Replication Report for Extrapolation and Bubbles

Barberis, Greenwood, Jin, and Shleifer (2018)

Yile Chen*

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Barberis et al. (2018) establish a model of bubbles with extrapolative belief that explains both price and volume dynamics. This Replication report is divided into four parts: Section 1 briefly summarizes the model setup and key predictions of the model. Section 2 surveys the literature and evaluates the contribution of the paper. Section 3 describes the numerical exercises of the replication. Finally, Section 4 focuses on limitations and areas for extensions. Supplementary code can be found here.

1 Summary

The model features an economy with finite periods, $t = 0, 1, ..., T$, and two assets, one riskless asset and one risky asset with a fixed supply of Q shares and a dividend payment $\tilde{D_T}$ at time T. The value $\tilde{D_T}$ is specified by an information process: $\tilde{D_T} = D_0 + \tilde{\epsilon_1} + ... + \tilde{\epsilon_T}$ where $\tilde{\epsilon_t} \sim N(0, \sigma_\epsilon^2)$. D_0 is the initial information, and $\tilde{\epsilon_t}$ is cash flow shock realized at time t.

There are two classes of traders: fundamental investors and extrapolators, both subject to short-selling constraints. Though they trade aggressively against mispricing, fun-

*MSc student in Finance at UBC Sauder. Student ID number: 55908420. Submitted as a project report for COMM673. All errors are my own.

damental traders are modeled to be boundedly rational. That is, they do not possess full knowledge of how the rest of the investors (i.e., extrapolators) behave but assume they will simply hold the amount of asset proportional to their population weight. Maximizing CARA utility over the next period's wealth, the per capita demand of fundamental traders N_f is specified in (1), which is the expected price change scaled by the trader's risk aversion and her estimate of risk.

$$N_f = \frac{D_t - \gamma\sigma_\epsilon^2(T-t-1)Q - P_t}{\gamma\sigma_\epsilon^2} \tag{1}$$

The other type of traders are extrapolators, whose demand N_i is a weighted average of two components: a value signal that captures fundamentals and a growth signal that captures extrapolation (shown by (2)). The growth signal is a positive function of extrapolator enthusiasm X_t, which governs how extrapolation takes place. X_t is a weighted function of its value last period and the price change last period. This specification ensures a fading memory-like belief pattern such that recent price changes are weighted more than those in the ancient past.

$$N_i = w_i \underbrace{\left(\frac{D_t - \gamma\sigma_\epsilon^2(T-t-1)Q - P_t}{\gamma\sigma_\epsilon^2}\right)}_{\text{Value signal } (V_t)} + (1-w_i) \underbrace{\left(\frac{X_t}{\gamma\sigma_\epsilon^2}\right)}_{\text{Growth Signal } (G_t)} \tag{2}$$

$$where \quad X_t = \theta X_{t-1} + (1-\theta)(P_{t-1} - P_{t-2})$$

A critical aspect of the model concerns the weighting given by extrapolators to the two signals. Instead of maintaining constant weights, extrapolators periodically switch between the growth signal and the value signal. Barberis et al. (2018) refer to these shifts as 'wavering', which they propose arises from the random allocation of attention to the signals and encapsulates the fear-versus-greed dilemma. Wavering is independent and identically distributed over time and among extrapolators, and is modeled as $w_{i,t} =$

$\bar{w}_i + \tilde{u_{i,t}}, \quad where \quad \tilde{u_{i,t}} \sim N(0, \sigma_u^2)$.

In equilibrium, the aggregate demand of the risky asset equals its aggregate supply. A unique market clearing price is given by (3) (Proposition 1), where I^* is the set of investors with positive demands at t, and μ_i represents the proportion of investor i among all investors. As shown, P_t tracks the expected value of cash flow D_t closely and comprises an extrapolation element, a positive function of extrapolator enthusiasm X_t. P_f in equation (4) denotes the fundamental value in a hypothetical scenario where only fundamental traders exist in the economy, and it is calculated for comparison purposes.

$$P_t = D_t + \underbrace{\frac{\Sigma_{i \in I^*} \mu_i (1 - w_{i,t})}{\Sigma_{i \in I^*} \mu_i w_{i,t}} X_t}_{\text{Extrapolation component}} - \gamma \sigma_\epsilon^2 Q \frac{(\Sigma_{i \in I^*} \mu_i w_{i,t})(T - t - 1) + 1}{\Sigma_{i \in I^*} \mu_i w_{i,t}} \tag{3}$$

$$P_f = D_t - \gamma \sigma_\epsilon^2 (T - t) Q \tag{4}$$

With a few numerical examples (which will be described in detail later in the replication section), the authors show that the model can generate bubble episodes that align with the five-phase narrative (i.e., displacement, boom, euphoria, profit-taking, and panic) by Kindleberger (1978) and empirical evidence on historical bubbles. In particular, 'wavering' is shown to be an important feature for the generation of excessive trading volume around the peak of a bubble. During periods of overvaluation, the magnitudes of both the growth signal and the value signal are high, so any slight shifts between the two signals can lead to sizable changes in demands and, therefore, high trading volume. Furthermore, when the wavering and cash flow shocks are sufficiently large, not only fundamental traders but also some extrapolators will leave the market when the risky asset is extremely overvalued. This results in a "price spiral", as only the most optimistic extrapolators remain in the market.

