Information Processing and Non-Bayesian Learning in Financial Markets*

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Abstract. Ample empirical and experimental evidence documents that individuals place greater weight on information gained through personal experience – a phenomenon that Tversky and Kahneman (1974) call availability bias. I embed this bias in an overlapping generations equilibrium model in which the period that investors first enter the market establishes the starting point of their experience history. The difference in the individuals’ experience leads to heterogeneity among agents and perceived noise trading. The model captures several empirical findings. It explains why returns on high-volume trading days tend to revert. Furthermore, it provides explanations for a high trading volume, a connection between trading volume and volatility, excess volatility, and overreaction and reversal patterns. Consistent with empirical evidence, young investors buy high and sell low, trade frequently, and obtain lower returns. For intraday trading, it predicts a high trading volume around the opening hours, especially for cross-listed stocks.

Keywords: Heuristic Learning, Heterogeneous Beliefs, Overlapping Generations Model, Behavioral Finance.

JEL Classification: G02, G12

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1. Introduction

Extensive evidence from psychology and empirical finance suggests that people place greater weight on information gained through personal experience. First described by Tversky and Kahneman (1974) as availability bias, this finding has gained considerable support in recent empirical finance literature. For example, Malmendier and Nagel (2011) show that the predictions by investors who have experienced low stock market returns throughout their lives are more cautious. Graham and Harvey (2001) find that previous market performance positively correlates with the average CFO’s one-year and ten-year perceived risk premium.

A key feature of availability bias is its resultant heterogeneity. As agents differ in age and experience, they are not affected by the same experiences in the same way. Older investors have a longer experience history, and are therefore biased by all their observations. In contrast, younger investors have a shorter span of experience and are more responsive to new observations, as indicated empirically by Malmendier and Nagel (2013) and Vissing-Jorgensen (2003). The resulting differences in perception prompt disagreement among investors and are a natural source of heterogeneity. In financial markets, this disagreement influences individual trading behavior and aggregate market data. Although its appearance is empirically very well documented, however, existing models of financial markets disregard this source of heterogeneity.

In this paper, I introduce an overlapping generations equilibrium model in which individuals overvalue personal experience. The individuals’ market entrance determines which past information was directly observed by the individuals, and therefore especially anchored in the individuals’ mind. The base-case model distinguishes between two groups: young investors in their initial period of exposure to financial markets and adult investors who were in the market during the prior period. In the case of availability bias, this diversity in the experience background leads to a difference in the reaction to current and past news and to heterogeneity across agents. Agents can observe this difference in opinion through the deviation of the realized price from the perceived rational price. However, there is only one public signal in the market, which everyone can observe. Thus, the agents reasonably believe in noise-trading and are willing to trade.

This model and its multi-generation extension replicate and link empirical findings and infer new predictions. In particular, the model provides an explanation for the pattern of overreaction and correction, interaction between volatility and trading volume, and investor-specific trading behavior.

The model connects the overreaction and reversal pattern to the empirical findings of Greenwood and Shleifer (2014), who show that investors’ expectations negatively correlate to model-based expected returns. When a new signal arises, all agents in the market experience it. Therefore, the impact on prices is exaggerated – leading to overreaction. When investors exit the market after some time or gain experience, this impact fades – leading to reversal. Thus, when the average investor’s expectations are high, the prices are (too) high and will mean-revert over time. This is consistent with the findings of Greenwood and Shleifer (2014).

Extreme public signals induce significant changes in the investors’ expectations and escalate disagreement among them. Therefore, volatility and trading volume correlate positively. Further, my model supports the empirical finding that returns on high-volume days tend to reverse, as e.g. described in Gallant et al. (1992) and Campbell et al. (1993). On high-volume trading days, the price changes are more likely to be caused by an initial
overreaction than by a reversal. The overreaction fades in the following time and returns reverse.

The multi-generation extension of the model also provides explanations for investor-specific findings. Younger (i.e., less-experienced) investors are more prone to overreact to new information because their experiential data sample is small. Therefore, they change their portfolio more drastically than older investors and tend to invest more in stock markets when recent signals have been positive. Because prices mean-revert, their performance is low on average. In sum, young investors tend to buy high and sell low, trade frequently, and earn lower returns. This is consistent with the equivalent empirical findings of Barber and Odean (2001).

Extensions of the model provide intuition into further features of financial markets. Weighting negative outcomes stronger than positive outcomes produces a negative skewness and higher kurtosis. A multiple-asset extension together with learning from portfolio performance links assets not only through correlation but also through the degree of learning. A model extension in which investors can consult advisors after poor dividend performance leads to a time-varying rationality in investor’s behavior.

Depending on the interpretation of an investor’s life-cycle, my model not only offers insights into long-term financial asset pricing phenomena but also provides predictions for intraday trading. Especially for cross-listed stocks, investors enter the market at different times. The model explains high trading volumes around the opening hours of an exchange. It provides the testable hypothesis that the effect of a high trading volume around the opening hours is more pronounced for cross-listed stocks than single-listed stocks. The model also enables predictions about which investors are sellers and buyers in a transaction. On days featuring recent positive information, market incumbents are more affected by this information than entering investors. Therefore, the entering investors sell their stock to the incumbents. On days with recent bad news, trading behavior is predicted to exhibit the opposite pattern.

The inclusion of availability bias, or in other words learning from experiences, is recent in the modeling of financial markets. This paper contributes to the recent literature by including the availability bias in an overlapping generations model. In a recent supplemental working paper Collin-Dufresne et al. (2014) introduce the availability bias in an overlapping generations production economy with Epstein-Zin preferences. Focusing on pricing effects, they find e.g. time-varying over- and undervaluation and a resulting over- and under-investment.

In a related paper, Barberis et al. (2013) construct a model in which investors form beliefs concerning future stock performance by extrapolating from past returns. In their model, an infinitely-lived investor overestimates the importance of recent news. In contrast, in my model, agents react to new observations in different ways, depending on their history of experiences. Therefore, in addition to general predictions with respect to prices and volatilities, I obtain predictions regarding individual trading behavior.

Hirshleifer and Yu (2013), Altı and Tetlock (2014), Barberis and Shleifer (2003), and Fuster et al. (2012) include the extrapolation of past state variables (either returns or fundamentals) in their models. However, in none of these models, investors differ with respect to their past learning experience. Therefore, my overlapping generations model can explain investor-specific trading behavior and makes predictions in environments in which the market entrance and exit of investors plays an important role.

My model contributes to the literature that deals with differences in beliefs. Among others Bhamra and Uppal (2014), Schmedders and Kubler (2012), and Garleanu and Panageas

In contrast to overconfidence and other branches of the behavioral finance literature (e.g. Dumas et al. (2009), Daniel et al. (1998), Daniel et al. (2001), Gervais and Odean (2001), Odean (1998), and Scheinkman and Xiong (2003)), in my model, investors need not believe in someone having the informational advantage for beating the market. They (only) attempt to learn about the model’s parameters, thereby committing availability bias. Moreover, my model does not rely on private information, which is not observed by empiricists. Information becomes heterogeneous through investors’ interpretations and their perceptions.

Finally, in contrast to several streams of the rational learning literature, with availability bias the effect of learning does not fade. Learning remains important, even after more than 70 years of market data have been observed.

This paper is organized as follows: Section 2 provides the general intuition in a two-generations model. Section 3 generalizes the model to a multi-generations setup. Section 4 shows the implications and effects of biased learning through simulations. Section 5 extends the model and demonstrates consistency with further empirical findings and Section 6 concludes.

2. Two-generations Economy with Availability Bias

The following model introduces the differences in the availability of information in an overlapping generations model. First, I provide the underlying intuition of the model in a two-generations setup. Then, I generalize my approach to a multi-generations model. This extension is a better representation of the real world and, therefore, also explains more anomalies than the two-generations model. However, the driving mechanisms are better illustrated in the two-generations version.

