Price and Volume Dynamics in Bubbles*

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Abstract

We propose a model of bubbles based on two ingredients: extrapolation and the disposition effect. We show that the model generates the sharp rise in both prices and volume observed in most bubble episodes, and then test the model’s predictions using novel data on the 2014-15 Chinese stock market bubble. Consistent with the model, stocks traded by extrapolative investors exhibit larger price increases during the bubble, while those traded by investors with disposition effects go up much less. Moreover, the increase in volume during the bubble is driven primarily by the subset of investors who are both more extrapolative and more prone to the disposition effect: these investors are quick to buy a stock with good past performance, but also quick to sell it if its price continues to rise.

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1 Introduction

Asset bubbles span the history of modern finance, from the Dutch tulip mania in the 17th century to the recent U.S. housing bubble. For decades, explaining the existence of bubbles has been challenging for traditional finance theory. Moreover, the dynamic patterns of prices and trading volume in a bubble remain a puzzle. A bubble usually starts with a run-up, during which asset prices rise above the fundamental value and continue to increase for a substantial period of time. Eventually, the bubble ends in a crash during which prices fall back to, or even drop below, the fundamental value. Along with rising prices, volume also increases significantly in the run-up—often manifested by a trading frenzy—but then drops sharply in the crash. In some cases, the rise and fall in volume is even greater than in prices. These empirical characteristics raise two important questions about bubbles: What is the mechanism causing the run-up and the subsequent crash? And why do investors trade so much during a bubble?

Recent efforts to explain bubbles place the concept of extrapolation—forming beliefs about future price changes based on past price changes—at the center of the discussion. Extrapolative investors tend to buy assets whose values have recently gone up, in expectation that prices will rise even further. While it has been shown that this mechanism can shed light on the price dynamics in a bubble (Barberis et al. 2017; DeFusco et al. 2017; Glaeser and Nathanson 2017), it is not straightforward to see how extrapolation can explain the volume patterns.¹ When investors all form beliefs by extrapolating past returns, they tend to form similar beliefs and will not trade with each other, but this stands in sharp contrast to the high volume observed across many historical bubble episodes.

In this paper, we propose that a simple and natural way to understand both price and volume dynamics in bubbles is to incorporate the disposition effect into the basic framework of extrapolation. Prevalent among both individuals and institutions across various markets

¹Both Barberis et al. (2017) and DeFusco et al. (2017) explicitly address the high volume in a bubble, by coupling extrapolation with some additional ingredients. Barberis et al. (2017) assume that investors “waver” between a extrapolative signal and a value signal, and this wavering assumption induces greater disagreement among extrapolators as an asset’s price rises above its fundamental value in a bubble. DeFusco et al. (2017) assume that extrapolators have different expected investment horizons, and that short-term expectations are more sensitive than long-term expectations to past returns. As a result, positive past price changes in a bubble disproportionately attract short-horizon investors, who then push up trading volume.
(Frazzini 2006; Barber and Odean 2013), the disposition effect is the trading phenomenon whereby investors tend to sell stocks trading at a gain and hold on to stocks with losses (Shefrin and Statman 1985; Odean 1998). Together, extrapolation and the disposition effect characterize an investor who *buys* an asset if its price goes up, but *sells* that asset if its price goes up even further.

We present a model in which investors are both extrapolative and prone to the disposition effect, and show that the model can generate a bubble episode featuring a sharp rise in both prices and volume. In the model, positive dividend shocks trigger some initial price increases for a stock, and extrapolating these good returns, investors push up stock prices even further. As prices rise, extrapolation and the disposition effect take turns in dominating an investor’s portfolio decision: when he is *not* invested in the stock, extrapolation induces him to buy it; when he *is* invested in the stock, the disposition effect prompts him to sell it. As a result, investors end up buying and selling the stock back and forth amongst themselves, generating large volume.

Using a novel dataset from the Shenzhen Stock Exchange which contains the complete trading history for all Chinese individual investors, we test the model’s predictions in the context of the Chinese stock market bubble from 2014 to 2015. This bubble, affecting all domestically listed firms and involving over 100 million investors, followed the typical trajectory: it featured a run-up that spanned six months, followed by a crash in which prices fell to their pre-bubble levels; and both prices and volume rose to record highs, with prices doubling and volume more than quadrupling. Combined with our data, this episode offers a unique chance to investigate a market-wide bubble at the investor level. Our empirical results not only support this novel framework we propose, but also document some new facts about bubbles.

We develop our basic framework using a setting in which a continuum of risk-neutral investors allocate their wealth between a stock and cash, where the stock represents the risky asset potentially subject to a bubble. Investors form their beliefs about future price changes based on an extrapolative signal, which is an exponentially weighted average of past price changes. As such, a streak of positive past price changes would turn the extrapolative signal positive, inducing optimistic beliefs about future price changes. We depart from previous
models of extrapolation in a significant way by assuming that investors’ utility depends not only on expected wealth, but also on realized gains and losses. This additional element of “realization utility” prompts investors to sell stocks with gains and hold on to stocks with losses, leading to a positive disposition effect.\footnote{Researchers have proposed other mechanisms to explain the disposition effect, such as non-standard beliefs (e.g., Peng 2017) and cognitive dissonance (e.g., Chang et al. 2016). Using these other mechanisms to model the disposition effect produces similar predictions.}

This setting delivers the following key result: when investors exhibit both extrapolative beliefs and the disposition effect—we call these investors disposition extrapolators—positive fundamental shocks can trigger a bubble episode featuring both a price run-up and high volume. On the one hand, they extrapolate the positive price changes induced by positive fundamental news and, in expectation of high future returns, push up stock prices even further. On the other hand, the tension between their extrapolative beliefs and their disposition to sell winners drives up aggregate volume. During the bubble, investors are divided based on their current holdings: those holding cash are induced by extrapolative beliefs to invest in the stock, but those already invested in the stock are eager to sell due to realization utility. As prices rise in the run-up, this divide widens: cash holders’ tendency to buy and stock investors’ tendency to sell both intensify, and they trade a lot by swapping each other’s asset positions. This highlights the conflict between beliefs and preferences an investor faces in a rising market: when out of the market, he is tempted to enter due to extrapolative beliefs, but as soon as he is in the market, realization utility kicks in, prompting him to sell and exit. As a result, investors end up switching back and forth between cash and the stock, pushing up aggregate volume.

In addition to explaining some basic facts about prices and volume in bubbles, the model makes new predictions. We first derive its prediction for prices: in a bubble, assets traded more by extrapolators have higher returns, whereas assets traded more by disposition-prone investors have lower returns. We then examine holdings and volume at the investor level by switching to a heterogeneous-agent setting that features two additional types of investors: extrapolation-only and disposition-only. Using pairwise comparisons, we derive the model’s prediction for holdings: an investor’s holding in the run-up increases in his degree of extrapolation and decreases in his degree of disposition. Finally, by decomposing total volume by
investor type, we derive the model’s prediction for volume: disposition extrapolators increase their volume more than other investors do and are largely responsible for the rise in total volume.

We examine these predictions using account-level transactions and holding records for a representative sample of Chinese individuals. In addition to covering the 2014-15 stock market bubble, the data also contain their complete trading history prior to the bubble, allowing us to measure each investor’s degrees of extrapolation and disposition ex ante. Specifically, the degree of extrapolation is proxied by the propensity to buy winners, and the degree of disposition is proxied by the propensity to sell losers. We then use these investor-level measures of trading behavior to test the model’s predictions.

First, we test the prediction for prices, using the cross section of Chinese stocks as the test assets. For a stock, we first look at who are the investors trading it in the run-up. Then we average the degrees of extrapolation or disposition across all these investors, weighting by how much they trade that stock during the run-up. These stock-level measures of extrapolation and disposition then explain how much a stock’s price rises in the run-up. Consistent with the prediction, we find that stocks traded more by extrapolative investors have higher returns, and stocks traded more by disposition-prone investors have lower returns. For example, a one-standard-deviation increase in the degree of extrapolation implies a 23-percentage-point increase in stock returns. One interpretation of this result is that extrapolators are responsible for these price increases, but an alternative one is that extrapolators only begin to trade after prices have gone up. To rule out the latter interpretation, we construct two ex-ante measures using trading volume prior to the bubble as weights, and we find similar results when using these measures as the instruments.

Next, we test the prediction for holdings by showing that, as the bubble progressed, extrapolative investors invested more while disposition-prone investors invested less. We first investors into five groups based on their degrees of extrapolation and disposition, and then compare group-level holdings throughout the bubble. Before the bubble starts, stock holdings measured in RMB exhibit little difference across the five groups, evolving almost in parallel. As the bubble builds up, however, holding patterns begin to diverge. At the peak, the most extrapolative investors on average hold 30,000 RMB (around 5,000 USD) more
stocks than the least extrapolative ones. Similarly, the most disposition-prone investors on average hold 30,000 RMB fewer stocks than the least disposition-prone ones. These differences are statistically significant and robust to alternative measures of holdings. A regression-based approach produces similar results.

Finally, we examine the prediction for volume by analyzing the role of disposition extrapolators in driving up volume. First, we show that these investors increase their volume more than others do in the run-up. At the peak, they increase volume by six times while other investors increase by less than four times. As a result, the fraction of total volume accounted for by disposition extrapolators rises from 70% to 77%. Moreover, we provide evidence on the mechanism behind the increase in volume: compared with other investors, disposition extrapolators trade more at the extensive margin by liquidating existing positions and initiating new positions, and they trade more amongst themselves.

Whether bubbles are rational and whether crashes are predictable are the subjects of considerate debate (e.g., Fama 2014; Greenwood et al. 2017). In this paper, we define bubbles by their empirical characteristics—the long period of rising prices, the talk of overvaluation in the run-up, and the subsequent crash—and try to make sense of their price and volume dynamics. More broadly, our framework can be applied to explain other phenomena, such as the fact that rising markets are accompanied by higher volume than falling markets (Stein 1995; Statman et al. 2006; Griffin et al. 2006).

We propose a model of bubbles based on two well-documented phenomena: extrapolation and the disposition effect. Like Glaeser and Nathanson (2017), Barberis et al. (2017), and DeFusco et al. (2017), our model highlights the role of extrapolation in explaining the price patterns. The model’s key innovation is a novel mechanism for volume based on the interaction between extrapolation with the disposition effect. Unlike Scheinkman and Xiong (2003) and Barberis et al. (2017), where volume rises due to greater disagreement in beliefs, in our model, it is driven by the conflict between beliefs and preferences.

