is calculated by dividing the total RMB trading amount by 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. Robust t-statistics appear in parentheses. *** $p<.01$; ** $p<.05$; * $p<.1$.

the following two equations:

$$\text{initial buys}_{i,t} = b_0\left(b_1 + \frac{1}{\sum_{\tau=1}^{T}\theta^{\tau}}\sum_{\tau=1}^{T}\theta^{\tau} r_{i,t-\tau}\right), \tag{12}$$

$$\text{subsequent trades}_{i,t} = b_0\left(b_1 + \frac{1}{\sum_{\tau=1}^{T}\theta^{\tau}}\sum_{\tau=1}^{T}\theta^{\tau} r_{i,t-\tau} - \beta \times \overline{r}_{i,t}\right), \tag{13}$$

where i indexes stocks, t indexes week, T represents the look-back window, r represents stock return, and $\overline{r}$ represents holding-period return. For each stock in each week from 2005 to 2013, we aggregate across investors to get stock-level measures of initial buys and subsequent trades. We assume that there is a noise term that is normally distributed with a mean of zero and estimate the above two equations using maximum likelihood estimation (MLE).

Table 7
Model counterfactuals

	All investors (1)	Benchmark: No bias (2)	Benchmark: No disposition extrapolators (3)
Empirical estimates			
θ	0.64	0	0.92
	(0.003)		(0.001)
β	0.54	0	0.41
	(0.002)		(0.001)
Model outputs			
Peak price	190	120	131
Peak volume	0.46	0.25	0.36

This table reports peak price and volume under three sets of parameters. θ represents the degree of extrapolation and β represents the degree of disposition. In column 1, using the full sample of investors including disposition extrapolators, we estimate θ and β from the following two equations:

$$\text{initial buys}_{i,t} = b_0 \left(b_1 + \frac{1}{\sum_{\tau=1}^{T} \theta^\tau} \sum_{\tau=1}^{T} \theta^\tau r_{i,t-\tau} \right),$$

$$\text{subsequent trades}_{i,t} = b_0 \left(b_1 + \frac{1}{\sum_{\tau=1}^{T} \theta^\tau} \sum_{\tau=1}^{T} \theta^\tau r_{i,t-\tau} - \beta \times \bar{r}_{i,t} \right),$$

where i indexes stocks, t indexes week, T represents the look-back window, r represents stock return, and $\bar{r}$ represents holding-period return. For each stock in each week from 2005 to 2013, we aggregate across investors to get stock-level measures of initial buys and subsequent trades. Parameters are estimated and standard errors are calculated using MLE by assuming that errors are normally distributed. In column 2, we consider a benchmark case of no extrapolation and no disposition effects by setting both θ and β to zero. In column 3, we consider a second benchmark by reestimating the above two equations, but exclude disposition extrapolators from the sample; disposition extrapolators have both *DOX* and *DOD* above the median. Model outputs are calculated by plugging the estimated parameters back into the baseline model. Standard errors appear in parentheses.

Table 7, column 1, reports the estimated parameters and the standard errors. With the moment conditions specified above, we have the following estimates: $\theta = 0.64$ and $\beta = 0.54$. These are consistent with earlier evidence that Chinese investors have a short extrapolation horizon and display strong disposition effects. Plugging these two parameters back into the model, we find that the peak price and volume are 190 and 0.46, respectively.

We then consider two benchmarks for comparison and show their results in columns 2 and 3 of Table 7. In column 2, we assume no extrapolation or disposition effects by setting both θ and β to zero, under which peak price and volume are 120 and 0.25, respectively. Compared to the first benchmark, our mechanism increases peak price by 58% and peak volume by 84%. In column 2, we assume that disposition extrapolators exit the market by excluding their transactions from the sample and reestimate the two equations. The new estimates, $\theta = 0.92$ and $\beta = 0.41$, suggest lower degrees of extrapolation and disposition. Under these parameters, peak volume and price are 131 and 0.36, respectively. Compared to the second benchmark, our mechanism increases peak price by 45% and peak volume by 28%. We view the second benchmark more realistic and therefore conclude that, based on the model counterfactuals, our mechanism can increase the peak volume by around another 30%.