2.1 INVESTORS AND ASSETS

Consider a discrete-time financial market with one risky and one riskless asset. The latter pays the risk-free rate \( r_f \) in each period \( t = 1, \ldots, \infty \) and is perfectly elastic in supply. The risky asset is available in unit supply and trades in a frictionless capital market. It can be interpreted as the market portfolio. Dividends \( d_t \) paid by the risky asset in each period are normally distributed with mean \( \delta \) and variance \( \Sigma \)

\[
d_t \sim N(\delta, \Sigma).
\]  

(1)

Investors live for three periods. During each period, a new generation enters the market and chooses its initial portfolio. The initial generation becomes adult and changes its portfolio, considering previous periods experiences. Finally, the previous adult generation retires.
For simplicity, I assume a constant population with equally many first period, second period, and retired investors in the market. Only the first two generations actively trade because retired investors do not buy assets for the next period. Thus, in the remainder of this paper I ignore the retired generation. The generation entering the market and the generation that traded during the prior period are called Initial generation and Adult generation, respectively. Thus, the Initial and the Adult investors represent half of the active population. The overlapping generations and an individual’s life are illustrated in Figure 1.

2.2 BELIEFS ABOUT DIVIDENDS

Investors’ expectations regarding future dividends depend on both their experience in receiving dividends while being in the market and dividends that occurred prior to their market entrance. However, and this is the key assumption, the dividends that investors personally experience have a greater influence over their perceptions of future dividends. To quantify that experience and how dividends have been observable when trade is taking place and prices are determined, I define whether period $t$ dividends appear before or after price determination. I assume that dividends are first paid and then prices are formed. Thus, $d_t$ is known when prices are determined, and period $t$ dividends belong to those who bought shares in period $t - 1$.

The initial generation has just entered the financial market and has not personally observed prior dividends. Therefore, the initial generation weights all historical dividends equally and forms rational expectations regarding the mean dividend. In the remainder of this paper, I indicate subjective expectations using the first letter of the generation in which they are formed as a superscript

$$E_t^i [d_{t+1}] = \bar{d}_t.$$  \hfill (2)
This assumption is equivalent to stating that investors have correct priors when entering the market. However, this assumption is not crucial because, for more generations, the initial investor’s perception loses importance.

The adult generation differs from the initial generation in that it has experienced the payment of the period $t$ dividend. Therefore, the adult generation places special weight on this experience. To capture the availability bias, I assume that the adult generation’s dividend expectations equal the initial generation’s dividend expectations, except that the adult generation over-weights the latest dividend observation by a constant factor $m$

$$E_t^a[d_{t+1}] = \frac{d_t + m d_t}{1 + m}.$$  

(3)

For $m = 0$, the adult generation’s expectations are rational. For $m > 0$, the only deviation from rationality is the over-weighting of the previous dividend, which occurred after its members market entrance.

For simplicity, I assume, as in Lewellen and Shanken (2002), that the variance $\Sigma$ of the dividend process is common knowledge and equals

$$Var_t^a(d_{t+1}) = Var_t^a(d_{t+1}) = \frac{t + 1}{t} \Sigma.$$  

(4)

2.3 OPTIMAL PORTFOLIO CHOICES AND PRICES

In the absence of interim consumption, investors maximize their CARA utility out of terminal wealth, $\omega_t$ by choosing the optimal portfolio $x_t$. The initial and adult generation differ in two important aspects. First, the horizon until retirement is nearer for the adult generation (one period left) than for the initial generation (two periods left). Second, individuals from the adult generation emphasize the most recent observation over observations before they entered the market.

Since the adult generation has a one-period investment horizon, its investors maximize their next-period utility out of wealth, given their current expectations (indicated by the operator $E_t^a$)

$$\max_{x_t^a} E_t^a \left[ -\exp \left( -2\gamma w_{t+1}^r(x_t^a) \right) \right].$$  

(5)

Terminal wealth equals

$$w_{t+1}^r = x_t^a \left( p_{t+1} + d_{t+1} - (1 + r_f) \cdot p_t \right) + (1 + r_f) w_t^a,$$

(6)

where $w_t^a$ denotes the period $t$ wealth of the adult investors, and $w_{t+1}^r$ denotes the period $t + 1$ wealth of the retired generation. $x_t^a$ denotes the number of shares bought. This optimization problem results in the standard optimal portfolio share

$$x_t^a = \frac{1}{2\gamma Var_t^a(d_{t+1} + p_{t+1})} \cdot (E_t^a [p_{t+1} + d_{t+1}] - (1 + r_f) p_t).$$  

(7)

This equation specifies the adult generation’s investment given its perception of the price and dividend process. The adult generation’s perception of the dividend stream has already
been specified in Equations (3) and (4). However, in contrast to the dividend process, the price process depends on the perception of both generations and, therefore, will be treated later.

Since the initial generation’s retirement is two periods distant, it maximizes its wealth for two periods from now as a function of this and next period’s portfolio choice

\[
\max_{x^i_t, x^{a}_{t+1}} E^i_t \left[ -\exp \left(-2\gamma w^i_{t+2}(x^i_t, x^{a}_{t+1}) \right) \right].
\]

Terminal wealth is determined by

\[
w^i_{t+2} = x^a_{t+2} \left((p^i_{t+2} + d^i_{t+2}) - (1 + r_f)p^i_{t+1}\right)
+ (1 + r_f) \left((1 + r_f)w^i_t + x^i_t \left((p^i_{t+1} + d^i_{t+1}) - (1 + r_f)p^i_t\right)\right).
\]

I assume that the initial generation does not consider the influence of future portfolio choices and maximizes its utility out of next period wealth, accreted by the risk-free rate. The assumption is made for the perspicuity of the model. Appendix 1 contains the computations for non-myopic investors. In the myopic approach, the optimal portfolio choice at time \(t\) equals

\[
x^i_t = \frac{E^i_t [p^i_{t+1} + d^i_{t+1}] - (1 + r_f)p^i_t}{2\gamma(1 + r_f)\cdot \text{Var}^i_t (p^i_{t+1} + d^i_{t+1})}.
\]

This equation specifies the initial generation’s investment given its perception of the dividend and price process. Having derived general expressions of demands for the risky asset by both generations, I now calculate prices by applying the market-clearing condition

\[
\frac{1}{2}x^a_t + \frac{1}{2}x^i_t = 1.
\]

The resulting price process \(p_t\) has the form

\[
p_t = \left(\frac{1 + r_f}{4\gamma \text{Var}^a_t (d^a_{t+1} + p^a_{t+1})} + \frac{1}{4\gamma \text{Var}^i_t (d^i_{t+1} + p^i_{t+1})}\right)^{-1} - 1.
\]

This expression shows that the price depends on both generations’ subjective perceptions of the dividend and price process. Because future prices are endogenously determined, investors’ price expectations depend not only on their expectations about future dividends but also on their perceptions of other investors’ behavior.

2.4 BELIEFS ABOUT PRICES AND REALIZED PRICES

Investors infer the rational price by studying underlying market mechanisms. Doing so results in a price process structurally similar to that described in Equation (12). However,
each generation estimates the future price process without knowing the other generation’s perceptions. There is only one source of universally available information in the model. Thus, I assume that investors believe the conclusions they draw from their observations to be correct, and that everyone who acts rationally must have drawn the same conclusions. Therefore, investors replace other investors’ expectations with their own when assessing their perceived rational prices.

Because generations’ dividend expectations differ, their price expectations vary. Their differing expectations are expressed in market-established asset prices, which deviate from subjectively expected prices. Under the assumption that investors trust their own expectations, they attribute the deviation in observed prices from subjectively expected prices to the actions of noise traders. Noise traders’ perceived influence on price is denoted by \( \epsilon \).