We contribute to the empirical research on bubbles using a novel dataset whose unique features make our analysis distinctive in two ways. First, with a long time series of data, we

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3Previous work on bubbles has used fund-level quarterly holdings (Brunnermeier and Nagel 2004; Greenwood and Nagel 2009), aggregate daily holdings (Griffin et al. 2011), and intraday transactions (Xiong and Yu 2011). A few papers examine the same bubble episode using account-level data from a brokerage firm: Bian
estimate investors’ degrees of extrapolation and disposition outside the bubble episode. This out-of-sample estimation allows us to show that investors who already exhibited extrapolative behavior prior to the bubble were responsible for the rising prices during the bubble. Second, whereas previous work focuses on explaining the patterns of prices and holdings in a bubble, our account-level transaction data provides some first-hand evidence on volume.

Finally, we contribute to a growing literature that connects investor behavior to asset prices. Other papers have examined how investor behavior can drive certain features of price and return patterns. Unlike these papers, our paper discusses the implications of investor behavior for prices and volume in the more specific context of financial bubbles.

The rest of this paper proceeds as follows. In Section 2, we describe the bubble episode and elaborate on the data. In Section 3, we present the model and derive its new predictions. In Section 4, we empirically test these predictions. We conclude in Section 5.

2 Background and data

2.1 Overview of the bubble

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

et al. (2017a) study leverage networks and market contagion, and Bian et al. (2017b) study the contribution of leverage-induced fire sales to the market crash.

For example, Frazzini (2006) examines the implications of the disposition effect for return predictability following earnings announcement; Kaniel et al. (2008) argue that contrarian behavior among individual investors may induce short-term price reversion; and, more recently, Cassella and Gulen (2017) show the time-series predictability of the price-dividend ratio depends on the degree of extrapolation.

Financial media and commentators almost unanimously call the episode a bubble. For example, a Wall Street Journal article (https://www.wsj.com/articles/china-market-bubble-still-taking-on-air-1433500241)
Like many historical bubbles, this bubble was triggered in part by new information about the economy. Around July 2014, the media began to speculate on the market’s performance going forward. The next four months witnessed the emergence of numerous arguments for taking a bullish position in the stock 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. In the new economic model, the government would give these companies a bigger role to play, boosting their share prices.

At that time, the credibility of this theory was unclear, because very few policies had been enacted. Nonetheless, many investors were convinced by these anecdotes, and their conviction was reinforced by prominent media such as the People’s Daily (the official mouthpiece of the Chinese Communist Party), whose front-page articles strongly urged investors to place their trust in the stock market. Before long, speculation turned into reality: the market experienced a run-up spanning six months, during which time most Chinese stocks doubled in value.

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

Facing these dramatic market movements, the China Securities Regulatory Commission (CSRC) became increasingly wary of the mounting leverage investors were taking on. It was particularly concerned about the prevalence of outside-market leverage (or shadow leverage), a type of leverage financed by trust companies rather than broker-dealers, making it difficult for the CSRC to monitor and regulate its usage. In mid-June 2015, after conducting a pre-

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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.
liminary investigation, the CSRC pulled the plug on outside-market leverage, which triggered the subsequent market crash. Following an initial slump, many leverage accounts faced margin calls, forcing investors to liquidate their entire positions; selling pressure from these fire sales dragged prices down even further and forced more accounts into liquidation, thereby creating a negative price spiral. Indeed, during the crash, prices fell much faster than they rose: SZCI dropped by almost 40% in just one month. Although the government responded immediately with various measures to prop up the market, the recovery was short-lived: the market plummeted again in mid-August and continued to fall until September.

Given the discussion above, we adopt the following timeline to study this bubble: (1) January 1, 2014, to June 30, 2014, is the pre-bubble period, because the media reported nothing about a bubble and price reactions in the market were muted; 2) July 1, 2014, to November 17, 2014, is the preparation period, because the media contained some discussions but there were no strong market reactions; (3) November 18, 2014, to June 12, 2015, is the run-up, manifested by intensive media coverage and strong market reactions; and (4) June 13, 2015, to September 15, 2015, is the crash. In Figure 1, these different periods are highlighted in shaded areas.

2.2 The data

We use account-level transaction and holding data provided by the SZSE to study this bubble episode. Therefore, we are only concerned with stocks traded on the SZSE. Founded in 1990, the SZSE is one of the two stock exchanges in mainland China (the other being the Shanghai Stock Exchange). It currently lists over 1,800 Chinese companies and is the eighth largest exchange in the world by total market capitalization. A firm can elect to go public on one of the exchange’s three boards, the Main Board, the SME Board, and ChiNext, which are subject to different listing requirements.⁶

We choose 2005 as the starting point of our analysis, because several reforms at the

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⁶Historically, large state-owned enterprises have tended to cluster on the Main Board, whereas smaller firms cluster on the SME Board, but in recent years, the two boards have been listing increasingly similar firms. The third board, ChiNext, was inaugurated in 2009. With less stringent listing standards, it attracts innovative and fast-growing enterprises from high-tech industries. During the recent stock bubble, ChiNext stocks were the center of media attention, because they exhibited greater price increases and were traded more heavily.
beginning of 2005 significantly broadened household access to the stock market. Furthermore, we focus on individual investors because they make up the largest single category of investors in the Chinese stock market. At the SZSE, individuals hold approximately 45% of tradable shares and account for 85% of total trading volume. During this bubble, they became even more active, responsible for over 90% of total volume right before the bubble burst. An individual can have two types of accounts: a regular account for standard transactions, and a margin account for leveraged trading and short-selling. In this study, we focus on regular accounts to abstract away from the effect of leverage on prices and volume. Because the number of regular accounts with at least one transaction exceeds 50 million, we randomly select 500,000 as the main sample. This sample is representative of the investor population in terms of their trading characteristics and demographics. We acknowledge the behavior of institutions is equally interesting and leave its exploration for future research.

We further restrict the sample to individuals with small holdings, defined by a balance less than 100,000 RMB by the end of 2013 (around 16,000 USD). In doing so, we exclude large individual accounts, a significant proportion of which were de-facto managed by institutions that provide shadow leverage to these accounts. Representing over 80% of the investor population, these small individual accounts were mostly owned by typical Chinese mom-and-pop investors. Although, on average, they only held a low balance in their accounts, together they remained the largest force in the market, accounting for 20% of ownership and 50% of volume at the peak of the bubble.

We acquire account-level transaction data for this sample of investors, provided by the SZSE. This dataset has a structure similar to the one used by Odean (1998): each observation specifies the buyer and seller, date, time, price, quantity, and security code. The time variable specifies the order of intraday transactions, allowing us to precisely infer the nature of each transaction (e.g., whether an investor is opening a new position or buying additional shares for an existing position). In addition, we can identify both the buyer and the seller for

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7In theory, each investor can only own one regular account. In practice, however, some investors hold multiple regular accounts. The China Securities Regulatory Commission relaxed this policy on April 13, 2015, by allowing an individual to have multiple accounts; this does not overlap with our estimation period. Cases in which an investor holds multiple regular accounts often occur in the earlier part of the sample period, possibly due to less strict rule enforcement in the early 2000s. We treat these multiple accounts as independent in subsequent analysis, because duplicated accounts are likely opened by other individuals using the same ID.
each transaction. The second dataset is the month-end holding data, which contains each account’s portfolio composition at the end of every month.

We complement our analysis with two additional datasets. The first one is investor characteristic data, which contain demographic information collected from brokerage firms and trading characteristics based on past transactions. Most of these variables encode categories instead of raw numbers. For example, for investor age, 1 indicates investors between 18 and 25 years old, and 2 indicates those between 26 and 30. The Appendix contains a complete set of definitions for categorical variables. The second dataset records non-transaction changes in share ownerships, which we use to calculate account-level returns. All the price and return data are from the exchange.

3 A model of bubbles

3.1 The setup

Market. There are $T+1$ dates, denoted by $t = 0, 1, \ldots, T$. On date $t$, a risk-neutral investor allocates his wealth $W_t$ between two assets: a risk-free option (cash) with returns normalized to zero, and a risky option (stock) with a fixed supply of $Q$ shares. Due to risk neutrality, he is either holding cash or fully invested in the stock. No transaction costs exist. The stock, representing the asset 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

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

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

The market features a continuum of investors subject to both short-selling and borrowing

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8For example, shares purchased through IPO subscriptions will not show up in the transaction data, but will in non-transaction changes in share ownerships. Omitting the cost of IPO shares will bias the calculation of portfolio returns upward.
constraints. When making portfolio decisions, they are prone to both extrapolation and the disposition effect. For this reason, we also label them as disposition extrapolators. Extrapolation is modeled in the standard way by assuming investors form their beliefs about future price changes based on past price changes. To model the disposition effect, however, we need to choose from several plausible mechanisms. Motivated by growing evidence from experimental and transactional data, we consider realization utility as the main driver behind the disposition effect. Throughout this paper, we think of extrapolation as a feature of beliefs, and the disposition effect as a feature of preferences.

**Beliefs.** Disposition extrapolators form their beliefs based on an extrapolative signal. The extrapolative signal on date $t$, denoted by $X_t$, is specified by

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

where $0 < \theta \leq 1$, and $X_1$ measures investor enthusiasm on date 1. It is an exponentially weighted average of past price changes, where more recent ones are weighted more heavily. The degree of overweighting is determined by the parameter $\theta$: as $\theta$ decreases, investors increasingly overweight recent price changes. Thus, a lower $\theta$ corresponds to a higher degree of extrapolation.

We deviate slightly from this basic framework of extrapolation by assuming investors also incorporate a value signal, defined by $D_t - P_t$, in their belief formation. Because the sum of all future dividend shocks is zero in expectation and investors are risk neutral, the cumulative dividend reflects the stock’s fundamental value, and the value signal represents rational expectations about future price changes. This assumption allows dividend shocks to affect stock prices via the value signal. For a continuum of investors, we further assume

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9The short-selling constraint is a common assumption in existing models of bubbles (e.g., Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; Barberis et al., 2017). It accurately describes the Chinese stock market: the government only lifted the ban on short-selling in 2010, and to date, it has been exercised only on a small scale. The borrowing-constraint assumption is mainly for tractability. Otherwise, risk-neutral investors will seek to take on infinite leverage when the stock’s expected price change is positive.

10Alternatively, if the market features both fundamental traders and disposition extrapolators, dividend shocks can be introduced via the expectations of fundamental traders. In this case, we don’t need to add the value signal to extrapolators’ expectations, but can assume they are entirely driven by the extrapolative signal. The price and volume dynamics in this alternative setting are similar to the current setting.
each investor’s beliefs are subject to a random noise, $\epsilon_{i,t}$, distributed $N(0, \sigma^2_\epsilon)$ and i.i.d. over time. This noise term generates some initial disagreement that leads investors to trade even in the absence of any dividend shocks. Importantly, the dispersion of beliefs is held constant at $\sigma^2_\epsilon$, which means volume cannot rise in the model simply from greater dispersion in beliefs.