3.5 Discussion

3.5.1 Additional evidence on volume. So far, we have been primarily concerned with overall trading volume, without separately examining different types of trade. In the Internet Appendix, we document two other facts about the composition of volume during a bubble. First, we show that much of the volume comes from trading on the extensive margin rather than on the intensive margin. Second, investors as a whole increasingly trade new stocks; that is, stocks they have not traded before. Both sets of facts are consistent with an extension of our baseline model in which investors have a CARA utility function.

3.5.2 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 5, which 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, leverage constraints (dummy variable for having a margin account), prior trading experience with warrants, demographic variables (such as gender, age, and education), and survey-based characteristics (such as self-reported income, wealth, investment horizon, risk tolerance, investment objective, and asset allocation). This wealth of control variables validates the robustness of extrapolation and disposition in explaining volume.

We 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 contributed to the high volume. Because we use only regular accounts, as opposed to margin accounts, our volume results are not driven by the use of *regulated* leverage. We also controlled for the ownership of a margin account in investor-level regressions. However, since we do not observe the *shadow* leverage that investors took during this period (Bian et al. 2018a; Bian et al. 2018b), we cannot directly 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, Nathanson, and Zwick 2020). Given the nature of our empirical design, we cannot include new investors in our analysis. However, we find that, even at the peak of the bubble, investors who had entered the market after the run-up was already underway accounted for less than 20% of volume. Therefore, such investors are unlikely to fully explain the volume.

3.5.3 Implications for theory. Our volume results cannot be easily explained by other theories of bubbles. First, theories based on extrapolation (e.g., Barberis et al. 2018; DeFusco, Nathanson, and Zwick 2020) do not differentiate disposition extrapolators from pure extrapolators and are therefore silent on the difference between those investor groups during the bubble. Our results clearly show that the addition of the disposition effect makes a significant difference to 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 in different directions. Our interpretation, however, suggests a different form of “wavering”: instead of “wavering” between different signals, disposition extrapolators “waver” between beliefs and preferences.

Our results are consistent with the notion that the high volume is driven by short-term speculation (e.g., DeFusco, Nathanson, and Zwick 2020): 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, Nathanson, and Zwick (2020), 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 so that they trade more.

Finally, it is difficult to reconcile our results with 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 rise in volume across investor groups. It is not obvious why disposition extrapolators would become more overconfident in a bubble than other investors do. On the other hand, dynamic versions of overconfidence-based theories (e.g., Gervais and Odean 2001) often posit good past returns as a source of overconfidence. But, according to that theory, the pure extrapolators—those who ride the bubble more aggressively and profit more in the run-up—should trade the most.

4. 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, evidence has been scarce. Empirically identifying extrapolators is difficult without detailed transaction or survey data. Furthermore, showing a contemporaneous association between extrapolators and prices is nonconclusive: it is consistent not only with extrapolators driving up prices but also with the reverse argument that prices go up first and subsequently attract more trading from extrapolators. In this section, we take advantage of the granular nature of our data to examine the role of extrapolators in driving up stock prices during the 2014–2015 Chinese stock market bubble. While we do not establish causality, the evidence is nonetheless consistent with the model’s prediction and can rule out the reverse-causality argument above.

Table 8
Regressing stock returns on stock-level measures of extrapolation and disposition