To distinguish forces that actually drive the market and determine prices (i.e., individual expectations and the market-clearing mechanism) from individual perceptions of those forces, I introduce a new sign \( B \) or \( B^a \) (in which \( B \) denotes belief, and the superscript denotes the respective generation), which refers to the investors’ perception of the price process. The initial generation’s belief is

\[
B^i_t (p_t) = \frac{1}{1 + r_f} E^i_t [p_{t+1} + d_{t+1}] - \frac{4\gamma}{2 + r_f} Var^i_t (p_{t+1} + d_{t+1}) + \epsilon^i_t.
\]

The initial generation has replaced the adult generation’s expectations with its own. The adult generation’s subjective rational prices are determined accordingly

\[
B^a_t (p_t) = \frac{1}{1 + r_f} E^a_t [p_{t+1} + d_{t+1}] - \frac{4\gamma}{2 + r_f} Var^a_t (p_{t+1} + d_{t+1}) + \epsilon^a_t.
\]

The additional \( \epsilon \)-term in Equation (13) and Equation (14) describes the noise perceived in prices. For now, I assume and will later show that the perceived influence of noise traders’ trading volume on price realization, meaning the deviation of realized prices from subjectively rational prices, is normally distributed with a mean of zero and variance \( \Sigma_N \)

\[
\epsilon_t \sim N(0, \Sigma_N).
\]

As with the dividend process, I assume that before entering the market, investors are certain about the size of the noise-trader variance and do not update their beliefs thereafter.

There are two reasons why the sum of the price plus dividends expected in the next period can deviate from the perspective of the initial generation.\(^1\) The first reason is rational. It is a variation in the dividends, which is captured by the variance term \( \Sigma \). The total variance in the next period prices plus dividends attributable to this rational effect (from the perspective of investors at time \( t \)) is \( \hat{\Sigma}_{t+1} = (1 + \frac{1}{r_f(t+1)})^2 \cdot \frac{1}{2 + r_f} \Sigma \). The second reason is the perceived noise traders’ activity, which leads to a variation in price according to \( \Sigma_N \). Thus, the total perceived variance in the future price plus dividend equals

\[
Var^a_t (p_{t+1} + d_{t+1}) = Var^i_t (p_{t+1} + d_{t+1}) = \Sigma_N + \hat{\Sigma}_{t+1}.
\]

\(^1\) The adult generation can be treated in an analogous way.
Given investors’ belief in their own rationality, they expect the next-period price to equal the current perceived rational price (except for smaller effects of rational learning). This perceived rational price is the component in the price which is not attributed to distortions by noise traders. Applying this insight to the price process perceived by the initial generation, as given by equation (13), results in

$$E^t_i [p_{t+1}] = \frac{1}{r_f} \bar{d}_t - 4 \gamma (1 + r_f) \left( \frac{1}{2 + r_f} \right) (z(t + 1) \Sigma + \frac{1}{r_f} \Sigma_N). \quad (17)$$

The term $z(t)$ describes the rational learning effect on price uncertainty (compare Lewellen and Shanken (2002)) and equals $z(t) = \sum_{k=1}^{\infty} \frac{1}{(1 + r_f)^k} \left( 1 + \frac{1}{r_f(t+k)} \right)^{1+\gamma}$. For mature markets, it can be approximated by $\lim_{t \to \infty} z(t) = \frac{1}{r_f}$.

The adult generation’s perception of the effect of noise trading on prices differs from that of the initial generation. Performing calculations equivalent to those for the initial generation, I obtain the expected price of the adult generation as

$$E^a_i [p_{t+1}] = \frac{1}{r_f} \left( \bar{d}_t + m d_t \right) \left( 1 + r_f \right) \left( 1 + m \right) - 4 \gamma (1 + r_f) \left( \frac{1}{2 + r_f} \right) (z(t + 1) \Sigma + \frac{1}{r_f} \Sigma_N). \quad (18)$$

Inserting these results into Equation (12), I receive the price

$$p_t = \frac{(1 + r_f)}{r_f (2 + r_f)} \left( \frac{\bar{d}_t}{1 + m} + \frac{(\bar{d}_t + m d_t)}{1 + m} - 4 \gamma (r_f z(t) \Sigma + \Sigma_N) \right). \quad (19)$$

The price process varies over time with the dividend $d_t$. The first reason for this result is the variation of the mean dividend $\bar{d}_t$. This effect, although rational, diminishes over time and is negligible in mature markets. The second reason for the variation in prices results from the availability bias, represented by the term $m d_t$. For $m = 0$, the model describes the rational pricing mechanisms in mature markets. For $m > 0$, the period $t$ dividend overly influences the price (through the adult generation), thereby creating excess volatility. Because all investors encounter this behavioral bias after entering the market, its effect persists over time. Thus, even in mature markets, availability bias remains important.

2.5 FIRST RESULTS

The two-generations base-case model already provides an explanation for several market anomalies. Many of them directly or indirectly relate to the overreaction and reversal pattern generated by the availability bias. Investors overweight recent observations and invest accordingly, driving overreaction in prices. After some time, this effect fades, as investors who have observed the most recent dividend exit the market or acquire experience. The first channel of market exit is already incorporated in the two-generations model. However, individual experiential learning can be studied only in a multi-generation extension of the model. In the following, I explain the results provided by the two-generations model and the potential of the multi-generation extension.

First, volatility in stock-market returns is higher as prices react more to recent news than in the rational case. This effect is monotone in the availability bias parameter $m$. 
illustrated in Table I. Second, investors trade more throughout their lives (compare Table II.). This can be explained by investors revising their perceptions frequently, especially relative to the representative investor. However, the base-case model cannot predict which generations trade the most because there is only one chronological point at which investors change their portfolio.

Another explanation provided by the two-generations model pertains to volatility clustering. In the two-generations model, an extreme dividend overly influences prices because it has been observed by half of the population. These investors exit the market in the next period. Therefore, the price impact of that dividend then disappears. Thus, the two-generations model captures very short-term volatility clustering. For multiple generations, the fading-out takes longer, resulting in longer clusters in volatility.

The nearly immediate exit from the market after the first dividend observation leads to some phenomena being absent in a two-generations setup. One is the positive correlation between trading volume and volatility. In the two-generations model, the correlation between trading volume and volatility is almost zero: In the first trading period, entering investors have not observed a dividend and therefore trade against recent news. In the second period, they are affected by availability bias and trade in the direction of the previous dividend. Thus, when an extremely low dividend is followed by an extremely high dividend, the absolute return is very high, but the trading volume is low. In contrast, the correlation will be positive in the multi-generational extension of the model (four or more generations), as extreme news generates a greater disagreement among investors and significant changes in prices.

3. Multi-generation Economy with Availability Bias

In the two-generations model, the investors exit the market shortly after learning about the dividends through personal experience. However, in practice, investors act on the market for longer periods and have more time to observe data and revise their initial perceptions. Thus, the influence of previous dividends remains in the market for a longer period. Therefore, having illustrated the basic idea with a two-generations model, I advance to a multi-generations model with more than two investors. This extended model is afterward used to show the predictions made.

3.1 BELIEFS ABOUT DIVIDENDS

In a \( n \) generations model, investors live for \( n + 1 \) periods. Because the nomenclature must now distinguish more than two generations, I enumerate each generation, starting with the initial generation (agent 1: \( a_1 \)) and ending with the oldest (agent n: \( a_n \)). In the multi-generations model, investors gain experience with the dividend process for longer than one period. Therefore, it is necessary to specify how they form expectations during the subsequent periods.

As in the two-generations model, the initial generation entering the market has rational expectations

\[
E^{a_1}_t [d_{t+1}] = d_t.
\]
However, this assumption is not crucial because, for more generations, the initial investor’s perception loses importance. The expectations of the second-youngest generation, which has been in the market for one period, correspond to those of the adult individuals in the two-generations model, because both have the same experience background. I assume that the older generations, which have been in the market for more than one period, place a greater weight on the average observed dividend. Thus, the expectations of the older generations equal

$$E^a_i [d_{t+1}] = \frac{d_2 + m \cdot d_{e,t}}{1 + m} \quad \text{for } n \geq i \geq 2. \quad (21)$$

In this notation, $\bar{d}_{e,t}$ is the mean observed dividend after the market entrance. Thus, the mean dividend since the second-youngest generation entered the market is $\bar{d}_{a,2}^e = d_t$. For the third-youngest generation, it is $\bar{d}_{a,3}^e = \frac{1}{2}(d_t + d_{t-1})$, and for the fourth-youngest generation $\bar{d}_{a,4}^e = \frac{1}{3}(d_t + d_{t-1} + d_{t-2})$, and so on. Thus, for the $k$th-youngest generation ($k \geq 2$), I obtain a mean observed dividend since market entrance of

$$\bar{d}_{a,k}^e = \frac{1}{k-1} \sum_{i=2}^{k} d_{t-i+2}. \quad (22)$$

In this specification, a generation overweights all previously experienced dividends equally. However, this assumption is not crucial, and other weighting functions can be implemented easily.