In sum, for disposition extrapolator $i$, his expectation about the price change from date $t$ to $t+1$, denoted by $E_{i,t}\Delta P_{t+1}$, is given by

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

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

**Preferences.** We first lay out an investor’s portfolio problem. Under risk neutrality, his goal is to maximize expected final wealth. Because, in each period, he can freely switch between cash and the stock, the dynamic-portfolio problem is equivalent to a two-period one: on date $t$, he maximizes $E_t(W_{t+1})$, the expected wealth by the next date.

To introduce realization utility, we assume disposition extrapolators solve this two-period portfolio problem with one major modification: their utility depends on not only the expected wealth by the next date, but also the profits realized on the current date. Specifically, on date $t$, they maximize the following utility function:

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

where the first term represents utility derived from wealth and the second term captures utility derived from profits. $\overline{P}_t$ represents the reference price, proxied by the average purchase price, and $P_t - \overline{P}_t$ measures the price change since purchase. $N_t$ denotes the number of shares held by the end of date $t$, and as a result, $(P_t - \overline{P}_t) (N_{t-1} - N_t)$ represents profits realized on the current date.

The second term, which we call 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 \((P_t - \bar{P}_t) (N_{t-1} - N_t)\) if sold; when \(P_t < \bar{P}_t\), the stock is trading at a loss and would reduce utility by \((\bar{P}_t - P_t) (N_{t-1} - N_t)\) if sold. As such, utility-maximizing investors tend to sell winners and hold on to losers. \(\beta\) is a parameter that measures the strength of realization utility, hence the degree of disposition: as \(\beta\) increases, investors display a stronger disposition effect. The indicator function, \(1\{N_{t-1} > 0\} and N_{t-1} > N_t\}, implies the realization-utility term only matters for stock investors when they sell their shares: cash holders’ \((N_{t-1} = 0)\) portfolio returns are always normalized to zero; stock investors who do not sell \((N_{t-1} \leq N_t)\) do not derive utility from realizing gains and losses.

In the current framework, we model the disposition effect in reduced form, by including a realization-utility term in investors’ original two-period portfolio problem. In the Appendix, by imposing some additional assumptions, we derive a similar two-period problem even for investors solving the full dynamic-portfolio problem. Specifically, we assume they derive utility from realized gains and losses, and they discount next period’s utility by a factor of \(\rho\), where \(0 \leq \rho < 1\). When \(\rho = \frac{1}{1+\beta}\) and \(E_t \Delta P_{t+1} + P_t - \bar{P}_t > 0\), this dynamic-portfolio problem reduces the same two-period problem specified by Equation (4).

**Share demand.** We next discuss the share-demand function for disposition extrapolators. To begin with, we denote the values of cash and stock investment at the end of date \(t\) by \(W^C_t\) and \(W^S_t\). The specific portfolio problem a disposition extrapolator faces depends on his current holding. If he is a cash holder, his objective is to maximize the expected wealth by the next date, subject to the belief-formation process in Equation (3). He switches to the stock if \(E_{i,t} \Delta P_{t+1} > 0\) and holds on to cash otherwise. Given that \(\epsilon_{i,t}\) is distributed \(N(0, \sigma^2_{\epsilon})\) and i.i.d., the share demand from cash investors is given by \(\Phi\left(E_t \Delta P_{t+1}/\sigma_\epsilon\right)\left(W^C_{X,t-1}/P_t\right)\), where \(\Phi(\cdot)\) denotes the cumulative probability function of the standard normal distribution.

In this expression, \(\Phi(E_t \Delta P_{t+1}/\sigma_\epsilon)\) represents the proportion of cash holders switching to the stock, and \(W^C_{X,t-1}/P_t\) represents the total wealth invested in cash (in number of shares) by the previous date.

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

$$H_t = \Phi \left( E_t \Delta P_{t+1}/\sigma \right) \left( W_{X_{t-1}}^C / P_t \right) + \Phi \left( \left( E_t \Delta P_{t+1} - \beta \left( P_t - P_t^* \right) \right) / \sigma \right) Q. \quad (5)$$

**Equilibrium price.** The economy has the following main variables: $X_t$, the extrapolative signal; $P_t$, the reference price; $\overline{P}_t$, the market-clearing price; $W_t^C$ and $W_t^S$, the wealth invested in cash and the stock; and $d_t$, the dividend shock. On date $t$, $X_t$, $W_{t-1}^C$, $W_{t-1}^S$, and $\overline{P}_{t-1}$ are all given from the previous date, and $d_t$ also becomes public information. With the market-clearing condition $H_t = Q$, we solve for the equilibrium price $P_t$.

**Parameter values.** We set $T = 100$, so we have a total of 101 dates. For simplicity, the dividend shocks from date 1 to 10 are set to zero. We then introduce four consecutive shocks—2, 4, 6, and 8—from date 11 to 14; the dividend shocks are set at zero afterward. $D_0$ is initially set at 100, and $X_1$ at zero. $\sigma$ is fixed at 2, which generates a moderate degree of belief errors. The value of $\theta$ is initially set at 0.8, a value consistent with the estimation by Cassella and Gulen (2017). We assume investors start with a wealth level of 100 and that $Q = 1/2$. For now, we hold constant the wealth distribution between cash and the stock; results are similar if we relax this assumption. Finally, we set $\beta = 1$. Later, in Section 3.3, we study the model’s comparative statics by varying some key parameter values.

### 3.2 Baseline results

**Prices.** Figure 2a plots the evolution of prices and dividends for the baseline scenario, where the solid line represents the stock price and the dashed line represents the dividend. From date 1 to 10, in the absence of any demand shocks or changes in beliefs, the price remains constant. Starting from 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. Forming beliefs according to Equation (3), investors only place a weight of 0.1 on the value signal and therefore underreact to these shocks in the beginning.

The subsequent price dynamics are directly tied to the evolution of investor beliefs, which are plotted in Figure 2b. Although the shocks end on date 15, the price continues
to rise for an extended period of time. Before the price reaches the dividend, the value
and extrapolative signals work in the same direction: the value signal suggests the stock is
undervalued, whereas the extrapolative signal suggests the upward trend will continue. In
Figure 2b, both the solid and dashed lines, corresponding to the extrapolative and value
signals, remain positive before date 20, the date when the price reaches the dividend.

As the price exceeds the dividend, the value signal turns negative, inducing investors to
sell instead. But the extrapolative signal remains positive: the signal is a weighted average
of past price changes, which have been consistently positive. Toward the end of the run-up,
the price does not rise as quickly as before, partly because of a negative value signal, and
partly because the initial dividend shocks recede into the past and extrapolators become less
excited. The value signal eventually becomes so negative that it outweighs the extrapolative
signal, triggering the price fall.

In Figure 2c, the dash-dot line represents the evolution of $P_t - \overline{P}_t$, a measure of current
gains for stock investors. It rises together with the price, indicating a stronger propensity to
sell in the run-up. Therefore, the disposition effect works to counteract price increases while
ensuring the existence of an equilibrium price. Moreover, it plays a crucial role in explaining
the high volume, which we now turn to.

**Trading volume.** On date $t$, total trading volume, denoted by $V_t$, is given by

$$V_t = \frac{1}{2} \left( \Phi \left( E_t \Delta P_{t+1} / \sigma_{\epsilon} \right) \left( W_{X_{t-1}} / P_t \right) + \Phi \left( \left( \beta \left( P_t - \overline{P}_t \right) - E_t \Delta P_{t+1} \right) / \sigma_{\epsilon} \right) Q \right). \quad (6)$$

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), respectively.
Because a buy matches a sell, the two terms always carry the same value. In Figure 3a,
the solid line, which represents total volume, is hump-shaped: it rises substantially with the
dividend shocks, continues to increase after the shocks end, and starts to decrease while the
price is still rising. Volume reaches its peak when $E_t \Delta P_{t+1}$ reaches its maximum, in other
words, when investors are most optimistic about the stock’s future returns; in comparison,
the price reaches its peak when $E_t \Delta P_{t+1}$ approaches zero. As a result, volume peaks before
price does: in Figure 3a, volume peaks on date 17, and price peaks on date 27. This pattern is consistent with the empirical evidence in DeFusco et al. (2017), in which they document a lead-lag relationship between the peak of volume and the peak of prices.

The reasoning for the price dynamics explains why cash holders, driven by their extrapolative beliefs, exhibit a stronger propensity to buy the stock as the bubble develops. Indeed, in Figure 3b, the solid line, which represents the expected price change from date \( t \) to \( t + 1 \), increases from 0 to 2. But higher expectations effectively discourage investors from selling, so what motivates them to sell so that the market clears? The answer is the disposition effect. In the run-up, \( P_t - \bar{P}_t \) rises sharply, suggesting the stock is associated with more gains. As such, although stock investors are inclined to hold on to the stock due to extrapolation, they also have an eagerness to sell, so that they can realize the gains in hand and successfully complete an investment episode. In equilibrium, the price rises so much that their preferences dominate their beliefs: in Figure 3b, \( \beta (P_t - \bar{P}_t) \) increases more than \( E_t \Delta P_{t+1} \), and \( \beta (P_t - \bar{P}_t) - E_t \Delta P_{t+1} \) remains positive for much of the bubble. As a result, many stock investors switch to cash.

The divide between cash holders and stock investors highlights the tension between extrapolative beliefs and the disposition effect in a rising market. As prices go up, they increasingly encourage opposite trading directions: extrapolation supports buying and the disposition effect supports selling. As the disposition effect switches on and off based on investors’ current holdings, they end up switching back and forth between cash and the stock. As a result, investors tend to trade on the extensive margin by liquidating existing positions and initiating new positions. This observation holds true in our baseline model, where the risk-neutral assumption eliminates intensive-margin trading. We show that it also holds when investors have constant absolute risk aversion (CARA) preferences, which allow them to trade on both the intensive and extensive margins.\(^{11}\)

Our mechanism is novel in the sense that it does not rely on more disagreement in beliefs, but uses the tension between extrapolation, a feature of beliefs, and the disposition effect.

\(^{11}\)When the model contains only one stock, investors tend to “exit-and-reenter” the entire market, a behavior echoed by Newton’s experience in the South Sea Bubble. In a multi-stock setting, extensive-margin trading involves liquidating existing holdings and simultaneously reinvesting the proceeds in some new stocks.
effect, a feature of preferences, as the source of volume.\textsuperscript{12} Because the disposition effect is very well documented and has been extensively studied, with detailed data we can quantify the disposition effect at the investor level and directly test our model’s new predictions. Moreover, by coupling extrapolative beliefs with realization utility, we show non-standard beliefs and non-standard preferences can potentially generate interesting implications for asset prices and investor behavior.