2 Literature

2.1 Bubbles

Before the publication of the paper, there were two main classes of models on bubbles, namely rational bubbles and heterogenous belief-based bubbles [1]. Nevertheless, neither of them can comprehensively reconcile price movements and volume dynamics.

According to a survey by Brunnermeier and Oehmke (2012), in a typical rational bubble model, shown by (5), price p_t can be decomposed into a fundamental component v_t and a bubble component b_t, where b_t is the future expected value discounted by a rate of r. By backward induction, this already eliminates many possibilities of bubbles – cases when bubbles cannot grow infinitely. Nevertheless, rational bubbles can develop and persist under settings such as overlapping generations (Delong et al., 1990; DeMarzo, Kaniel, and Kremer, 2008) and information frictions (Abreu and Brunnermeier, 2003). Despite their simplicity, rational bubble models fail to account for several important characteristics of bubbles. Firstly, with homogenous rational agents, high trading volume during bubble periods is left unexplained. Secondly, they are silent on why and how bubbles initiate. Since b_t is always non-negative, that is, bubbles are assumed to have already existed instead of emerging endogenously from the economy.

$$p_t = v_t + b_t \tag{5}$$

$$b_t = E_t[\frac{1}{1+r} b_{t+1}]$$

Another type of theoretical model is based on heterogeneous beliefs, as reviewed by Xiong (2013). Investors have different belief distributions, which are possibly due to psychological biases. These models typically include short-selling constraints, whereby bubbles arise when optimists push up prices while pessimists are unable to trade against

[1]Recently, there have also been a few papers on social networks with implications to bubbles. See Pedersen, 2022 and Li, 2023

the overvaluation. Intensive fluctuations of heterogeneous belief give rise to intensive trading and bubbles (even when the investors are, on average unbiased, as shown by Scheinkman and Xiong, 2003). The extrapolation-based bubble model by Barberis et al. (2018) shares a number of similarities with this class of models. They both allow for disagreement among investors, generate fluctuating beliefs, and effectively explain the trading frenzies observed during bubbles. However, unlike previous models where disagreements are exogenously generated to affect prices, Barberis et al. (2018) endogenize belief formation by intertwining it with price dynamics.

2.2 Extrapolative Beliefs

There is various empirical evidence suggesting that investors extrapolate from recent history while forming beliefs on economic variables. Harvy, Lahav, and Noussair (2007) find in a lab setting that participants in experimental markets exhibit adaptive learning behaviors. Individuals tend to form beliefs based on past trends in the market. Similarly, based on survey data from six different sources between 1963 and 2011, Greenwood and Shleifer (2014) find that investor expectations strongly correlate with past returns and investor inflows into mutual funds. This evidence contradicts the predictions of standard rational expectation models but supports behavioral interpretations involving investor extrapolation. Moreover, Da, Huang, and Jin (2021) recently found evidence of extrapolation in the cross-section, providing further support for the relevance of this behavioral bias.

Motivated by empirical evidence on investor expectation, there has been a recent wave of theoretical research on extrapolation (see a review by Barberis, 2018 Chapter 4). Compared to rational models that feature market fluctuations, e.g., habit formation and long-run risk, extrapolation–based models are more consistent with survey data. In Barberis et al. (2015), rational investors and extrapolators are modeled to maximize lifetime consumption utility (following CARA) in an infinite continuous time setup. Extrapolation is characterized by a measure named "sentiment" S_t, which captures the exponentially decaying weights of past price changes (shown by (6)). Then, extrapolators expect the market price to grow at $g^e_{p,t} \equiv E^e_t[dP_t]/dt = \lambda_0 + \lambda_1 S_t$.

$$S_t = \beta \int_{-\infty}^{t} e^{-\beta(t-s)} dP_{s-dt}, \quad \beta > 0 \tag{6}$$

The model predictions reconcile with various asset pricing phenomena in the data, including excess volatility and the value effect (P/D ratio predicts future return). However, the model leaves a few puzzles unsolved, such as equity premium and short-term price autocorrelation. A recent paper by Jin and Sui (2022) takes a step further and makes investors follow Epstein-Zin preferences and extrapolate according to a regime-switching scheme. Extrapolators believe that price grows at a rate of $g^e_{p,t} = (1-\theta)g_D + \theta\tilde{\mu}_t$, where μ_t governs the level of extrapolation by switching between a high value μ_H and a low value μ_L. After calibration, they show that the model generates high equity premium, return predictability, excessive volatility, and low correlation between stock returns and consumption growth. Barberis et al. (2018) contribute to this strand of literature by being, to the best of my knowledge, the first to incorporate extrapolation in a bubble model. The model is a natural extension of Barberies et al. (2015). Although it depicts investors in a more simplified way (in discrete finite periods with short-selling constraints), it captures key results of the more sophisticated extrapolation models and provides additional insights into mechanisms behind the high trading volume in a bubble.