In the above specification agents enter the market with rational priors and then start learning from experience. Agents become irrational after their first dividend experience, as their bias term is based on few observations. As agents age and progressively gain experience, the bias averages out. Thus, the old generations become progressively more rational. To distinguish between generations, I call the first initial. Agents with only a few years of market experience (excluding the initial generation) are called young. Finally, old agents are in the later phase of their lifecycle.

As in the two-generations model, I assume that the volatility of the dividends is known

$$\text{Var}^{a_i} (d_{t+1}) = \Sigma \quad \text{for } 1 \leq i \leq n. \quad (23)$$

### 3.2 Portfolio Choice and Prices

The next step is to determine the optimal holdings of the risky asset, which depend on each investor’s expectations. The initial generation, which has the same expectations as the initial generation in the two-generations model, now has an investment horizon of $n$ periods. The second-youngest generation, which has the same expectations as the adult generation in the previous model, has a remaining investment horizon of $n - 1$ periods. As in the two-period model, investors do not consider the influence of their future portfolio choice and maximize utility out of next period wealth, accreted by the risk-free rate.\(^2\) The resulting optimal quantity of shares held by the generations equals

\(^2\) This assumption is made for the perspicuity of the model. Calculations assuming non-myopic investors appear in Appendix 1.
The market-clearing condition generalizes to

\[ 1 = \frac{1}{n} \sum_{j=1}^{n} x_t^j. \]  

(25)

I choose the weighted average formulation because it is insensitive to the number of generations. The resulting price process \( p_t \) has the form

\[ p_t = G \left( \left( \sum_{i=1}^{n} (H_i \cdot E^{a_i} [p_{t+1} + d_{t+1}]) \right) - 1 \right). \]  

(26)

This price process is still a function of individual expectations. However, unlike dividends, future prices are determined endogenously. Therefore, the subjective price expectations depend on the individual’s assessment of other investors’ behavior.

3.3 BELIEFS ABOUT PRICES AND REALIZED PRICES

As before, investors believe that they have drawn correct conclusions out of the observed dividends. Consequently, they consider differences in their investment horizon but not differences of opinion. When inferring about the price process, each investor believes that all others share his/her opinion, except for some (perceived) noise traders, who distort prices. The belief about the price process, thus, equals

\[ B^{a_j}(p_t) = E^{a_j} [p_{t+1} + d_{t+1}] - 2n^\gamma \frac{r_f}{1 + r_f} \left( \frac{1 + r_f}{1 + r_f} \right)^{n-1} Var_{a_j}^i (d_{t+1} + p_{t+1}) + \epsilon_t^j. \]  

(27)

The final step in determining equilibrium prices is to insert investors’ expectations into the pricing Equation (26). The resulting price at time \( t \) equals

\[ p_t = a \frac{m}{1 + m} \sum_{i=0}^{n-2} d_t - b_i + c \cdot \frac{1}{1 + m} d_t - f \cdot (r_f z(t) \Sigma + \Sigma_N). \]  

(28)

This equation identifies two effects that become apparent later in the simulation. First, the longer investors live, the longer the extraordinary effect of a past dividend persists. Second, as more generations arrive in the market, the initial overreaction diminishes.

\[ a = \left( \frac{1 + r_f}{1 + r_f} \right)^{n-1}, \quad b_i = \left( \frac{1}{1 + r_f} \right)^{n-1}, \quad c = \left( \frac{m}{1 + r_f} \right)^{n-1} + \frac{1}{r_f}, \]  

\[ f = \frac{2n^\gamma \sum_{i=0}^{n-1} d_{t+1} p_{t+1} (1 + r_f) \Sigma + \Sigma_N}{(1 + r_f)^{n-1}}. \]
3.4 TRADING VOLUME AND VOLATILITY

The model is consistent with several empirical findings about volatility and trading volume. Therefore, I now derive the corresponding analytic expressions.

The variance in prices is best calculated from Equation (28). I obtain

\[ \text{Var}(p_t) = \frac{t-n+1}{t^2} \left( L_1 + \frac{1}{r_f(1+m)} \right)^2 \Sigma + \sum_{i=0}^{n-2} \left( L_1 + \frac{1}{r_f(1+m)} + L_2 M_i \right)^2 \Sigma \frac{t}{t^2}. \]  

(29)

This variance is larger than the price volatility under full rationality. In the latter case \((m = 0)\), the variance equals

\[ \text{Var}^{m=0}(p_t) = \frac{1}{r_f^2} \Sigma. \]  

(30)

Moreover, it is apparent from Equation (29) that the variance caused by perceived noise traders must be of order

\[ \Sigma_N \approx \sum_{i=0}^{n-2} \left( \frac{(1+r_f)^{(n-1)}}{(1+r_f)^{n-1}} \frac{m}{1+m} \left( \sum_{j=i+2}^{n} \frac{1}{(1+r_f)^{(n-j)}} \right) \right)^2 \Sigma. \]  

(31)

I ignore the randomness in \(d_t\) because, in the strict sense, it is not noise and converges to zero for mature markets \((t \to \infty)\).

An investor’s trading activity is defined as the change in his/her portfolio. When investors enter the market, they select their initial portfolio, maximizing their expected utility. One period later, the investors belong to the second-youngest generation and have the opportunity to change their portfolio. The situation repeats after the second period, when investors become the third-youngest-generation. Thus, an investor’s trading volume after being in the market for \(j\) periods \((TV^j_t)\) can be expressed as

\[ TV^j_t = x_{a, j+1}^{t+1} - x_{a, j}^t. \]  

(32)

Using the expressions for the portfolio holdings leads to

\[ TV^j_t = \frac{1}{2 \gamma(1+r_f)^{n-j}} \frac{(1+r_f)E^{(n+1)}_t [p_{t+1} + d_{t+1}] - E^{(n+1)}_{t+1} [p_{t+1} + d_{t+1}]}{(\Sigma_{t+2} + \Sigma_N)} \]  

(33)

\[ - \frac{1}{2 \gamma(1+r_f)^{n-j-1}} \frac{(1+r_f)p_{t+1}}{(\Sigma_{t+2} + \Sigma_N)} - \frac{p_t}{(\Sigma_{t+1} + \Sigma_N)} \cdot \]

The trading volume of an investor is influenced by the change in the investor’s expectation due to the observation of a new dividend (first line). The representative investor’s reaction is reflected in the price change (second line). The difference between the two generates trade.

5 The coefficients are \(L_1 = \frac{1}{(1+r_f)^{n-1}} \cdot \frac{m}{1+m}\), \(L_2 = \frac{(1+r_f)^{(n-1)}}{(1+r_f)^{n-1}} \cdot \frac{m}{1+m} \cdot t\), and \(M_i = \sum_{j=i+2}^{n} \frac{1}{(1+r_f)^{(n-j)}}\).
Two factors influence the intensity of investor $j$’s trading activity at time $t$. First, large deviations of the observed dividend from the average generate a high trading volume. Then, investors disagree about the relevance of the signal and its influence on future expectations. As this disagreement is not yet reflected in the asset holdings, it prompts trading. The deviations of prior dividends from the mean are already included in the portfolio choice. However, the fading of the disagreement also generates trade but to a lower extent. The second influential factor is the investor’s generational cohort. Young investors trade the most because they change perceptions most relative to the average investor.

4. Predictions and Effects of Biased Learning

This section shows the predictions described in the introduction with the help of simulations. It focuses on long-term asset pricing phenomena, which can be separated into pricing phenomena (e.g., overreaction and reversal), volatility patterns (excess volatility, volatility clustering, etc.), and connections between trading volume and volatility. Finally, I investigate investor-specific predictions, finding that young investors trade more intensively than older investors and obtain lower returns.