3.3 Comparative statics

The model’s main result—both prices and volume rise sharply following positive fundamental shocks—holds under a range of parameter values. Figure 4 shows the maximum prices and volumes when the value of a particular parameter changes, where the solid line represents peak prices and the dashed line represents peak volumes. Each graph corresponds to one key parameter in the model: $\theta$, the degree of extrapolation; $\beta$, the degree of disposition; $\sigma_\epsilon$, the variance of beliefs among investors; and $\gamma$, the weight placed on the extrapolative signal. For each graph, we generate the maximum prices and volumes by varying the corresponding parameter values along the horizontal axis while holding other parameter values fixed to their baseline levels.

The patterns in Figures 4a and 4b relate bubble size to the degrees of extrapolation and disposition. In Figure 4a, the peak price monotonically increases (decreases) in the degree of extrapolation ($\theta$). As $\theta$ decreases, the extrapolative signal becomes more sensitive to recent price changes, which means that, with the same dividend shocks, the immediate price increases are greater. Stronger price reactions feed into more optimistic beliefs via the extrapolative signal, pushing up prices even further. Figure 4b shows the price at peak decreases in the degree of disposition ($\beta$). A higher $\beta$ generates greater selling pressure in the run-up, hence a smaller bubble. These comparative statics lead to the following prediction:

\textsuperscript{12}In Scheinkman and Xiong (2003) and Barberis et al. (2017), volume rises due to greater dispersion in beliefs, which can arise either exogenously or endogenously in the model. In Scheinkman and Xiong (2003), investors are overconfident about their own private signals and form different expectations about future returns; in Barberis et al. (2017), investors waver between two signals whose values differ more during a bubble, leading to more dispersed beliefs.
Prediction 1  A more extrapolative investor base leads to a greater bubble, and a more disposition-prone investor base leads to a smaller bubble.

The patterns in Figures 4c and 4d do not immediately lead to any testable predictions, but shed light on some conceptual issues in the model. In Figure 4c, both the price and volume at peak decrease in $\sigma_\epsilon$, the dispersion of beliefs exogenously given in the population. With a higher $\sigma_\epsilon$, however, 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 divided by $\sigma_\epsilon$. Because these changes drive the rises in prices and volume, a higher $\sigma_\epsilon$ leads to a smaller bubble. This result reinforces the distinction between our model and models of disagreement, where a larger disagreement in beliefs leads to a greater bubble. Finally, in Figure 4d, the price at peak increases in $\gamma$, the weight placed on the extrapolative signal in the belief-formation process. The intuition is similar to the results in Figure 4a: as investors pay more attention to the extrapolative signal, they are able to push up prices even more.

3.4 A heterogeneous-agent model

We move on to discuss the model’s implications for holdings and volume at the investor level. In the setting we have presented so far, all investors are disposition extrapolators and the number of shares is fixed, which means per-capita holdings and volume do not vary across investors. We study a heterogeneous-agent setting by introducing two additional types of investors to the market: extrapolation-only and disposition-only. Extrapolation-only investors are subject to extrapolation but not the disposition effect: they form beliefs according to Equation (3) and maximize expected wealth at the next date. Disposition-only investors are subject to the disposition effect but not extrapolation: they form beliefs according to the random noise $\epsilon_{i,t}$ and maximize the utility function specified by Equation (4). The initial wealth distribution across the three types of investors is 80, 10, and 10, so that disposition extrapolators constitute the majority of the investor base. These numbers are roughly consistent with the empirical distribution we show later. The Appendix includes more details about the setup.

13 Alternatively, we can assume disposition-only investors form their expectations based on the value signal, $D_t - P_t$, subject to the random noise $\epsilon_{i,t}$. Results are similar and presented in the Appendix.
The four graphs in Figure 5 present some key results from the heterogeneous-agent model. Figures 5a and 5b present the dynamics of prices and volume. Given that most wealth is held by disposition extrapolators, the patterns are qualitatively and quantitatively similar to the homogeneous case. In Figures 5c and 5d, the solid, dashed, and dash-dot lines correspond to disposition extrapolators, extrapolation-only investors, and disposition-only investors, respectively. The results suggest that, during a bubble, the three types of investors take on rather different paths in terms of holdings and volume. In Figure 5c, extrapolation-only investors increase their holdings the most, whereas disposition-only investors, the least; disposition extrapolators fall in between. These results suggest the following prediction about holdings:

**Prediction 2** During the run-up of a bubble, an investor’s holding increases in his degree of extrapolation and decreases in his degree of disposition.

Figure 5d shows that, although extrapolation-only investors increase their holdings the most, they trade the least. Much of the high volume is driven by disposition extrapolators as they switch back and forth between cash and the stock. These results also highlight another observation: volume rises significantly only when extrapolation and the disposition effect co-exist in the same investor. If, instead, they are represented separately by extrapolation-only and disposition-only investors, volume at the peak is not nearly as large. These two types of investors each lack one essential ingredient: extrapolating on past price changes, extrapolation-only investors simply hold the stock and are not willing to sell; prompted by realization utility, disposition-only investors are eager to sell but unwilling to reenter the market. Based on these results, we make the following prediction about the composition of volume:

**Prediction 3** During the run-up of a bubble, disposition extrapolators increase their volume more than other investors do. As a result, they are largely responsible for the rise in aggregate volume.
4 Empirical Results

4.1 Measuring degrees of extrapolation and disposition

In this section, we bring the model’s predictions to the data. As an intermediate step, we first devise a systematic way to identify different types of investors based on their transactions. Specifically, we assign each investor a degree of extrapolation (DOX) and a degree of disposition (DOD), based on his transactions. In the context of the model, DOX represents $1 - \theta$, 1 minus the extrapolation horizon; DOD represents $\beta$, the weight placed on the disposition signal. Empirically, disposition extrapolators are characterized by a high DOX and a high DOD.

We start with the estimation of DOX. Conceptually, DOX measures the extent to which an investor uses a security’s past returns to form his beliefs about its future returns. As DOX increases, investors become more sensitive to recent price changes and thus more likely to purchase stocks with positive recent returns. This observation motivates us to look at buying behavior and define DOX as the propensity to buy past winners.

We pay attention to several technical issues when implementing this procedure. First, the definition of a winner stock depends on the horizon at which returns are evaluated. It is not straightforward from previous studies what horizon would apply to Chinese investors. To determine the extrapolation horizon, we examine the time lags at which trading flows depend on past returns. Similar to Barber et al. (2009), we regress stock-level trading flows by individuals on lagged returns using a panel of individual stocks. Results from Fama-MacBeth regressions show trading flows respond to returns up to 10 weeks ago, and most strongly to the most recent monthly return. As we show below, measures of DOX under different horizons are highly correlated. For simplicity, we adhere to the monthly DOX,

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14 A smaller $\theta$ means a greater weight placed on recent returns, thus a higher degree of extrapolation. Our measure of DOX, defined below, is not equivalent to $1 - \theta$, but a one-to-one correspondence exits between the two variables.

15 In the United States, prior research suggests that extrapolation horizon may extend up to three years back (Barber et al. 2009), and several authors also use the return over the last 12 months to identify extrapolators (Barberis et al. (2017)).

16 In the Appendix, we report results for three types of trading flows: Initial buy, the total number of shares from initiation; Sell, the total number of shares sold; Buy−Sell, the number of shares bought minus sold. As a robustness check, we run pooled regressions with double-clustered standard errors and find slightly longer horizons.
where a winner is defined by having a positive return in the previous month.

The second issue is the determination of which sample of transactions to use for estimation—*initial* buys only, or both *initial* and *additional* buys.\(^{17}\) The main concern with additional buys is that they may be associated with mechanisms other than beliefs. For example, in Barberis and Xiong (2012) and Chang et al. (2016), realization utility and cognitive dissonance prompt investors to treat gains and losses in their portfolios differently, suggesting these mechanisms have implications for all transactions with existing positions, including additional buys.\(^{18}\) However, the assertion that the main mechanism underlying investors’ initial buying behavior is beliefs is generally accepted.\(^{19}\) Therefore, to measure \(DOX\) more accurately, we use initial buys only.

The third issue is the time frame of the estimation period. First, we hope to separate the estimation period from the bubble, so that transactions used for estimation and transactions made during the bubble do not overlap. Second, the model implies investor behavior during bubbles can be explained by beliefs and preferences even in a non-bubble environment, and as such, the estimation period should exclude all previous episodes of bubbles. Based on these considerations, we use 2005-06 and 2009-13 as the estimation period: we exclude 2007-08 because those years covered a similar bubble-and-crash episode; we exclude post-2014 because that period overlapped with the recent stock market bubble we examine.\(^{20}\) With this time frame, we identify each investor’s \(DOX\) and \(DOD\) prior to the bubble.

To give an example of how we measure \(DOX\), suppose an investor made a total of 20 initial buys from 2005 to 2013. Among them, 5 were made during 2007-2008 and are therefore excluded. Among the remaining 15, 9 stocks have a positive return over a specified horizon.

\(^{17}\)When an investor buys a stock he previously held and liquidated, this transaction is considered an initial buy.

\(^{18}\)Odean (1998) finds investors tend to buy stocks additionally after their prices have gone down from the purchase price, which is rather different from the trend-chasing behavior they display in initial buys.

\(^{19}\)Another plausible mechanism that affects investors’ initial buying decisions is attention: stocks with extreme returns are more attention-grabbing. In the Chinese stock market, the most attention-grabbing stocks are those that hit daily price limits on a given day, with a 10% increase or decrease in returns, but after hitting price limits, these stocks are typically trading with zero liquidity.