3 Replication: numerical exercises

I replicate the numerical simulations to generate an exemplar bubble episode and reproduce figures confirming the key predictions of the paper. Code can be found in https://github.com/YileC928/Extrapolation_and_bubble_rep/blob/main/Extrapolation_and_Bubble_rep_with

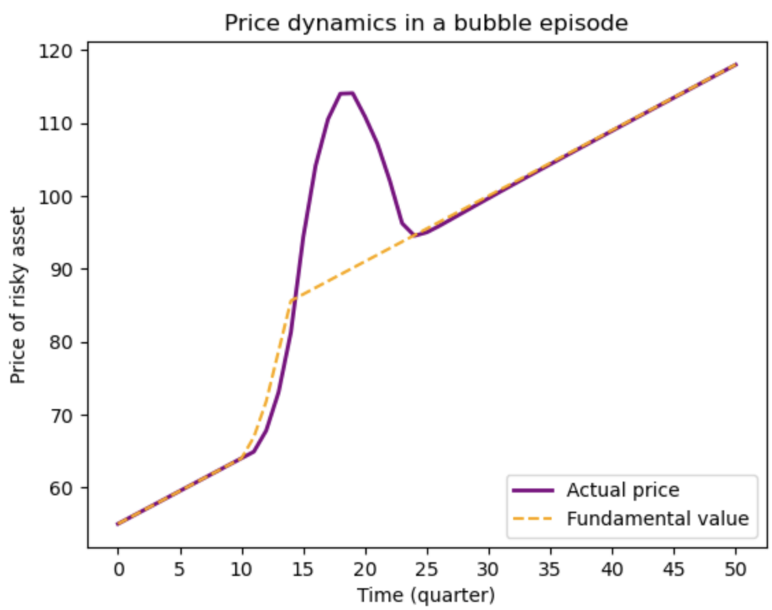
I simulated an economy of 50 time periods, i.e., 50 cash flow shocks, in which the first ten shocks are zero, followed by four strong positive shocks, 2, 4, 6, 6 in a sequence, and the rest of the shocks are all zero. The initial information of the cash flow payment D_0 is 100. 30% of the investors are fundamental traders, and the remaining 70% is equally divided by 50 extrapolators. The baseline weight $\bar{w}$ for the value signal is 0.1, and it wavers with a standard deviation σ_u of 0.03. The weight extrapolators put on the most rest price change θ is set to be 0.9, following the calculation in the XCAPM model (Barberis et al., 2015). A full list of parameters is in Table 1.

Table 1: Parameter Values for Simulation

Parameter Name	**Value**
D_0	100
T	20
σ_ϵ	3
Q	1
I	50
μ_f	0.3
μ_e	0.7
γ	0.1
θ	0.9
X_1	0.9
$\bar{w}$	0.1
ϵ_u	0.03

Figure 1 reproduces Figure 1 in the paper. The purple line represents the actual price, and the yellow line plots the fundamental value. As shown, after the positive shocks, the actual price soon departs from the fundamental value and soars to a peak that is 20 dollars higher than it should be. A bubble is formed. Then, when the cash flow shocks, together with the large price changes, recede into the past, the bubble deflates, and the price comes back to its fundamental level. Figure 2 plots extrapolator enthusiasm X_t over the period.

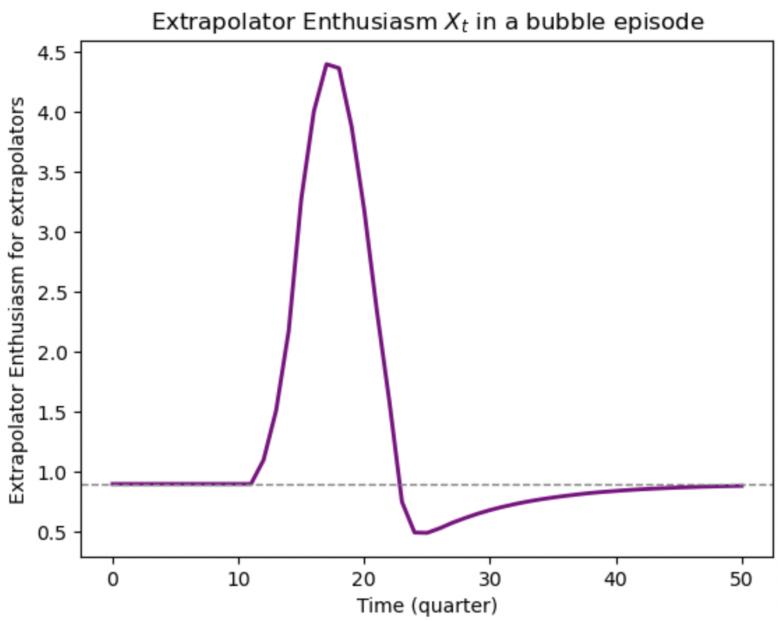
Figure 1: Price in a Bubble Episode



It tracks the price movement well: it peaks when the bubble is at its high and plummets as soon as it starts to crash.