For the simulation, I choose parameters that best match empirical findings. However, results in all cases, especially the directionality of the effects, are insensitive to the specific parameter values chosen. If not stated otherwise, the dividend process has a mean of 0.04 and a variance of $\Sigma = (0.01)^2$. Because my model does not consider inflation, I choose a real risk-free rate of $r_f = 0.01$. I focus on the effect of non-Bayesian learning through superseding $z(t)$ and $\bar{\Sigma}$ by the limiting values $1/r_f$ and $\Sigma$, respectively. The absolute risk-aversion parameter $\gamma$ is calibrated such that I obtain a mean price of 1 for each number of generations $n$.

4.1 PRICES OVERREACT AND REVERT

This section offers an intuition about why prices over-react and revert. Several factors, including the number of generations, influence the shape of that pattern.

In the two-generations model prices correlated almost perfectly with the dividend stream. However, this correlation attenuates beyond two generations, when the effects of availability bias of two (in a three-generations model) or more dividend observations overlay each other. To calculate the mean effect of one extreme dividend observation on the price process, I simulate $p = 1000$ independent price paths. Only at one point in time (after 100 periods), all paths have one extreme dividend (two standard deviations below the mean). This separates the effect of one dividend realization on the price process. All other effects cancel out on average. I iterate this process for two, three, four, five, six, and eight generations. Figure 2 shows the simulated price paths.

In the case of availability bias, the price overreacts in the direction of the dividend deviation and rebounds thereafter. The size of the overreaction attenuates across the

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6 As reference papers I choose among others, Campbell et al. (1993), Shiller (1981), Bansal and Yaron (2004), and Goyal and Welch (2003).

7 I choose $\gamma$ in the basic calculations based on the number of generations between 1.8865 and 2.8770.
number of simulated generations. The length of the correction is longer for models with more generations.

While the overreaction in the period following the dividend stems from an overestimation of its relevance, the attenuation is caused by two different effects. First, one experienced generation leaves and one inexperienced, unbiased generation enters the market each period. Thus, the effect of a period $t$ dividend evaporates when the old generation exits the market. The second correcting effect can be attributed to the observation of new dividends in subsequent periods. These new dividends reduce the effect of the period $t$ dividend on the mean experienced dividend ($\overline{d}_{e,t}$). The relative importance of these two effects depends on the length of an individual’s trading life. For models with a few generations, a high percentage of the total population exits the market each period. In these models, investors have left the market before they could learn about the dividend stream through experience. In multi-generations models, the fraction of investors exiting the market is significantly smaller. As a result, most investors observe the subsequent dividends and adjust their beliefs and bias. Thus, immediately following the overreaction, the correction is greater compared to later periods. Although the effect diminishes significantly, the dividend observation ceases to overly influence the market only when the last investor who has observed the dividend retires.

4.2 YOUNG INVESTORS TRADE MOST AND OBTAIN LOWER RETURNS

The youngest generation trades the most in this model (Table III.). In other words, the youngest generation disagrees the most with the representative investor’s interpretation of new observations. This finding is consistent with the empirical results of Barber and Odean (2001), who state that young investors trade more actively and obtain lower returns.

Trading volume declines with age in the two-, three-, and four-generations models. In contrast, the oldest investors resume trading in models featuring more than four generations. They trade less than the youngest investors but still more than the median generation because older generations become increasingly insensitive to new dividend observations. Thus, they disagree with the representative investor, who places intermediate importance on the new observation. Because a new, rational generation enters the market every period, the representative investor is drawn back toward more rational attitudes. Consequently, the youngest generations trade the most. For the same reason, a market with an influx of rational investors leads to an even higher trading volume among young investors and reduces the trading volume of older investors.

Besides trading more, young investors also earn lower returns. Because their investment strategies are the most pro-cyclical, they suffer the most from the mean reversion in prices. The average return increases with age, as illustrated in Table IV. The exception is the first generation, because it is assumed to enter the market with rational expectations. Under this assumption, the investment performance of the first generation surpasses that of the second generation. This initial assumption also influences the results of the two-generations model. However, the pattern becomes more obvious as the number of generations increases: young investors tend to buy high, sell low, trade frequently, and obtain lower returns. This is consistent with the empirical findings of e.g. Barber and Odean (2001).
4.3 VOLATILITY AND TRADING VOLUME INTERACTION

Availability bias leads to a positive correlation between volatility and trading volume, as documented e.g. in Karpoff (1987) and Lobato and Velasco (2000). Following an extreme signal, investors disagree the most with respect to its correct interpretation, accentuating trading volume. All agents overreact at the same time. This generates overreaction in prices and volatility in returns. As both effects occur simultaneously, the correlation between volume and volatility becomes positive. However, another effect works in the opposite direction. It results from young investors’ immediate switch from rational to availability-biased behavior (compare Section 2.5). This effect is influential only in models with few generations. In practice, investors likely observe more than two dividends in their lifetime. This reality favors the model with more generations in which the correlation is positive. Table VII. illustrates the results.

The return distribution strongly depends on the number of generations and the availability bias parameter (compare Figure 3). Returns vary more with higher availability bias parameters, but this effect diminishes as the number of generations increases. Because the most recent dividends are experienced by almost everyone, they overly influence current prices. This prompts an increase in volatility (compare Table V.). With my current model, an assumed dividend variance of \((0.01)^2\) and availability bias parameters between 0.2 and 0.3, I obtain standard deviations in returns of 0.1 to 0.15. Assuming that in actual practice, dividends are smoothed compared to earnings, I obtain a high return volatility at even lower availability bias levels. For literature on dividend smoothing, see Lintner (1956).

Apart from a higher variance, the distribution has fatter tails with a kurtosis exceeding 3. However, the effect is not large in this basic model. Empirical evidence indicates that investors remember extreme events – especially large negative shocks – more strongly than normal events. Under this modification, the model leads to negatively skewed returns with a higher kurtosis (cf. Section 5).

Absolute return deviations show significant autocorrelation in few-generations models (compare Table VI.). This can be attributed to price changes around the observation of an extreme dividend. Because the reaction to new observations diminishes with the number of generations, the autocorrelation also decreases. To maintain the effect cleanly investors weight all observed dividends equally in the base-case model. However, it can be assumed that investors weight their latest observations more than their initial observations. Under this modification, the model still maintains a high autocorrelation with a large number of generations (cf. Section 5).

4.4 RETURNS ON HIGH-VOLUME TRADING DATES TEND TO REVERT

Finally, I investigate the interactions between volatility and direction of price movements. The model replicates the empirical finding of e.g. Gallant et al. (1992) and Campbell et al. (1993) that returns on high-volume trading days tend to revert. I define high-volume trading days as those in which the volume reaches the upper decile. Table VIII. shows the percentage of negatively correlated returns on subsequent days. I compare the percentage on high-volume trading days with the unconditional percentage of negatively correlated returns.

The unconditional percentage of negatively correlated returns decreases with the number of generations. For more generations, the initial overreaction is lower, and the fade-out
persists longer. Returns are positively correlated during the fade-out phase. Therefore, the unconditional percentage of negatively correlated returns declines.

The percentage of negatively correlated returns on high-volume trading days exceeds the unconditional percentage of negatively correlated returns. The intuition behind this finding is that on high-volume trading days, price changes are more likely to be caused by an initial overreaction than by a reversal. This effect is hump-shaped with respect to the number of generations. The swell in the hump from two to four generations occurs because, for few-generations models, the correction is (almost) as immediate as the overreaction. This causes a high trading volume in both parts. The decreasing part of the hump from four to eight generations is explained in a manner similar to the explanation for unconditional probability. For exceptionally large deviations of the dividend from its mean, the model also predicts a high trading volume in the early stages of the reversion process. As this stage persists longer, the number of positively correlated returns increases.

In a portfolio sorted with respect to historical trading volume and returns (compare Table IX.), I observe that returns on high-volume days have special predictive power for future returns. Returns on these days tend to revert. On medium-volume or low-volume trading days, the predictive power diminishes. Moreover, the lower the trading volume, the lower is the tendency that returns revert. Returns show a small tendency for momentum on the lowest-volume days.