\(^{20}\)An argument can be made for the inclusion of 2007 and 2008, namely, that trades made during bubbles and crashes are equally, if not more, representative of investor behavior. To address this concern, we construct an alternative measure by including transactions made in 2007 and 2008, and this measure is highly correlated with the one we currently use. Moreover, the majority of investors in our sample entered the market after 2008, so including 2007 and 2008 in the estimation would have a limited effect on our analysis.
(e.g., 1 month before purchase). In this case, his $DOX$ is calculated as $9/15 = 0.6$.\footnote{We have also constructed a value-weighted version for $DOX$ using transaction values as weights, and the two measures are highly correlated.} Panel A of Table 1 reports the summary statistics for $DOX$, where each column represents the horizon at which winners are defined. When returns are evaluated at daily, weekly, monthly, and quarterly horizons, over 75% of Chinese investors are extrapolative, that is, have a $DOX$ greater than 0.5 (a benchmark value).\footnote{As a comparison, using data from Odean (1998), we find U.S. investors are most extrapolative when winners are defined by yearly returns, suggesting a much longer extrapolation horizon.} These $DOX$s are highly correlated: for example, the correlation coefficient between the weekly (monthly) and monthly (quarterly) $DOX$s is 0.54 (0.56). Extrapolation is most pronounced at the monthly horizon: over 80% are extrapolative on the monthly horizon; when an average investor starts a new position, there is a 65% chance that the stock is a winner over the last month.\footnote{In the main part of this paper, we define winners by raw returns; we have also constructed a measure using market-adjusted returns, which is highly correlated with the current one. Which version should be preferred is unclear: on the one hand, given their lack of sophistication, individual investors may respond more to raw returns than market-adjusted returns; on the other hand, market-adjusted returns can control for the overall market condition. Given their high correlation, results are robust to the change of specification.}

The estimation of $DOD$ adopts the same time frame but uses a different set of definitions for winners and losers, because returns need to be defined with respect to a reference price for the disposition effect. We assume investors use their most recent purchase price as the reference price: a winner is defined by having a positive return since purchase, and a loser, by a negative return. $DOD$ is then measured as the propensity to choose winners when selling stocks. For example, if an investor has sold 12 stocks, 9 of which are winners, his $DOD$ is measured as $9/12 = 0.75$.

The primary concern with this procedure is that the resulting measure for $DOD$ may be correlated with investment performance. As an extreme case, suppose an investor is doing so poorly that all the stocks in his portfolio are losers. When he randomly sells a stock, we would assign him a $DOD$ of 0, suggesting a negative disposition effect, even if he sells randomly and is not subject to any disposition effect. Odean (1998) addresses this concern by taking into account the returns of other stocks in the same portfolio. Unfortunately, given the large sample size and the high trading frequency of Chinese investors, we are limited by the computational power at the exchange from adopting the same approach.
Instead, we deal with this concern with the following steps. First, we show that, although \emph{DOD} and investment performance are indeed positively correlated in our sample, the correlation coefficient is so small (0.01) that it is unlikely to bias the estimation in any meaningful direction. Second, using data from Odean (1998), we show \emph{DOD} and \emph{PGR} – \emph{PLR}, the measure originally constructed by Odean (1998), are highly correlated with a correlation coefficient of 0.56. We also perform a similar exercise using a subsample of our data and find similar results. Third, we consider an alternative specification of \emph{DOD} based on both the propensity to sell winners and the propensity to buy losers additionally.\footnote{As noted before, Odean (1998) finds the tendency to sell winners is accompanied by the tendency to buy losers additionally. In fact, those who tend to sell winners and those who tend to additionally buy losers overlap substantially with each other. Therefore, the tendency to buy losers additionally can be seen as an alternative measure for the disposition effect.} In the previous example, the disposition effect can arise when the investor additionally buys a loser.

In Panel B of Table 1, the first column reports summary statistics of \emph{DOD} estimated using only sells. Indeed, the disposition effect is very prevalent among Chinese investors. More than 75\% of them have a \emph{DOD} greater than 0.5, suggesting an overwhelming tendency to sell winners versus losers. When an average investor sells, the probability of him selling a winner is 67\%. The second column reports the summary statistics for \emph{DOD} estimated using additional buys, and the third column concerns \emph{DOD} estimated using both sells and additional buys. The summary statistics are roughly the same across the three columns, showing very similar distributions; the correlation coefficient between the first two columns is 0.37, suggesting measures based on sells and additional buys are highly correlated. In what follows, we only report results for \emph{DOD} measured by sells; using the other two versions of \emph{DOD} produces similar results.

Finally, we examine their correlation with other investor characteristics. Prior literature shows (1) the disposition effect is correlated with investor sophistication and wealth (Dhar and Zhu 2006), (2) the disposition effect can be mitigated by trading experience (Feng and Seasholes 2005), and (3) males and females trade differently (Barber and Odean 2001). In Table 2, we compare the average \emph{DOX} and \emph{DOD} across different groups sorted on investor characteristics. Our results are roughly consistent with previous studies, but they also exhibit a few deviations. In Panel A, more experienced investors are more extrapolative, possibly
due to the speculative nature of Chinese markets. In Panel B, we find $DOX$ is approximately the same across accounts of different size. In addition, consistent with Dhar and Zhu (2006), wealthier investors display a lower disposition effect. In Panels C and D, we report significant age and gender effects: older, female investors tend to be more extrapolative and disposition-prone.

4.2 Price patterns

First, we test Prediction 1. Using the cross section of individual stocks, we test whether returns in the run-up were greater for stocks traded by more extrapolative investors and were smaller for stocks traded by more disposition-prone investors. For stock $j$, we calculate the volume-weighted $DOX$ of its investor base, given by

$$DOX_j = \sum_{i=1}^{N} \left( \frac{Volume_{i,j}}{\sum_{i=1}^{N} Volume_{i,j}} \right) DOX_i,$$

where $Volume_{i,j}$ is the number of $j$ shares traded by investor $i$ during the run-up (from November 18, 2014, to June 12, 2015). Throughout the paper, $DOX$ denotes the degree of extrapolation at the investor level, and $\overline{DOX}$ denotes the average degree of extrapolation at the stock level. $DOD$. With this measure, stocks traded more by extrapolative investors have a higher $DOX$, the average degree of extrapolation. Similarly, we calculate the average degree of disposition for stock $j$ by

$$DOD_j = \sum_{i=1}^{N} \left( \frac{Volume_{i,j}}{\sum_{i=1}^{N} Volume_{i,j}} \right) DOD_i,$$

where stocks traded more by disposition-prone investors have a higher $DOD$. Similarly, $DOD$ denotes the degree of disposition at the investor level, and $\overline{DOD}$ denotes the average degree of disposition at the stock level.

The sample features 1,582 individual stocks traded on SZSE. Panel A of Table 3 presents the summary statistics for $DOX$ and $DOD$. The mean value of $DOX$ is 0.66, and the majority of stocks have a $DOX$ between 0.64 and 0.68. These numbers are consistent with the majority of Chinese investors being extrapolative. The standard deviation of $DOX$ is
0.032, a number we use later to assess the economic significance of regression coefficients. \( \overline{DOD} \) has a similar distribution to \( \overline{DOX} \), with a standard deviation of 0.033.

We have no strong priors about how \( \overline{DOX} \) and \( \overline{DOD} \) should vary across different firms, but suspect young, small firms in high-growth industries would attract more extrapolators. In Panels B and C of Table 3, we compare the average \( \overline{DOX} \) and \( \overline{DOD} \) across different boards and industries.\(^{25}\) \( \overline{DOX} \) is rather similar across the three boards, but \( \overline{DOD} \) exhibits large differences: the investor base of ChiNext stocks is much less disposition-prone, and the difference is both economically and statistically significant. \( \overline{DOX} \) and \( \overline{DOD} \) also vary across industries: investors trading Finance and Public Utility stocks are more extrapolative and less disposition-prone; investors trading Properties and Conglomerates stocks are less extrapolative and more disposition-prone.

In Panel D of Table 3, we present the correlations of \( \overline{DOX} \) and \( \overline{DOD} \) with other firm-level characteristics. Several patterns stand out. First, the negative correlation between \( \overline{DOX} \) and \( MktCap \) (Market Capitalization) suggests small firms tend to attract more extrapolative investors. Second, the positive correlation between \( \overline{DOX} \) and \( Turnover \) suggests high-liquidity stocks, plausibly more speculative, attract more extrapolators. Third, the positive correlation between \( \overline{DOD} \) and \( B/M \) (Book-to-Market) suggests disposition-prone investors tend to cluster on value stocks, which is consistent with their contrarian tendency.

We now proceed to examine the relationship between returns and the two measures for extrapolation and disposition. As a benchmark, we run an OLS regression of the cumulative run-up return on \( \overline{DOX} \) and \( \overline{DOD} \). Results are reported in the first column of Panel A in Table 4. Indeed, we find the coefficient on \( \overline{DOX} \) is positive and significant at the 1\% level. In other words, during the run-up, firms that were more heavily traded by extrapolators had greater returns. The economic significance of this effect is large: a one-standard-deviation increase in \( \overline{DOX} \) implies a 2'3-percentage-point increase in returns. The coefficient on \( \overline{DOD} \) is negative and significant at the 1\% level. A one-standard-deviation increase in \( \overline{DOD} \) implies an 18-percentage-point decrease in returns.

We test the robustness of these results by adding more controls to the baseline regression.\(^{25}\) Recall each stock is listed on one of the three boards at the exchange: the Main Board lists mostly state-owned enterprises, the SME Board lists small and medium companies, and ChiNext lists high-growth, high-tech young firms.
In the second column, we control for several stock-level characteristics that have been shown to be correlated with bubble size: Volume (total number of shares traded during the run-up), Float (total number of tradable shares during the run-up), and Turnover (total number of shares traded divided by total number of tradable shares during the run-up). We also include as controls stock characteristics prior to the bubble (from January 1, 2014, to November 17, 2014), such as turnover and previous returns. In the third column, we additionally consider three firm-level characteristics, Beta, B/M and MktCap, as well as industry and board dummies. In Column 2 and 3, the coefficients on DOX and DOD are essentially unchanged, suggesting these control variables do not drive the previous results.

Although interpreting the results thus far as causal is tempting, in the sense that extrapolators caused prices to increase, we are wary of an alternative interpretation, namely, that extrapolators only began to trade stocks after their prices had increased. Indeed, because DOX and returns are calculated contemporaneously, an OLS regression cannot differentiate between these two stories. Finding an instrumental variable that is correlated with DOX ("the correlation requirement") and uncorrelated with the error term in the explanatory equation ("the exclusion restriction") could potentially address this concern.

One set of candidates, denoted by Pre-DOX and Pre-DOD, are constructed by using pre-bubble volume as weights in Equation (7) and (8). Specifically, they are defined by

\[
\text{Pre-DOX}_j = \sum_{i=1}^{N} \left( \frac{\text{PreVolume}_{i,j}}{\sum_{i=1}^{N} \text{PreVolume}_{i,j}} \right) \text{DOX}_i, \quad \text{and}
\]

\[
\text{Pre-DOD}_j = \sum_{i=1}^{N} \left( \frac{\text{PreVolume}_{i,j}}{\sum_{i=1}^{N} \text{PreVolume}_{i,j}} \right) \text{DOD}_i,
\]

where Volume$_{i,j}$ is the number of j shares traded by investor i prior to the run-up (from January 1, 2014, to November 17, 2014). Therefore, they measure each stock’s average degrees of extrapolation and disposition prior to the run-up. The correlation requirement is satisfied if Pre-DOX can predict DOX. For example, if investors have limited capacity to consider all stocks, they are drawn to those they have traded before, because these stocks are more familiar or salient. Indeed, regressing DOX on Pre-DOX results in a coefficient of 0.2 (t = 7.8) with an F-stat of 15.7. The exclusion restriction is satisfied if the transactions
investors made prior to the run-up did not affect returns in the run-up. This condition holds true in the specification $Pre-DOX$ and $Pre-DOD$: both $DOX$ ($DOD$) and weights are based on transactions before the run-up, which means they are ex-ante measures.