Figure 3 and Figure 4 replicate Figure 4 and Figure 5 in the paper, illustrating the trading activities and volume dynamics in the simulated economy. In Figure 3, the purple dotted line plots the share demands of the representative fundamental trader, and each grey line represents the position of an extrapolator. In Figure 4, the purple line shows the total trading volume among all traders in the economy, and the yellow dotted line plots the volume of trades that happens between extrapolators and fundamental investors. As shown, as soon as the positive cash flow shocks come into play, the excitement of

Figure 2: Extrapolator Enthusiasm in a Bubble Episode



extrapolators begins to build up, and they drastically increase their demand and buy from the fundamental investors. Meanwhile, when fundamental traders cut down their position to a point when the mispricing has been too wide to be justified, they exit the market because of the short-selling constraint. As demonstrated by Figure 5, the first peak of volume is attributed to trades between the two classes of investors. As the bubble develops, there is another peak of volume, which is made of trades among only extrapolators. As mentioned in section 1, extrapolators trade intensively during bubbles because of 'wavering'. Those who shift to a point where a high enough weight is put on the value signal will drastically decrease their demand and even temporarily exit the market (as the fundamental trader does), displayed by the jiggling grey lines around time 14-21 in Figure 4. Then, when the bubble deflates, extrapolator enthusiasm dies down, and fundamental investors buy from the extrapolators, leading to another peak of volume.

Figure 3: Demand in a Bubbles Episode

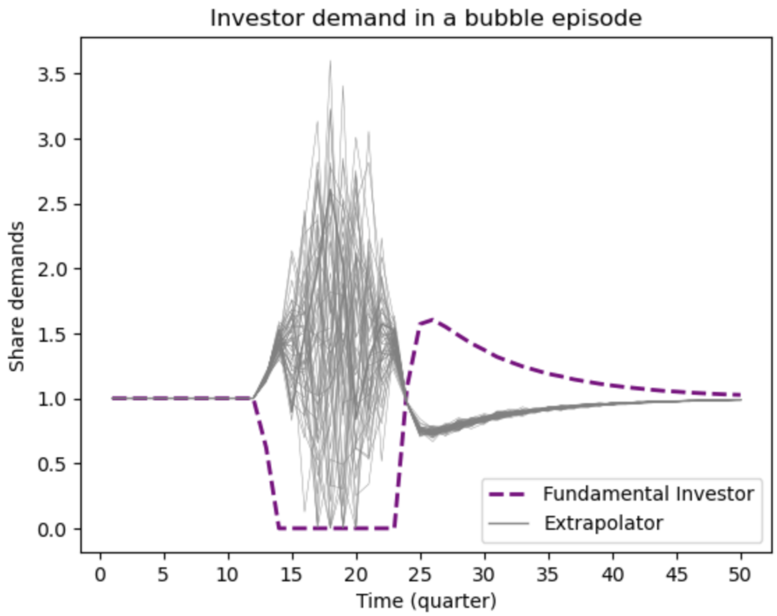
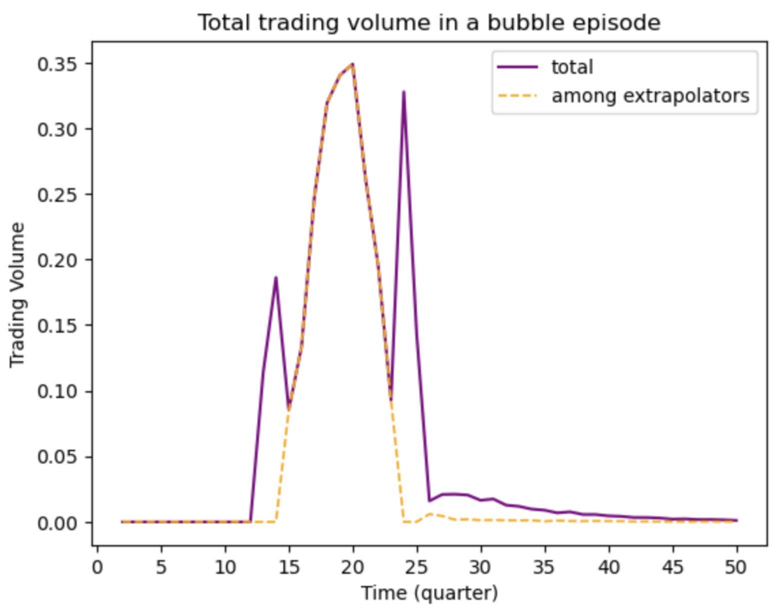


Figure 4: Total trading Volume in a Bubble Episode



4 Limitations and Extensions

While the paper performs well in explaining various asset pricing features, there is room for extension and future research. In this section, I examine areas for potential improvement and present the results of a few simple exploratory simulations. The areas include the distribution of wavering, the characterization of extrapolation, investor composition, and the role of speculators.