5. Extensions, Implications, and Explanations of Further Financial Anomalies

The model in this paper conveys the effect of availability bias in a general framework. It replicates several financial anomalies, including excessive volatility, a positive correlation between trading volume and volatility, and price overreaction and reversal. According to the empirical literature, other factors also affect the perceived importance of information. This section considers the recency of information and the direction of the dividend observation as factors. Additionally, the case of multiple assets in connection with learning from portfolio performance is considered. Another specification examines the effect of agents having the opportunity to consult a financial advisor following bad dividend performance. Moreover, the market entrance of individuals is interpreted in an intraday context. These extensions provide new explanations for empirical findings and infer new predictions.

5.1 STRONGER REACTION TO NEGATIVE NEWS

Empirical studies show that individuals better remember negative than positive events (compare McGraw et al. (2010)). Therefore, in this extension the bias term depends not only on the mean observed dividend after market entrance but especially values negative observations. In this manner the model provides a better fit with the higher moments of the empirical return distribution.

For the implementation, I take a weighted average of the original learning function, which weights all observations equally, and a minimum function, which captures only negative events. The factor $\xi$ determines the relative importance of the two parts. For $\xi = 0$, I obtain the original model, whereas for $\xi \to \infty$ the agents are exclusively biased toward negative news.
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\[
d_{m,t}^k = \frac{1}{\xi - 1} \sum_{i=2}^{k} \left[ \frac{1}{1 + \xi} d_{t-i+2} + \frac{\xi}{1 + \xi} \min(d_{t-i+2}, d_{t-i+2}) \right]. \tag{34}
\]

For the formation of dividend expectations I assume agents take a weighted average of their irrational component \(d_{m,t}^k\) and the rational expectation \(d_t\). It leads to agent \(k\)'s expectation

\[
E_t^a [d_{t+1}] = \frac{d_t + md_{m,t}^k}{1 + m}. \tag{35}
\]

Table X. illustrates the effect of the model parameter \(\xi\) on the higher moments of the return distribution. It shows that the stronger reaction to negative news generates a negative skewness. The skewness decreases in the parameter \(\xi\). For a greater asymmetric reaction to news, the kurtosis increases. Therefore, this extension is consistent with both negative skewness and higher kurtosis, as e.g. documented by Chen et al. (2001) and Jondeau and Rockinger (2012).

5.2 AVAILABILITY THROUGH NEWS

The basic model addresses learning by experience. Other factors such as the recency of news also influence the availability of information. Thus, alongside the mean dividend since market entrance, \(d_{e,t}\), I introduce another factor, \(d_{a,t}\), which is a weighted average of the three most recent time periods. Empirical evidence documents that the latest information is the most readily available. Therefore, I use a weighting scheme that is quadratic in the recency \((v_1 = 9, v_2 = 4, v_3 = 1)\)

\[
d_{a,t} = \frac{v_1 d_t + v_2 d_{t-1} + v_3 d_{t-2}}{v_1 + v_2 + v_3}. \tag{36}
\]

The individual expectations for the initial generation and the other generations equal

\[
E_t^a_i = \frac{(1 + m) \cdot d_t + f \cdot d_{a,t}}{1 + f + m}, \quad \text{and} \quad E_t^a_j = \frac{d_t + m \cdot d_{e,t} + f \cdot d_{a,t}}{1 + f + m} \quad \forall j = 2, \ldots, n. \tag{37}
\]

In this setup, the volatility clustering pattern is stable between models with different numbers of generations (compare Table XI.). The new common component of availability bias loosens the connection between overreaction and experience. Because investors do not disagree about this component, it does not generate trading. Thus, this extension offers the opportunity to disentangle the effects of overreaction and disagreement.

5.3 CONSULTING MONEY MANAGERS

Private investors have the opportunity to consult a financial advisor following bad dividend experience to get a more advanced opinion. The money managers tend to be more familiar with background statistics. Thus, if agents invest through professional managers, their investment becomes more rational. The influence of the generation’s bias on the price process decreases.
In this extension each generation is split into two sub-groups. The first invests its money according to its own knowledge and is affected by the generation’s experience. The second has ceased active trading and invests the money with an external money manager. These managers are able to learn correctly about the dividend distribution. The percentage of self-investing investors in a group depends on the experience of that generation. With every new, bad dividend observation, a percentage of individuals stops trading actively. The percentage of active traders in generation \( i \) at time \( t \) is given by \( q_{i,t} \) and equals

\[
q_{i,t} = 1 - \frac{2}{\pi} \arctan(n_{i,t}),
\]

with \( n_{i,t} \) representing the number of dividend shocks \( (d_t \leq \bar{d}_t - \sqrt{\Sigma}) \) observed by generation \( i \). It results in a time-varying composition of market participants. As described in Malmendier and Nagel (2011), a few periods after a bad dividend shock the self-directed agents consist mainly of young agents (compare Table XII.).

After a dividend shock the number of rational agents in the market increases. Then, the young investors disagree even more with the representative investor (compare Table XIII.) and trade more. The older investors disagree less with the representative investor and trade less. This extension strengthens the consistency with the findings of e.g. Barber and Odean (2001), that young investors trade more also for models with a higher number of generations.

5.4 MULTIPLE ASSETS

In an environment with multiple assets, the composition of an individual portfolio is not necessarily identical to that of the market portfolio. Thus, the two-asset framework is ideal for studying learning situations in which the degree of learning is not completely exogenous. As Glaser and Weber (2009) describe empirically, investors learn from both, recent market performance and recent portfolio performance. Applied to my model, their finding implies that the more the agents invest in one stock relative to the other, the more they learn out of it. Therefore, the following extension considers the case where the special weight that agents place on their dividend observations after market entrance depends on the number of shares bought

\[
E_t^{a_i} \left[ d_{t+1,j} \right] = \frac{d_{t,j} + m \tilde{d}_{a,i}^{a_i}}{1 + m} \quad \forall j \in \{1, 2\}, \quad \forall i \in \{2, ..., n\},
\]

with

\[
\tilde{d}_{a,i}^{a_i} = \sum_{k=2}^{i} \frac{w_{a-1,i}^{a_i-1} d_{t-k+2,j}}{w_{a-1,i}^{a_i-1} + w_{a-1,i}^{a_i-1}} \quad \text{and} \quad w_{a,i}^{a_i} = \frac{1 + \varepsilon \cdot x_{t-1,i}^{a_i-1}}{2 + \varepsilon \cdot (x_{t-1,i}^{a_i-1} + x_{t-1,i}^{a_i-1})}.
\]

The parameter \( \varepsilon \) captures the importance of portfolio experience relative to market experience. For the initial generation, expectations are the same as before and displayed in Equation (20).

In this extension a substitution in assets automatically implies a substitution in learning. Moreover, when considering learning through portfolio experiences, it is sensible to
allow agents to leave an asset aside, and as a result, stop learning about the asset. Thus, I introduce short-selling constraints in this extension.

Figure 4 illustrates the average effect of one extreme dividend observation at the beginning of an investor’s life on its dividend expectations throughout his life cycle. I distinguish between positive and negative dividend surprises, defined as two standard deviations astride the mean. The additional learning from portfolio performance in connection with short-selling constraints induces an asymmetric long-term reaction to news. After observing a negative dividend, agents undervalue the dividend expectations relative to new entering agents. They invest less and learn less from experience as a result. Thus, negative shocks fade slowly. In contrast, positive dividend observations lead agents to a higher investment and to more intensified learning from experience. It decreases the weight of the extreme dividend observation, and the effect of a positive shock on the dividend expectation fades faster.

The split in attention identifies another source of interdependence between the two assets. Attention to the performance of one stock depends on the investment in the other stock. Thus, agents’ learning about one stock is especially pronounced if the other asset is unappealing for investment. Consequently, overreaction to new information fades faster if biased investors are invested only in the respective asset. To illustrate this effect, Figure 5 shows the price path of one stock after a positive dividend surprise. In the first scenario, the second asset also experiences a positive shock and thus becomes equally attractive to young, biased investors. In the second scenario, the other asset has a negative shock and thus becomes less attractive to biased investors. Although diminished by the effect of short-selling constraints, the effect of the dividend observation on prices fades faster in the case of a negative shock to the other asset.