In Table 4, Column 4 of Panel A presents the 2SLS (two-stage least squares) regression results using $Pre-DOX$ and $Pre-DOD$ as instrumental variables with a full set of controls. The standard errors are much larger than before, which reduces the statistical significance of the coefficients. Nonetheless, the coefficient on $DOX$ remains statistically significant at the 10% level, whereas the coefficient on $DOD$ is significant at the 5% level. The economic significance of these coefficients is greater than before.

Lastly, we examine the relationship between the return in the crash and the average degrees of extrapolation and disposition in the run-up. In our model, because prices eventually return to the fundamental value, more severe crashes end larger bubbles. Therefore, when regressing crash returns on $DOX$ and $DOD$—both constructed using transactions before the crash—we expect the signs of the coefficients to flip. In Panel B of Table 4, we regress crash returns on $DOX$ and $DOD$ including a full set of controls. Indeed, the coefficient on $DOX$ is negative and statistically significant at the 1% level, which suggests stocks traded by more extrapolative investors in the run-up had a bigger crash. Similarly, the coefficient on $DOD$ is positive and statistically significant at the 5% level. However, we want to interpret these results with caution, because the government intervened in the crash with a large-scale capital injection that targeted certain stocks.

To conclude this section, we discuss the implications of these results for the bubble literature. Prominent models of bubbles point to several plausible sources of price pressure, such as extrapolation and heterogeneous beliefs. Although many of these theories are theoretically appealing, direct empirical evidence has been lacking in the literature, primarily due to data limitations. Using a novel dataset, we show how investors who already exhibited extrapolative behavior prior to the bubble were responsible for the rising prices during the bubble; furthermore, we quantify this effect. Conceptually, our model joins Glaeser and Nathanson

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26 A few exceptions include Mei et al. (2009) and Xiong and Yu (2011), who empirically confirm the relationship between bubble size and investor disagreement in two particular settings, and Brunnermeier and Nagel (2004), who provides evidence for synchronization risk by showing how hedge funds rode the tech bubble.
(2017), Barberis et al. (2017), and DeFusco et al. (2017) by highlighting extrapolation as the source of price pressure. Hence, in addition to directly testing our model’s prediction on prices, we also provide empirical support for extrapolation-based models in general.

4.3 Holdings

We next examine Prediction 2, which states that an investor’s stock holding during the run-up increases in his degree of extrapolation and decreases in his degree of disposition. Our analysis here not only directly tests one of the model’s predictions, but also provides additional support for Prediction 1 by showing extrapolators push up prices by increasing their holdings. To examine both parts of this prediction, we put each investor into one of five groups based on their $DOX$ and $DOD$ and then compare group-level holding patterns. This sorting approach provides an intuitive look at how holding patterns differ across groups with different $DOX$ and $DOD$ throughout the evolution of the bubble. We have also adopted a regression-based approach and find similar results.

The primary concern with sorting is that it may simultaneously capture other differences in investor characteristics that may be also related to holdings. Two variables, in particular, stand out in the discussion of holdings during a bubble. First, more sophisticated investors were able to ride the tech bubble and pull out before the crash (Brunnermeier 2009; Griffin et al. 2011), suggesting investor sophistication may affect holdings at various stages of a bubble. If sophistication and extrapolation are correlated, sorting on $DOX$ cannot differentiate between their effects on holdings. To proxy for investor sophistication, we use past investment performance and account turnover over the entire transaction history prior to the bubble, defined as the total dollar return divided by the average portfolio balance and the total number of shares traded divided by the average number of shares held, respectively. The underlying rationale is that sophisticated investors have better performance and that naive investors trade more often.

Second, new investors tend to be more heavily invested in bubble assets (Greenwood and

\footnote{Alternatively, we can take a regression-based approach by regressing the change in holdings on $DOX$ and $DOD$ while controlling for a collection of other investor characteristics. Results from this regression exercise are consistent with the sorting approach. See the Appendix for additional details.}
Nagel 2009). If experience and extrapolation are negatively correlated, and we show that an increase in holdings is associated with more extrapolation, these more extrapolative investors having less experience could be an alternative explanation. However, as Table 2 shows, the correlation between age (experience) and $DOX$ is positive in our data, which would work against our findings. Therefore, experience poses less of a concern to the sorting approach.

Using a triple-sorting approach, we classify investors into five groups based on $DOX$, with the ultimate goal being that the main variation across groups arises from $DOX$. First, we sort them into five brackets by investment performance. Second, within each bracket, we sort them into five brackets by account turnover, resulting in 25 smaller brackets. Third, within each of the 25 smaller brackets, we further sort them into the five smallest brackets by $DOX$, denoted by 1 to 5. Finally, all investors in smallest bracket $i$ are combined to form Group $i$, where $i = 1, ..., 5$. As a result, the five groups indexed by $i$ have similar investment performance and turnover, but different $DOX$. Sorting investors based on $DOD$ uses a similar procedure.

Panel A of Table 5 compares investor characteristics across the five groups sorted on $DOX$. As designed, $DOX$ increases monotonically from Group 1 to 5, whereas the two proxies for investor sophistication are roughly constant. We also examine other investor characteristics: except for a few demographic variables, these characteristics show little variation across groups. Notably, high-$DOX$ groups tend to have older and more experienced investors, and a greater fraction of females. Panel B of Table 5 compares the five groups sorted on $DOD$. Similar to Panel A, $DOD$ also increases monotonically from Group 1 to 5, whereas the proxies for investor sophistication remain roughly constant across groups.

After sorting investors into groups, we compare their holding patterns throughout the bubble. As a benchmark, Figures 6a and 6b plot the evolutions of per-capita holdings for all investors, in RMB and in number of shares, respectively. The average RMB holding steadily increased in the run-up, but fell in the crash, because of the drop in prices; the average share holding rose both in the run-up and in the crash. For now, we are concerned with group-level differences in RMB holdings. Instead of directly reporting the average RMB holdings, we report the difference between each group and the average population in terms of RMB holdings, so that we can observe group-level differences more clearly.
Figure 7a shows the results. The five groups exhibited similar holding patterns prior to the bubble: their average holdings moved roughly in parallel, and we found no obvious sign of an upward or downward trend for any of the five groups. Starting from July 2014, holding patterns started to diverge, as the high-DOX groups began to increase their holdings much more than the low-DOX groups. Their difference was most dramatic at the peak of the bubble: by May 2015, the per-capita holding of Group 5 (high-DOX) had exceeded the benchmark by almost 15,000 RMB and that of Group 1 (low-DOX) by almost 30,000 RMB. This difference is rather sizable, given that an average investor held about 120,000 RMB in his account at the end of May 2015. Put differently, Group 5 investors held 13% (29%) more stocks in their accounts than the average investor (Group 1). Moreover, holding patterns exhibited strong monotonicity across groups: as DOX increased from Group 1 to 5, the per-capita holdings also increased monotonically. Therefore, consistent with the first part of Prediction 2, an investor’s holding during the run-up of the bubble increased in his degree of extrapolation.

In Figure 7b, we examine holding patterns for groups sorted on DOD. Likewise, the average holdings exhibited similar patterns prior to the bubble, but realized substantial divergence in the run-up. As DOD increased from Group 1 to 5, the per-capita holdings decreased monotonically. Group-level differences have a magnitude similar to those reported in 7a. Hence, consistent with the second part of Prediction 2, an investor’s holding during the run-up decreased in his degree of disposition.

In Figures 7c and 7d, we plot the per-capita RMB holdings for the top and bottom groups sorted on DOX and DOD, along with their 95% confidence intervals. These graphs clearly show that the difference in holdings between the two groups is not only economically meaningful, but also statistically significant: in both graphs, the 95% confidence intervals for the two groups did not overlap with each other at the peak of the bubble; in fact, they did not cross each other almost throughout the entire run-up period.

Finally, one concern associated with measuring holdings in RMB is that high-DOX investors, often chasing after past winners, may accumulate more capital gains during the run-up, thereby appearing to have higher balances in their portfolio. To address this concern, we instead use the number of shares to measure holdings, and find essentially the same
patterns. See the Appendix for more details.

4.4 Volume patterns

Composition of volume. Prediction 3, concerning the source of the high volume in a bubble, suggests disposition extrapolators increase their volume more than other investors and are largely responsible for the increase in total volume. To test this prediction, we classify investors into different groups based on their trading styles, using two sets of definitions. With the first set of definitions, we use 0.5 as the absolute cutoff point, where 0.5 represents the benchmark value under random choice. Under the second, we use the median values in the investor population as the relative cutoff points.\(^{28}\) Investor types are defined by the following criteria: disposition extrapolators have both \(DOX\) and \(DOD\) above the cutoff; extrapolation-only (disposition-only) investors have \(DOX\) above (below) the cutoff and \(DOD\) below (above) the cutoff; the rest are other investors. These four groups turn out to have rather different sample sizes; in particular, because investors are often subject simultaneously to both extrapolation and the disposition effect, disposition extrapolators represent the majority. We omit other investors in subsequent analysis, partly due to their small sample size (1%), and partly for clearer exposition.

In Figure 8a, we plot the evolution of volume for each group, where volume, normalized to 1 at the beginning of 2014, is defined by the total number of shares traded. Volumes were very similar across groups prior to the bubble: hovering around the value of 1, the three lines are almost indistinguishable from each other in the pre-bubble period. However, in the run-up, disposition extrapolators increased their volume much more than other investors did: at peak, their volume increased by almost six times, whereas that of disposition-only (extrapolation-only) investors increased by about four (three) times. Similar results hold for turnover as an alternative measure for volume: our previous results show extrapolation-only investors increased their holdings more than disposition extrapolators, which suggests their difference in turnover should be even greater. To see group-level differences more clearly, Figure 8b plots the difference in volume between disposition extrapolators and two

\(^{28}\)Throughout this section, we only report results under the absolute cutoffs; results under the relative cutoffs are similar and shown in the Appendix.
other types of investors. Indeed, these differences were around zero prior to the bubble but increased substantially in the run-up.