	A. Return $(t+1)$, run-up (%)				B. Return $(t+1)$, crash (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{DOX}\ (t+1)$	2.90***			0.70**	3.69***			−4.49***
	(9.38)			(2.07)	(4.91)			(−3.20)
$\overline{DOX}\ (t)$		0.35**	0.35**			−1.83**	−1.86***	
		(2.26)	(2.25)			(−3.02)	(−3.13)	
Return (t)	−0.13**	−0.09	−0.09	−0.10	0.03	0.05	0.05	0.06
	(−2.18)	(−1.42)	(−1.41)	(−1.57)	(0.16)	(0.26)	(0.27)	(0.33)
BETA (t)	−0.10	−0.33	−0.11	−0.15	0.21	−0.94	−0.75	−0.95
	(−0.37)	(−1.08)	(−0.37)	(−0.53)	(0.28)	(−1.25)	(−0.80)	(−0.97)
SIZE (t)	−0.00	−0.01***			0.01	0.00		
	(−1.65)	(−3.32)			(1.07)	(0.06)		
B/M (t)	0.14	−0.05			0.47**	0.09		
	(1.59)	(−0.60)			(2.41)	(0.47)		
Turnover (t)	−3.91**	−0.92	−1.50	−1.29	−10.64	−5.07	−5.46	−4.74
	(−2.19)	(−0.49)	(−0.74)	(−0.64)	(−1.50)	(−0.66)	(−0.65)	(−0.55)
FLOAT (t)	0.00	0.00	−0.00	−0.00	0.00	0.00	0.00	0.00
	(0.66)	(1.29)	(−0.85)	(−0.71)	(0.51)	(0.75)	(0.53)	(0.18)
VOL (t)	−0.00	−0.00	0.00	0.00	−0.00	−0.00	−0.00	−0.00
	(−0.46)	(−0.27)	(0.42)	(0.32)	(−0.42)	(−0.49)	(−0.63)	(−0.32)
Board FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size and B/M bins	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	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	.13	.04	.04	.08	.08	.05	.05	.10

This table reports panel regression results by regressing weekly future returns on weekly stock-level exposure to extrapolation. 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 trading amount by total market capitalization. *FLOAT* is the number of tradable shares. *VOL* is the number of shares traded. Robust t-statistics appear in parentheses. *** p<.01; ** p<.05; * p<.1.

To gain more statistical power and facilitate our empirical strategy, we construct a panel of weekly stock returns and characteristics, in which the stock-level degree of extrapolation is constructed as in Equation (10) in the previous section. 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). Panel A of Table 8 reports the regression results. As a benchmark, in column 1, we first run the "wrong" regression by regressing returns *contemporaneously* on $\overline{DOX}$. The resultant coefficient is significantly positive, but as discussed above, the interpretation is unclear.

To address the reverse-causality concern, we use 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.[27] 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 35-basis-point higher returns in the following week, which amounts to roughly 9% for the entire run-up. While the t-statistic is not huge, it is still sizable given the short sample period. In comparison, most other standard asset pricing factors appear to have little predictive power for future returns. Column 3 confirms the results in column 2 by controlling for size and value nonlinearly with size and value bins. In column 4, we run an IV regression by instrumenting current $\overline{DOX}$ using lagged $\overline{DOX}$. Consistent with the predictive regressions, the coefficient for $\overline{DOX}$ is positive and significant. A one-standard-deviation increase in the instrumented $\overline{DOX}$ is associated with a 70-basis-point increase in weekly returns, which amounts to 18% for the entire run-up. Given that the market almost doubled during this period, the explanatory power of extrapolation is rather substantial.

Panel B repeats nearly the same set of regressions presented in panel A, except the regressions are trained on the crash. While the contemporaneous regression still produces a positive coefficient, the predictive regressions and the IV regression 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 avoid spurious results, such as those in columns 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 that extrapolators have a substantial negative impact on prices during the crash. Overall, although we do not causally show the relationship between extrapolation and prices, we find evidence that is consistent with the notion of extrapolative bubbles.

5. Conclusion

We examine a recent bubble in the Chinese stock market, using detailed account-level data from a large Chinese brokerage. To explain the joint dynamics of price and volume in a bubble, we 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. Evidence supports the model's mechanisms for volume and price. We further quantify the contribution of our proposed mechanism by showing that it can induce an additional 30% increase in trading volume during a bubble. Overall, our analysis shows that the combination of nonstandard beliefs and nonstandard preferences can be used to shed light on long-standing asset pricing puzzles, such as financial bubbles.

[27] In other words, investors have a preferred habitat (Vayanos and Vila 2021). Indeed, $\overline{DOX}$ exhibits strong autocorrelation, with a AR(1) coefficient of 0.45 at the weekly frequency.

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