4.1 Is extrapolator's wavering i.i.d?

Barberis et al. (2018) assume that wavering is i.i.d. across investors and across time. This assumption is vital for generating high volume during the peak of the bubble. Because if extrapolator beliefs are biased toward the same direction, there will be less trading. A natural question to ask is: Do extrapolators wavers in the data? and if they do, is wavering really distributed independently across investors and across different stages of a bubble? Barberis et al. (2018) back up their assumption by presenting holdings of five hedge funds and ten mutual funds during the technology bubble and suggest that a few of them exhibit wavering. Among those who do, waverings do not seem to be correlated. However, what they show is rather descriptive and is only based on a small sample. Also, hedge funds and mutual funds are not representative candidates for extrapolators. Further evidence (e.g., on retail investors) is needed, and I conjecture that it is likely that extrapolator wavering is not i.i.d. since past literature has discovered various factors (e.g., herding and social learning) contributing to correlated trading behaviors (Pedersen, 2022; Cookson et al., 2023; Barber, 2022).

To see how the level of correlation in wavering affects the predictions in Section 3, I generated multiple series of extrapolation weights. As expected, correlated wavering does not change the dynamics of price and extrapolator enthusiasm, but leads to less intense trading during and lower trading volume at the peak of the bubble. Nevertheless, with a moderate level of correlation, there is still a considerable amount of trades among extrapolators during the bubble (Figure 5); only when wavering is strongly correlated will the high trading volumes dissipate (Figure 6).

Figure 5: Total trading Volume under correlated wavering (rho = 0.5)

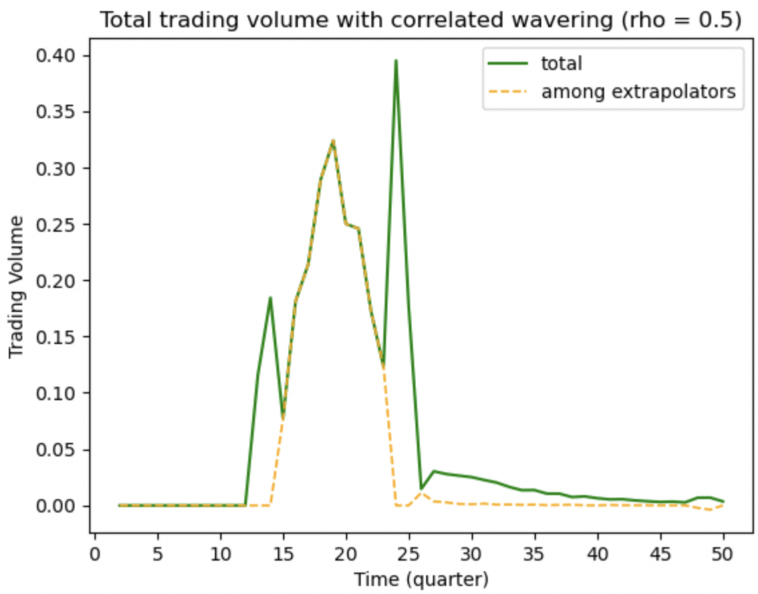
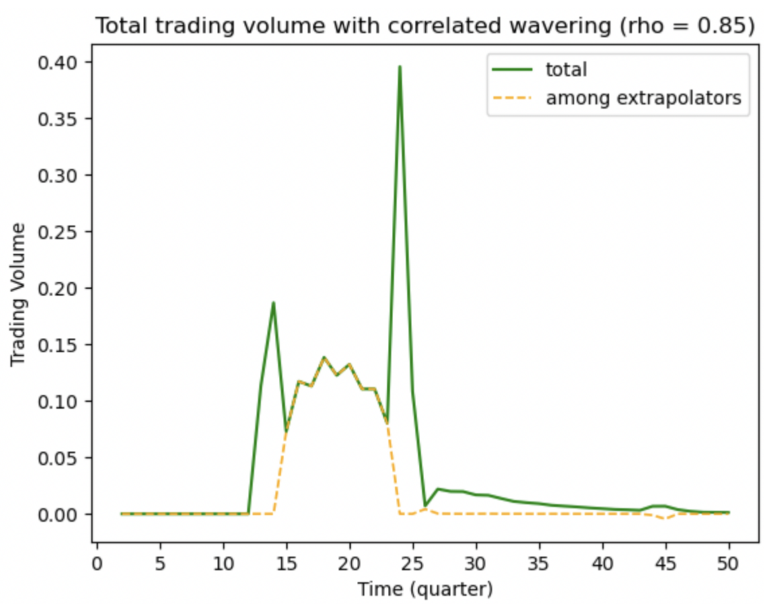


Figure 6: Total trading Volume under correlated wavering (rho = 0.85)



4.2 Charaterization of extrapolation

Understanding why and how investors extrapolate is the basis for formally modeling such behaviors. It is possible that people suffer from small sample bias (Rabin, 2002), use an oversimplified model to forecast returns (Hong, Stein, and Yu, 2007), or learn from prior experiences (Malmendier and Nagel, 2007). For example, a recent cross-sectional study by Da, Huang, and Jin (2021) shows two important characteristics of investor extrapolation, as shown by the regression equation in (8). Firstly, investors weigh the recent past more than the distant past. Secondly, negative returns are weighted more than positive returns (higher $\lambda_{1,n}$ and $\lambda_{2,n}$); and they attribute both facts to salience. Barberies et al. (2018) incorporate the first characteristics with the exponential decay function for the extrapolator enthusiasm parameter X_t, but the model does not reflect the second feature.