We next decompose total volume by groups. In Figure 9a, we plot the fraction of total volume for which each of the three investor groups accounted. Indeed, as the bubble progressed, disposition extrapolators accounted for an increasing fraction of total volume: their trading constituted 70% of total volume prior to the bubble, but the number reached 77% at its peak. In Figure 9b, we zoom into the run-up period to examine volume composition in more detail. As the graph shows, the fraction of volume coming from disposition extrapolators and the level of total volume are positively correlated, with a coefficient of 0.79. This positive correlation suggests that, whenever volume rose at the aggregate level, disposition extrapolators increased their volume more than other investors.

To put these numbers into perspective, we provide some back-of-the-envelope analysis to support our claim that disposition extrapolators were largely responsible for the high trading volume. In our sample, total volume at peak increased by 520%, where disposition extrapolators were responsible for 407%, extrapolation-only investors for 63%, and disposition-only investors for 46% (the remaining 4% accounted for by other investors). The high percentage of disposition extrapolators in the population drives part of this result, but even on a per-capita basis, the contribution from a disposition extrapolator is substantially greater than from an investor with a different trading style—in 79% greater than an extrapolation-only investor and 40% greater than a disposition-only investor. If the market consisted of half extrapolation-only investors and half disposition-only investors, total volume would only increase by 375%, which is 145% less than what we observe. Therefore, the rise in volume was indeed mostly driven by disposition extrapolators.

Finally, in Figures 8 and 9, differences in volume began to disappear in the crash: in Figure 8, disposition extrapolators substantially decreased their volume in the crash, and by the end of September 2015, their volume had already returned to a level similar to other investors. A similar pattern is evident in Figure 9, where the fraction of total volume accounted for by disposition extrapolators dropped significantly in the crash.
**Extensive vs. intensive margin.** So far, we have shown disposition extrapolators increased their volume much more than other investors. But in what ways were they trading differently? Our model implies disposition extrapolators were trading more aggressively on the extensive margin by constantly liquidating existing positions and initiating new positions. These transactions directly change the set of assets investors hold and are therefore distinct from trading on the intensive margin, where investors trade by additional buying and partial selling of existing positions.

To test this implication, we decompose disposition extrapolators’ volume into the extensive and intensive margins. In Figures 10a and 10b, volumes from extensive-margin and intensive-margin trading are represented by the shaded areas, using different colors. In each graph, we then plot the fraction of volume accounted for by disposition extrapolators, represented by the solid and dashed lines, respectively. It is straightforward to see disposition extrapolators increasingly constituted a greater fraction of extensive-margin volume: their weight increased from around 65% prior to the bubble to 75% at the peak of the bubble. Their weight in intensive-margin volume, however, remained rather constant, merely increasing from 74% to 77%. In other words, disposition extrapolators were trading rather similarly to other investors on the intensive margin, but were trading more heavily on the extensive margin.

As a comparison, in Figures 10c and 10d, we also plot the fractions of extensive-margin and intensive-margin volumes accounted for by extrapolation-only investors, using the solid and dashed lines, respectively. We find the opposite patterns: their weight in extensive-margin volume dropped by 7%, from 22% prior to the bubble to 15% at the peak of the bubble, whereas their weight in intensive-margin volume only dropped by 2%. Hence, compared with other investors, disposition extrapolators were trading more aggressively on the extensive margin.

**Within-group vs. cross-group trading.** Finally, we examine how much volume occurs among investors with similar investing styles, and how much is across investors of different styles. An important theme of our model is that disposition extrapolators drive up volume by trading *among themselves*, and this result is echoed by Barberis et al. (2017), where
extrapolators trade with each other to generate the large volume. Conversely, a model like the X-CAPM (Barberis et al. 2015) predicts that much of the volume comes from trading across groups, between extrapolators and fundamental traders. We have shown disposition extrapolators traded much more during the bubble, and they did so mostly on the extensive margin. But who is on the other end of these transactions—other disposition extrapolators, or investors with different trading styles?

To answer this question, we decompose total volume into within-group trading and cross-group trading. Note our sample size is more limited than before: for us to classify a transaction into within-group or cross-group, both the buyer and seller must be included in our sample of investors. Because the sample covers around 1% of active investors, we are only able to classify about 0.01% of all transactions. Therefore, we need to interpret these results with caution. For the same reason, instead of reporting results at the weekly level as before, we aggregate them at the monthly level to reduce noise and for clearer exposition.

Figure 11a shows disposition extrapolators’ volume, where the solid line represents the fraction of within-group volume, and the shaded area represents total volume based on all the transactions that are classified. Indeed, the extent of within-group trading among disposition extrapolators moved rather closely with the evolution of the bubble, rising in the run-up and falling in the crash. In Figure 11b, the red dashed line represents the fraction of cross-group volume accounted for by disposition extrapolators, which remained rather constant throughout the bubble. In Figures 11c and 11d, we perform the same exercise for extrapolation-only investors, but do not find a similar pattern. The fraction of within-group volume dropped in the run-up for extrapolation-only investors. Therefore, compared with other investors, disposition extrapolators were increasingly trading amongst themselves in the bubble.

5 Conclusion

We examine a recent bubble episode in the Chinese stock market, using a novel dataset from the Shenzhen Stock Exchange. The dataset covers a long panel of account-level transaction and holding data for 500,000 Chinese individual investors. To make sense of the
joint dynamics of prices and volume, we present a model of bubbles based on extrapolation and the disposition effect. Like previous models of extrapolative beliefs, investors push up stock prices above the fundamental value by extrapolating on past returns. Moreover, the model highlights a novel mechanism for volume—the coexistence of extrapolation and the disposition effect in the same investor. In the run-up, investors constantly struggle between beliefs and preferences: when invested in cash, they are induced by extrapolative beliefs to buy; when invested in the stock, they are prompted by realization utility to sell. By trading amongst themselves, investors generate high volume. We empirically test the model’s new predictions on prices, holdings, and volume in a bubble. Our results show (1) extrapolation prompted investors to increase holdings, thereby pushing up prices, and (2) investors subject to both extrapolation and the disposition effect were largely responsible for the rise in volume.
References


Figure 1: Prices and trading volume at SZSE

Note: The thick blue line plots the closing price of SZCI (in thousands), and the thin red line plots the total number of shares traded at SZSE (with the scale on the right axis). The time frame is from January 2014 to September 2015. The pre-bubble period is from January 1, 2014, to June 30, 2014; the run-up period is from November 19, 2014, to June 12, 2015; the crash period is from June 13, 2015, to September 15, 2015.
Figure 2: Prices and signals in the baseline case

Note: In Figure 2a, the dashed line represents the dividend, and the solid line represents the stock price. In Figure 2b, the solid line represents $X_t$, the dashed line represents $D_t - P_t$, and the dash-dot line represents $E_t \Delta P_{t+1}$, defined by $E_t \Delta P_{t+1} = \gamma X_t + (1 - \gamma) (D_t - P_t)$, where $\gamma = 0.9$. In Figure 2c, the dash-dot line represents the difference between the current stock price and the reference price, $P_t - \bar{P}_t$. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\epsilon = 2$, $D_0 = 100$, $X_1 = 0$, and $Q = 1/2$. 
Figure 3: Trading volume in the baseline case

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

Note: This figure presents the price and volume at peak under parameters that are different from the baseline scenario. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. In the baseline scenario, the parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_\varepsilon = 2$, and $\gamma = 0.9$. The title of each sub-figure represents the parameter concerned.
Figure 5: Results under the heterogeneous-agent setting
Note: This figure presents results under the heterogeneous-agent setting. The initial wealth distribution across disposition extrapolators, extrapolation-only investors, and disposition-only investors is given by 80, 10, and 10. There is a total of 101 dates. The dividend shocks are set to zero except for dates 11 to 14, on which the dividend shocks are 2, 4, 6, and 8, respectively. Other parameter values are $\theta = 0.8$, $\beta = 1$, $\sigma_e = 2$, and $\gamma = 0.9$. 
Figure 6: Per-capita holdings for the entire sample of investors
Note: This figure plots the evolutions of month-end holdings for the entire sample of investors. Figure 6a plots the per-capita holding in RMB for all investors, and Figure 6b plots the per-capita holding in number of shares for all investors.
Figure 7: Holdings patterns by groups

Note: This figure plots the evolutions of month-end holdings for groups sorted on DOX and DOD. In Figures 7a and 7b, the lines represent the difference between each group’s average RMB holding and the average RMB holding of the entire sample. In Figures 7c and 7d, the solid lines represent average RMB holdings, and the dashed lines represent 95% confidence intervals.
Figure 8: The evolution of volume by groups
Note: The three lines in Figure 8a represent the evolution of volume for three investor groups: disposition extrapolators, extrapolation-only investors, and disposition-only investors. Disposition extrapolators are investors with both $DOX$ and $DOD$ above the cutoffs; extrapolation-only investors are those with $DOX$ above and $DOD$ below the cutoffs; disposition-only investors are those with $DOX$ below and $DOD$ above the cutoffs. The two lines in Figure 8b represent the difference in volume between disposition extrapolators and other two types of investors. For each group, volume is normalized to 1 at the beginning of 2014.
Figure 9: The decomposition of total volume by groups

Note: Figure 9a plot the composition of total volume, where the three lines correspond to the fractions of total volume accounted for by three types of investors. The scale on the left represents disposition extrapolators, and the scale on the right represents extrapolation-only and disposition-only investors. In Figure 9b, the solid line represents the fraction of total volume accounted for by disposition extrapolators during the run-up and the crash of the bubble, and the shaded areas represent total volume.
Figure 10: The decomposition of volume by extensive and intensive margins

Note: In Figures 10a and 10c, the shaded blue areas represent volume from trading on the extensive margin, and the solid blue lines represent the fraction of extensive-margin volume accounted for by disposition extrapolators and extrapolation-only investors, respectively. In Figures 10b and 10d, the shaded red areas represent volume from trading on the intensive margin, and the dashed red lines represent the fraction of intensive-margin volume accounted for by disposition extrapolators and extrapolation-only investors, respectively. In each graph, the left axis represents the scale for the shaded area, and the right axis represents the scale for the line.
Figure 11: The decomposition of volume by within-group and cross-group trading

Note: In Figures 11a and 11c, the shaded blue areas represent volume from trading among the same type of investors, and the solid blue lines represent the fraction of within-group volume accounted for by disposition extrapolators and extrapolation-only investors, respectively. In Figures 11b and 11d, the shaded red areas represent volume from trading between different types of investors, and the dashed red lines represent the fraction of cross-group volume accounted for by disposition extrapolators and extrapolation-only investors, respectively. In each graph, the left axis represents the scale for the shaded area, and the right axis represents the scale for the line.
Table 1: Summary statistics for DOX and DOD

Note: This table reports the summary statistics for DOX and DOD. The two measures are computed using transactions from 2005 to 2013, excluding 2007-2008. To make sure an investor is active, we require him to make at least 5 new buys and 17 subsequent trades to be included. These two filters correspond to the 5th-percentile levels among all investors. DOX is calculated by dividing the number of initial buys for a winner stock to the total number of initial buys, where a stock is a winner if its past return over a specific horizon is positive. The five columns in Panel A correspond to the five horizons we consider: daily, weekly, monthly, quarterly, and yearly. In the first column of Panel B, DOD is calculated by dividing the number of sells with a winner stock to the total number of sells, where a stock is a winner if its return since the most recent purchase is positive. In the second column, DOD is calculated by dividing the number of additional buys with a loser stock by the total number of additional buys, where a stock is a loser if its return since the most recent purchase is negative. In the third column, DOD is calculated by pooling together sells and additional buys.