5.5 DIVIDEND POLICY IMPLICATIONS

Availability bias makes the price process more responsive to recent dividend news. Because one-time shocks lead to especially large price fluctuations, managers have an incentive to smooth dividends.

This extension studies the effect of dividend smoothing on the price process. Therefore, I determine the average effect of one extreme dividend observation under different scenarios. In the first scenario, no smoothing is applied, and the dividend shock is made public immediately. In the second scenario, the dividend shock is smoothed over $z > 1$ periods.

Figure 6 shows the effect of dividend smoothing. It plots the results for different lengths of the smoothing period. I observe that dividend smoothing promotes a reduction in the short-term overreaction; i.e., price reactions remain closer to the rational price and prices are less volatile under dividend smoothing. However, it leaves the medium-term and long-term effects almost unchanged, as the effect of the dividend observation averages out under all scenarios. With regard to policy regulation, the model illustrates that investors’ reaction to news should be taken into account when determining the optimal policy regulation.

5.6 NON-CONSTANT POPULATION (INTRADAY TRADING)

In the prior section, the interpretation of the model focused on long-term effects of availability bias. However, when interpreting market entrance on a daily basis, the model provides explanations and predictions for intraday trading. I obtain the effect that the
"population" is not constant, in particular for multi-listed shares. Whenever a new market opens, large numbers of new investors with different experience histories enter. My model predicts that trading volume and volatility are especially high throughout the opening hours of a stock exchange. This prediction holds for the opening market and markets that are already trading.

6. Conclusion

This paper embeds the fact that individuals place greater weight on information gained through personal experience in an overlapping generations equilibrium model. The investors’ market entrance determines the starting point of their experience. Young generations who have initially entered the market have no personal experience with historical dividends. Consequently, new dividends substantially affect their perceptions. In contrast, older generations have more experience, and their perception varies less when new information arises. Because the dividend stream is the only information accessible to everyone, all investors assume that they have drawn the correct conclusions from of their observations. Thus, investors attribute market reactions that vary from their expectations to noise trading and are willing to trade.

This model provides explanations for several long-term asset pricing puzzles and infers new intraday predictions. For example, it offers an intuition about why returns on high-volume trading days generally reverse. Moreover, it replicates a connection between trading volume, volatility, and other asset pricing patterns. A stronger reaction to negative news provides an explanation for a negative skewness and higher kurtosis. My model implies that firms have an incentive to smooth dividends. Finally, it predicts a high trading volume around the opening hours of a stock exchange, an effect especially pronounced for cross-listed stocks.

Unlike other behavioral biases, such as overconfidence and self-attribution bias, the effects of availability bias are relatively unexplored in financial research. Availability bias is a natural source of heterogeneity. This paper demonstrates that including heuristic learning and the resulting heterogeneity in diverse financial models is a promising field of research.
7. Appendix

1. Non-myopic Agents

I solve this model in a learning equilibrium with CARA utility functions and a Gaussian-normal environment. The solution technique is similar to the one used in Albagli (2012). Each agent assumes to be in a rational environment with noise traders. Therefore, they conjecture a similar structure of the price and dividend process as in the rational case. There is one main difference: The deviation of the perceived rational price from the current realized price is attributed to noise traders – meaning the error term in the price process.

Moreover, as $\tilde{\Sigma}$ is decreasing in time, this period’s perceived rational price does not coincide with the next period’s expected price. However, this effect is negligible, even in non-mature markets, and the following derivations are independent of the exact specification of $\tilde{\Sigma}$.

For inferring the period $t$ value of the value function, investors take the expectations of the next period value function. As agents assume to be rational they do not take the
change in their irrational component into account when calculating their current value function. Therefore, investor $j$'s value function at time $t$ equals

$$J(w^j_t, M^j_t, j, t) = E_t^j [J(w^{j+1}_{t+1}, M^{j+1}_{t+1}, j+1, t+1)]$$

(A4)

$$= -\zeta_{j,t} \cdot \exp(-\alpha_{j+1}(1 + r_f)w_t^j - \alpha_{j+1}x_{j,t}A_Q M_t^j - \frac{1}{2} M_t^j \Gamma_j M_t^j) + \frac{1}{2} (\alpha_{j+1}x_{j,t}B_Q + M_t^j \Gamma_j M_t^j) \Xi_j (V_j^{AB} M_t^j + B_Q x_{j,t} \alpha_{j+1})), $$

with

$$V_j^{AB} = A_T V_{j+1}^{a_j} B_m, \quad \quad V_j^{AA} = A_T V_{j+1}^{a_j} A_m, \quad \quad (A5)$$

$$\Xi_j = (\Sigma + B_T V_{j+1}^{a_j} B_m)^{-1}, \quad \quad \zeta_{j,t} = \det(I_3 + 2\Xi_j)^{-\frac{1}{2}}. $$

The term $V_{j+1}^{a_j}$ denotes investor $j$'s perception of his/her next period term $V_{j+1} = V_{j+1}^{a_j}$. The derivation with respect to $x_{j,t}$ leads to

$$x_{j,t} = A_T x_{j+1} \Xi_j V_j^{AB} \alpha_{j+1} \Gamma_j M_t^j, \quad \quad (A6)$$

with $\Gamma_j = B_Q \Xi_j B_Q^T$. The terminal value $\alpha_{N+1} = 2\gamma$ follows from the terminal condition of the value function $J(w^{N+1}_t, M^{N+1}_t, N + 1, t) = \exp(-2\gamma w^{N+1}_t)$. The value function and the terminal condition lead to the recursive definition of the matrix $V_j$ (with $V_{N+1} = 0$).

The remaining calculations follow the structure described in the main paper. Using the individual portfolio weights $x_{j,t}$ and the market-clearing condition, prices at time $t$ can be calculated. Investors do not take the differences in beliefs into account when forming their price expectations. Therefore, they replace other investors' perception by their own when forming their perceived rational price $\bar{p}^a$. 


References

Albagli, E. (2012) Investment horizons and asset prices under asymmetric information, unpublished working paper, University of Southern California.


Table I. Volatility – Two Generations

This table shows the volatility in returns under varying availability bias parameters in a two-generations economy. The dividend stream is simulated using mean of $\delta = 0.04$ and a standard deviation of $\sqrt{\Sigma} = 0.01$. The risk-free rate equals $r_f = 0.01$. I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>$m$</th>
<th>$\sigma_{\text{return}}$ for overreaction parameter $m = 0.10$</th>
<th>$m = 0.20$</th>
<th>$m = 0.30$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.012$</td>
<td>$0.077$</td>
<td>$0.154$</td>
<td>$0.187$</td>
</tr>
</tbody>
</table>

Table II. Trading Volume after First Period – Two Generations

This table shows the change in investors’ portfolios agents after the first period in a two-generations economy. Trading after the first period monotonically increases under the availability bias parameter $m$. The dividend stream is simulated using a mean of $\delta = 0.04$ and a variance of $\Sigma = 0.01^2$. The risk-free rate equals $r_f = 0.01$. Focusing on non-Bayesian learning, risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>$m = 0$</th>
<th>$TV$ for overreaction parameter $m = 0.10$</th>
<th>$m = 0.20$</th>
<th>$m = 0.30$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.01$</td>
<td>$1.71$</td>
<td>$3.16$</td>
<td>$4.35$</td>
</tr>
</tbody>
</table>

Table III. Trading Volume

This table illustrates the average absolute trading volume after period $j$. The trading volume $TV_j$ is defined as in Equation (32). For the simulation, I focus on non-Bayesian learning and choose the basic parametrization, i.e., a mean dividend of $\delta = 0.04$ and a variance of $\Sigma = 0.01^2$. The risk-free rate is $r_f = 0.01$. The availability bias parameter $m$ equals 0.2. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Trading after Period</th>
<th>$n = 2$</th>
<th>$n = 3$</th>
<th>$n = 4$</th>
<th>$n = 5$</th>
<th>$n = 6$</th>
<th>$n = 8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.16</td>
<td>2.79</td>
<td>2.76</td>
<td>2.83</td>
<td>2.89</td>
<td>3.08</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>1.07</td>
<td>1.35</td>
<td>1.54</td>
<td>1.67</td>
<td>1.91</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>-</td>
<td>0.84</td>
<td>0.67</td>
<td>0.60</td>
<td>0.62</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.01</td>
<td>0.81</td>
<td>0.53</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.07</td>
<td>0.73</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.90</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.02</td>
</tr>
</tbody>
</table>
Table IV. Individual Portfolio Performance