$$ER_{i,t} = \lambda_0 + \lambda_{1,p} \sum_{s=0}^{n} \mathbb{1}_{\{R_{i,t-s} \geq 0\}} w_{s,p} R_{i,t-s} + \lambda_{1,n} \sum_{s=0}^{n} \mathbb{1}_{\{R_{i,t-s} < 0\}} w_{s,n} R_{i,t-s} + \epsilon_{i,t}, \tag{7}$$

$$where \;\; w_{s,p} = \frac{\lambda_{2,p}^{s}}{\sum_{j=0}^{n} \lambda_{2,p}^{j}} \;\; and \;\; w_{s,p} = \frac{\lambda_{2,n}^{s}}{\sum_{j=0}^{n} \lambda_{2,n}^{j}}$$

To explore how asymmetric extrapolation can play a role in Barberis et al. (2018), I modify the expression for extrapolator enthusiasm to (8), where (1-θ_n) and (1-θ_p) are the different weights an extrapolator puts on the most recent positive and negative price changes.

$$X_t = \begin{cases} \theta_p X_{t-1} + (1-\theta_p)(P_{t-1} - P_{t-2}) & P_{t-1} - P_{t-2} \geq 0 \\ \theta_n X_{t-1} + (1-\theta_n)(P_{t-1} - P_{t-2}) & P_{t-1} - P_{t-2} < 0 \end{cases} \tag{8}$$

The figures below show dynamics when $\theta_n = 0.86$ and $\theta_p = 0.9$ (θ in Section 3). As shown, with more weight on the negative price changes, the bubble period is shorter, with a more drastic drop in price (Figure 7) and extrapolator enthusiasm (Figure 8), and when the bubble bursts, share demand of extrapolators plummets to the bottom and takes a long time to move back to the steady state (Figure 9). The trading volume during the crash stage is much higher than that in Section 3, as there are much more trades between fundamental traders and the 'panicked' extrapolators.

Figure 7: Price in a bubble episode under asymmetric extrapolation

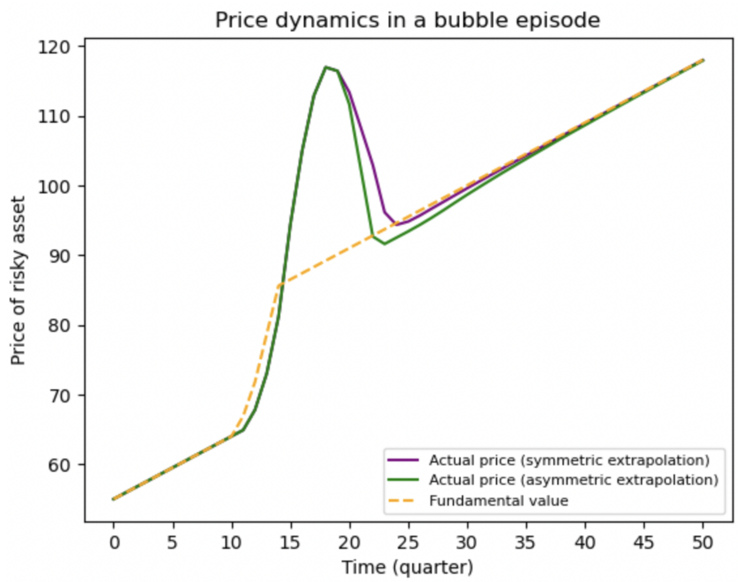


Figure 8: Extrapolator Enthusiasm in a bubble episode under asymmetric extrapolation