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<th>Panel B: DOD</th>
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Table 2: The averages of DOX and DOD across different investor groups

Note: This table reports the mean value of DOX and DOD across different investor groups. The definitions of DOX and DOD can be found in Table 1. Experience, account size, and investor age are calculated as of the end of 2013.
### Panel A: Distributional properties

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### Panel B: Mean value by board

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### Panel C: Mean value by industry

<table>
<thead>
<tr>
<th></th>
<th>Finance</th>
<th>Public Utility</th>
<th>Properties</th>
<th>Conglomerates</th>
<th>Industrials</th>
<th>Commerce</th>
</tr>
</thead>
<tbody>
<tr>
<td>$DOX$</td>
<td>0.670</td>
<td>0.670</td>
<td>0.657</td>
<td>0.653</td>
<td>0.661</td>
<td>0.667</td>
</tr>
<tr>
<td>$DOD$</td>
<td>0.630</td>
<td>0.628</td>
<td>0.655</td>
<td>0.652</td>
<td>0.646</td>
<td>0.653</td>
</tr>
</tbody>
</table>

### Panel D: Correlation with other independent variables

<table>
<thead>
<tr>
<th></th>
<th>$DOX$</th>
<th>$DOD$</th>
<th>Beta</th>
<th>MktCap</th>
<th>B/M</th>
<th>Turnover</th>
<th>Float</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>$DOX$</td>
<td>1.000</td>
<td>-0.218</td>
<td>0.011</td>
<td>-0.097</td>
<td>-0.019</td>
<td>0.063</td>
<td>-0.039</td>
<td>-0.010</td>
</tr>
<tr>
<td>$DOD$</td>
<td>-0.218</td>
<td>1.000</td>
<td>0.005</td>
<td>0.018</td>
<td>0.202</td>
<td>-0.164</td>
<td>0.146</td>
<td>0.105</td>
</tr>
</tbody>
</table>

Table 3: Summary statistics of $DOX$ and $DOD$  
Note: This table reports the summary statistics of $DOX$ and $DOD$. Panel A concerns their distributional properties. Panel B presents their mean values across different boards. Panel C presents the mean values across different industries. Panel D shows the correlation coefficients with other variables. $MktCap$ is the total market capitalization, and $B/M$ is the book-to-market ratio, both constructed by the end of 2013. $Volume$, $Float$, and $Turnover$ are defined by the average number (in millions) of shares daily traded, the average number (in millions) of tradable shares, and the ratio of total value of shares traded to float, respectively.
<table>
<thead>
<tr>
<th></th>
<th>Panel A: run-up</th>
<th>Panel B: crash</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td><strong>DOX</strong></td>
<td>7.24***</td>
<td>7.12***</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.72)</td>
</tr>
<tr>
<td><strong>DOD</strong></td>
<td>-5.36***</td>
<td>-5.14***</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
<td>(0.71)</td>
</tr>
<tr>
<td><strong>Turnover</strong></td>
<td>6.71***</td>
<td>6.28***</td>
</tr>
<tr>
<td></td>
<td>(1.33)</td>
<td>(1.32)</td>
</tr>
<tr>
<td><strong>Float</strong></td>
<td>0.036</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.16)</td>
</tr>
<tr>
<td><strong>Volume</strong></td>
<td>0.63</td>
<td>-2.14</td>
</tr>
<tr>
<td></td>
<td>(1.89)</td>
<td>(1.92)</td>
</tr>
<tr>
<td><strong>Beta</strong></td>
<td>-0.026</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.11)</td>
</tr>
<tr>
<td><strong>B/M</strong></td>
<td>0.032</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.10)</td>
</tr>
<tr>
<td><strong>MktCap</strong></td>
<td>-19.5***</td>
<td>-18.8***</td>
</tr>
<tr>
<td></td>
<td>(3.74)</td>
<td>(4.44)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.15</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td>(0.72)</td>
<td>(0.73)</td>
</tr>
</tbody>
</table>

Pre-bubble characteristics: No, Yes
Post-bubble characteristics: No, No, No, No, Yes
Industry FE: No, No, Yes, Yes
Board FE: No, No, Yes, Yes

<table>
<thead>
<tr>
<th>N</th>
<th>1,582</th>
<th>1,582</th>
<th>1,582</th>
<th>1,582</th>
<th>1,478</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.115</td>
<td>0.136</td>
<td>0.182</td>
<td>0.170</td>
<td>0.090</td>
</tr>
</tbody>
</table>

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

Table 4: Regressions of run-up and crash returns on average degrees of extrapolation and disposition

Note: This table reports results of regressing returns on the average degrees of extrapolation and disposition. Panel A reports the results when the dependent variable is the return during the run-up, and Panel B reports the results when the dependent variable is the return during the crash. The run-up is from November 18, 2014, to June 12, 2015, and the crash is from June 15 to September 30, 2015. The average degree of extrapolation, denoted by $DOX$, is constructed using the volume-weighted $DOX$ of the investor base. $DOD$ is constructed similarly. $Volume$, $Float$, and $Turnover$ are defined by the average number (in millions) of shares daily traded, the average number (in millions) of tradable shares, and the ratio of total value of shares traded to float, respectively. Pre-bubble (post-bubble) characteristics include $Volume$, $Float$, and $Turnover$, which are similarly defined, and previous returns. The 2SLS regression in Panel A uses $Pre-DOX$ and $Pre-DOD$ as instrumental variables, where $Pre-DOX$ and $Pre-DOD$ are constructed using the trading volume from January 1, 2014, to November 17, 2014 as weights.
<table>
<thead>
<tr>
<th>Panel A: Sorting on DOX</th>
<th>DOX</th>
<th>DOD</th>
<th>Account size</th>
<th>Experience</th>
<th>Investor age</th>
<th>Female</th>
<th>Trading value</th>
<th>Average balance</th>
<th>Number of positions</th>
<th>Turnover</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>0.45</td>
<td>0.70</td>
<td>1.50</td>
<td>6.24</td>
<td>5.25</td>
<td>0.40</td>
<td>0.83</td>
<td>0.04</td>
<td>1.96</td>
<td>24.9</td>
<td>0.45</td>
</tr>
<tr>
<td>Group 2</td>
<td>0.60</td>
<td>0.68</td>
<td>1.53</td>
<td>6.58</td>
<td>5.55</td>
<td>0.43</td>
<td>0.91</td>
<td>0.04</td>
<td>2.05</td>
<td>24.8</td>
<td>0.44</td>
</tr>
<tr>
<td>Group 3</td>
<td>0.68</td>
<td>0.68</td>
<td>1.53</td>
<td>6.69</td>
<td>5.65</td>
<td>0.47</td>
<td>0.95</td>
<td>0.04</td>
<td>2.11</td>
<td>25.2</td>
<td>0.46</td>
</tr>
<tr>
<td>Group 4</td>
<td>0.76</td>
<td>0.68</td>
<td>1.51</td>
<td>6.80</td>
<td>5.73</td>
<td>0.50</td>
<td>0.93</td>
<td>0.04</td>
<td>2.10</td>
<td>24.7</td>
<td>0.46</td>
</tr>
<tr>
<td>Group 5</td>
<td>0.86</td>
<td>0.68</td>
<td>1.45</td>
<td>6.78</td>
<td>5.68</td>
<td>0.52</td>
<td>0.92</td>
<td>0.04</td>
<td>2.01</td>
<td>24.6</td>
<td>0.46</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Sorting on DOD</th>
<th>DOX</th>
<th>DOD</th>
<th>Account size</th>
<th>Experience</th>
<th>Investor age</th>
<th>Female</th>
<th>Trading value</th>
<th>Average balance</th>
<th>Number of positions</th>
<th>Turnover</th>
<th>Annual return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>0.66</td>
<td>0.48</td>
<td>1.48</td>
<td>6.55</td>
<td>5.25</td>
<td>0.38</td>
<td>1.13</td>
<td>0.05</td>
<td>1.91</td>
<td>25.9</td>
<td>0.46</td>
</tr>
<tr>
<td>Group 2</td>
<td>0.64</td>
<td>0.61</td>
<td>1.51</td>
<td>6.62</td>
<td>5.41</td>
<td>0.43</td>
<td>0.92</td>
<td>0.04</td>
<td>1.98</td>
<td>25.4</td>
<td>0.45</td>
</tr>
<tr>
<td>Group 3</td>
<td>0.64</td>
<td>0.69</td>
<td>1.51</td>
<td>6.63</td>
<td>5.55</td>
<td>0.47</td>
<td>0.86</td>
<td>0.04</td>
<td>2.06</td>
<td>24.8</td>
<td>0.45</td>
</tr>
<tr>
<td>Group 4</td>
<td>0.64</td>
<td>0.77</td>
<td>1.51</td>
<td>6.67</td>
<td>5.77</td>
<td>0.50</td>
<td>0.83</td>
<td>0.04</td>
<td>2.11</td>
<td>24.4</td>
<td>0.45</td>
</tr>
<tr>
<td>Group 5</td>
<td>0.63</td>
<td>0.87</td>
<td>1.50</td>
<td>6.61</td>
<td>5.89</td>
<td>0.54</td>
<td>0.78</td>
<td>0.03</td>
<td>2.17</td>
<td>23.7</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Table 5: Average investor characteristics across groups sorted on DOX and DOD
Note: This table reports the average investor characteristics for the groups sorted on DOX and DOD, respectively. Definitions of DOX and DOD can be found in Table 1. Definitions of account size, experience, and investor age can be found in Table 2. Trading value is the average value (in million RMB) of all transactions made each year. Average balance is the average year-end account balance (in million RMB). Number of positions is the average number of stocks held by an investor in the year-end account. Turnover is calculated by dividing trading value to average balance. Annual portfolio return is calculated by dividing the RMB return by the average account balance.