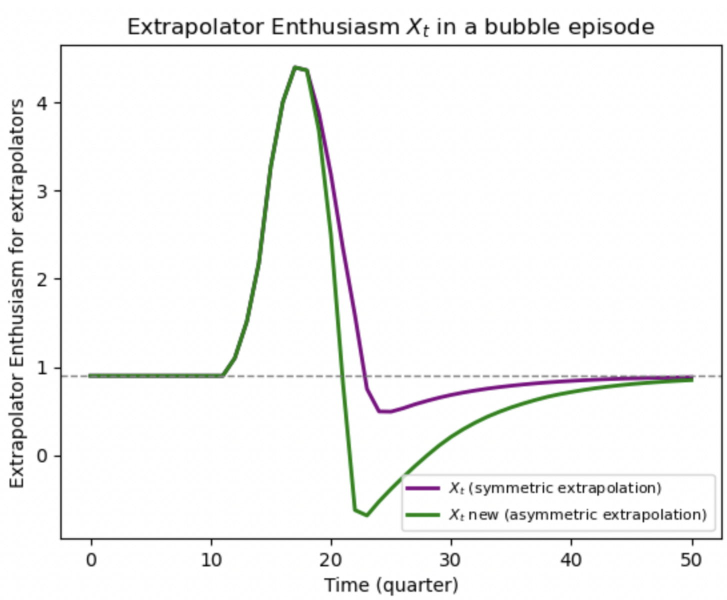


Figure 9: Total trading Volume under asymmetric extrapolation

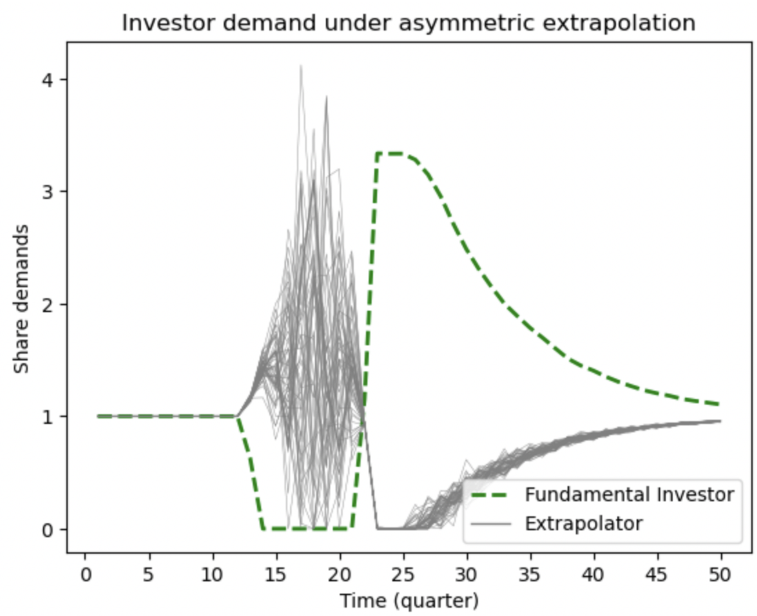
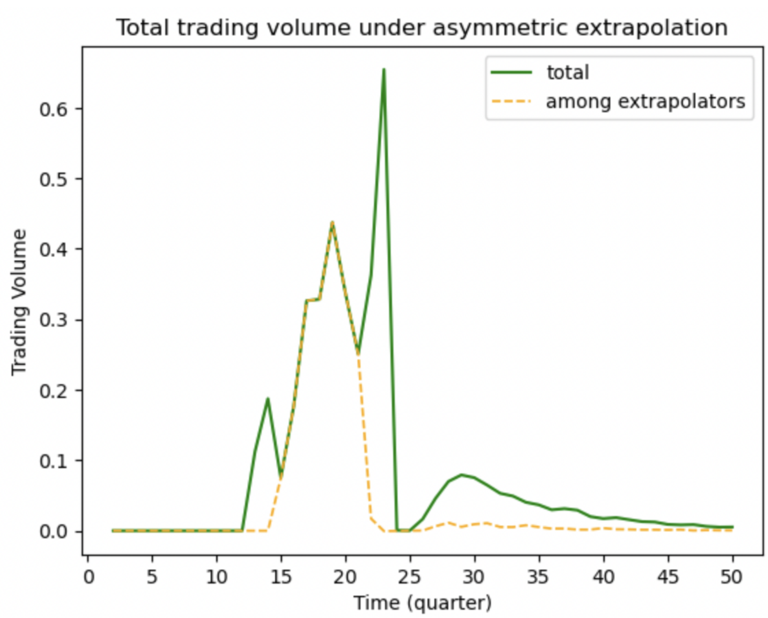


Figure 10: Total trading Volume under asymmetric extrapolation



4.3 Investor Composition

In Barberis et al. (2018), fundamental investors and extrapolators comprise fixed proportions of the population. However, empirical studies have shown that investor composition can change during a bubble episode. Specifically, new extrapolators who are particularly optimistic about the risky asset tend to enter the market during periods of high overvaluation and extrapolator enthusiasm. Greenwood and Nagel (2009) show that during the technology bubble, there is a large inflow into the mutual funds that tilted toward the technology stocks prior to the peak of the bubble. Greenwood and Shleifer's study (2014) documents a strong correlation between investors' return expectations (based on surveys) and mutual fund inflows. For example, bullish expectations from the Gallup survey tend to be accompanied by a high inflow into equity mutual funds. Li (2023) focuses on the recent meme stock frenzy and shows that the percentage ownership of households in Gamestop rises from less than 30% to 80% from 2020 Q1 to 2021 Q4.

To explore this idea, I model the population of extrapolators as a simple linear function of extrapolator enthusiasm. $\mu_t^e = \bar{\mu^e} + \beta(X_t - \bar{X}_t)$, where μ_t^e is the proportion of extrapolators in the economy at time t, and X_t is extrapolator enthusiasm at time t, and $\bar{\mu^e}$ and $\bar{X}_t$ are the steady state level of the two variables. β governs how new extrapolators inflow into the market in periods of exuberance. I simulate with $\beta = 0.03$. The economy starts with 70% of extrapolators, and when the bubble grows, new extrapolators enter. At the peak of the bubble, around 81% of the population is extrapolators. This number falls to around 68% when the bubble crashes and returns to the steady state level gradually afterward. As shown by Figure 11, the bubble is larger than the baseline scenario in Section 3. The pattern of trading volume is similar to that in section 3, except that it takes longer for investor demand to come back to the steady state (Figure 12).

Figure 11: Price in a Bubble Episode with dynamic investor composition

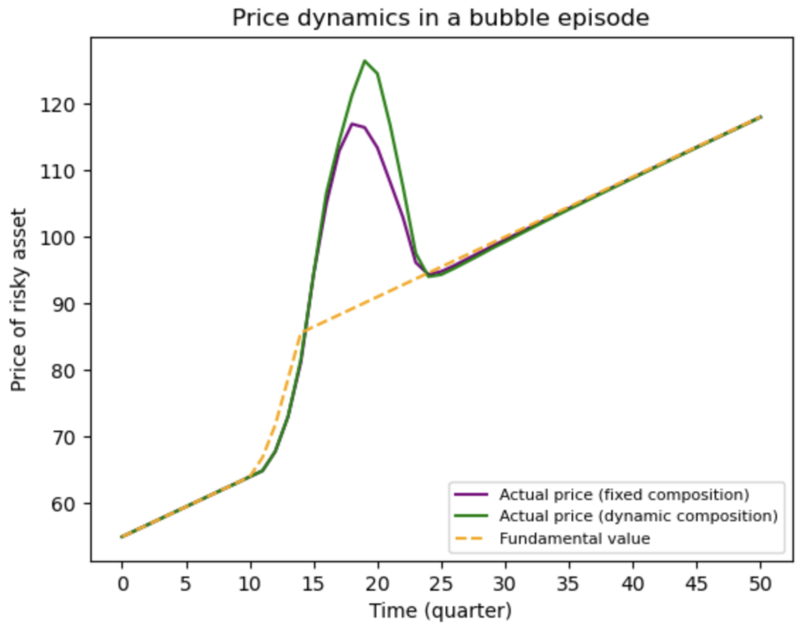
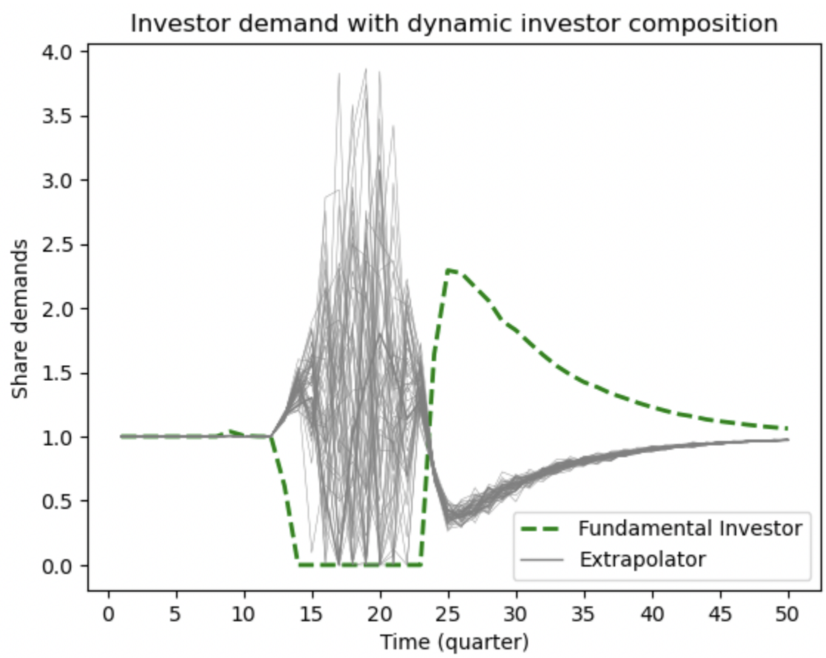


Figure 12: Demand in a Bubbles Episode with dynamic investor composition



4.4 The role of speculators

In Barberis et al. (2018), fundamental traders are defined to be boundedly rational and subject to strict short-selling constraints. This assumption plays an important role in generating the bubble and high trading volumes. However, the model fails to capture the fact that sophisticated speculators are also capable of "riding the bubble". Brunnermeier and Nagel (2004) show that rational speculators ride the technology bubble instead of exerting a correcting force of mispricing. They focus on trading activities of hedge funds, which is one of the most close-to-rational investor classes. They use data on investor holdings and find that hedge funds overweight highly-priced technology stocks in the run-up, whereas sophisticatedly avoid the downturn. In addition to the motive for profits, there are a few potential reasons preventing arbitragers from trading aggressively against overvaluation. According to Shleifer and Vishny (1997), funds face limits to arbitrage. They operate in fear of outflow following short-term losses, as clients may attribute any losses to the incompetence of the fund managers (Allen and Gorton, 1993; Sato, 2009). To retain and attract clients, money managers are reluctant to bet on the prompt correction of prices and even be incentivized to trade overvalued assets. Furthermore, there may be information friction dragging the price correction. Abreu and Brunnermeier (2003) characterize this feature in their model, where each investor sequentially becomes aware of the bubble, whereas no individual investor can bring down the bubble alone. Only synchronized divestment can create enough selling pressure to lead to a crash. Therefore, on the one hand, investors tend to avoid crashes; on the other, since the bubble is never common knowledge, they attempt to ride it as long as possible.

Given the limited time, I did not find a straightforward way to capture this feature, but it is certainly an intriguing avenue for future research.

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