This table illustrates the average individual portfolio performance measured by the excess return of an investor belonging to generation \( j \). Excluding the first generation, the performance increases with age. For the simulation, I select the basic parametrization, i.e., a mean dividend of 0.04 and a standard deviation of 0.01. The risk-free rate equals \( r_f = 0.01 \). The availability bias parameter \( m \) equals 0.2. I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Individual Portfolio Performance of Generation</th>
<th>n = 2</th>
<th>n = 3</th>
<th>n = 4</th>
<th>n = 5</th>
<th>n = 6</th>
<th>n = 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.292</td>
<td>0.184</td>
<td>0.139</td>
<td>0.118</td>
<td>0.092</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.215</td>
<td>-0.069</td>
<td>-0.052</td>
<td>-0.052</td>
<td>-0.028</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>-0.018</td>
<td>-0.005</td>
<td>-0.001</td>
<td>-0.010</td>
<td>0.001</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>-</td>
<td>0.031</td>
<td>0.026</td>
<td>0.014</td>
<td>0.018</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.046</td>
<td>0.030</td>
<td>0.030</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.042</td>
<td>0.038</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.045</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.051</td>
</tr>
</tbody>
</table>

Table V. Volatility

This table shows volatility in returns for varying availability bias parameters \( m \). The return volatility increases with the availability bias parameter \( m \) and declines with the number of generations. I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. The dividend stream is simulated using a mean of 0.04 and a standard deviation of 0.01. The risk-free rate equals \( r_f = 0.01 \). Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>( \sigma_{\text{return}} ) for ( \sigma_{\text{return}} ) overreaction parameter</th>
<th>n = 2</th>
<th>n = 3</th>
<th>n = 4</th>
<th>n = 5</th>
<th>n = 6</th>
<th>n = 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m = 0 )</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td>( m = 0.10 )</td>
<td>0.077</td>
<td>0.069</td>
<td>0.062</td>
<td>0.055</td>
<td>0.052</td>
<td>0.043</td>
</tr>
<tr>
<td>( m = 0.20 )</td>
<td>0.134</td>
<td>0.120</td>
<td>0.105</td>
<td>0.094</td>
<td>0.087</td>
<td>0.070</td>
</tr>
<tr>
<td>( m = 0.30 )</td>
<td>0.187</td>
<td>0.165</td>
<td>0.144</td>
<td>0.127</td>
<td>0.118</td>
<td>0.094</td>
</tr>
</tbody>
</table>

Table VI. Volatility Clustering

This table shows the autocorrelation in absolute return deviations for up to three lags. For the simulation, I choose a mean dividend of \( \delta = 0.04 \) and a variance of \( \Sigma = (0.01)^2 \). The risk-free rate is \( r_f = 0.01 \). I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. The availability bias parameter \( m \) equals \( m = 0.2 \). Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Autocorrelation in ( \sigma_{\text{return}} )</th>
<th>n = 2</th>
<th>n = 3</th>
<th>n = 4</th>
<th>n = 5</th>
<th>n = 6</th>
<th>n = 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>lag = 1</td>
<td>0.221</td>
<td>0.082</td>
<td>0.064</td>
<td>0.057</td>
<td>0.052</td>
<td>0.045</td>
</tr>
<tr>
<td>lag = 2</td>
<td>0.000</td>
<td>0.037</td>
<td>0.018</td>
<td>0.015</td>
<td>0.014</td>
<td>0.013</td>
</tr>
<tr>
<td>lag = 3</td>
<td>0.000</td>
<td>0.000</td>
<td>0.014</td>
<td>0.008</td>
<td>0.007</td>
<td>0.006</td>
</tr>
</tbody>
</table>
Table VII. Trading Volume – Absolute Return Regression

This table shows the $\beta$-coefficient of a regression of returns on trading volume $TV_t = \alpha + \beta |r_t| + \epsilon_t$. The underlying dividend stream is simulated using a mean of $\delta = 0.04$ and a variance of $\Sigma = (0.01)^2$. The availability bias parameter equals $m = 0.2$. Focusing on non-Bayesian learning, I exclude the first 100 periods from the calculation. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>$n = 2$</th>
<th>$n = 3$</th>
<th>$n = 4$</th>
<th>$n = 5$</th>
<th>$n = 6$</th>
<th>$n = 8$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table VIII. High Trading Volume Returns Revert

This table shows the percentage of negatively correlated returns. I distinguish between high trading volume (highest 7.7%) returns and all returns. The dividend stream is simulated using a mean of $\delta = 0.04$ and a variance of $\Sigma = (0.01)^2$. The risk-free rate equals $r_f = 0.01$. I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Percentage of negatively correlated returns</th>
<th>$n = 2$</th>
<th>$n = 3$</th>
<th>$n = 4$</th>
<th>$n = 5$</th>
<th>$n = 6$</th>
<th>$n = 8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Trade</td>
<td>60.9%</td>
<td>68.4%</td>
<td>74.0%</td>
<td>73.7%</td>
<td>71.1%</td>
<td>66.4%</td>
</tr>
<tr>
<td>All</td>
<td>61.3%</td>
<td>54.2%</td>
<td>51.7%</td>
<td>49.9%</td>
<td>48.4%</td>
<td>45.0%</td>
</tr>
</tbody>
</table>

Table IX. High Volume Returns tend to Revert – Portfolio Sort

This table illustrates the average next period return after a trading day, which is categorized by volume and returns. High-/low-volume days are defined as days in which trade is in the highest/lowest decile. High-/low-return days are defined as days in which the return in the highest/lowest decile. The underlying model includes four generations. On high-volume trading days returns tend to revert. On low-volume trading days returns show a smaller tendency for momentum. For the simulation, I focus on non-Bayesian learning and exclude the first 100 time periods from the calculation. I choose a mean dividend of $\delta = 0.04$ and a variance of $\Sigma = (0.01)^2$. The risk-free rate is $r_f = 0.01$. The availability bias parameter $m$ equals $m = 0.2$. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>high returns</th>
<th>medium returns</th>
<th>low returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Trading Volume</td>
<td>-0.031</td>
<td>0.043</td>
</tr>
<tr>
<td>Medium Trading Volume</td>
<td>0.021</td>
<td>0.043</td>
</tr>
<tr>
<td>Low Trading Volume</td>
<td>0.050</td>
<td>0.041</td>
</tr>
</tbody>
</table>
Table X. Higher Moments – Stronger Reaction to Negative News

This table shows the variance, skewness, and kurtosis for different setups of the modeling parameter $\xi$. For $\xi \to \infty$, agents exclusively overreact to negative information, whereas for $\xi = 0$ the reaction is equivalent for good and bad news. $\xi = 1$ illustrates a stronger reaction to negative news, but overreaction is prompted by both kinds of information. When investors react more to negative than to positive news, skewness is negative and kurtosis is significantly above 3. For the simulation, I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. I choose a mean dividend of $\delta = 0.04$ and a variance of $\Sigma = (0.01)^2$. The risk-free rate is $r_f = 0.01$. The availability bias parameter equals $m = 0.2$. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>$\xi \to \infty$</th>
<th>n-Generations Model</th>
<th>$\xi = 1$</th>
<th>n-Generations Model</th>
<th>$\xi = 0$</th>
<th>n-Generations Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>std</td>
<td>skew</td>
<td>kurt</td>
<td>std</td>
<td>skew</td>
</tr>
<tr>
<td>$n = 2$</td>
<td>0.133</td>
<td>0.639</td>
<td>5.642</td>
<td>0.104</td>
<td>0.285</td>
</tr>
<tr>
<td>$n = 3$</td>
<td>0.073</td>
<td>-0.335</td>
<td>4.187</td>
<td>0.093</td>
<td>0.027</td>
</tr>
<tr>
<td>$n = 4$</td>
<td>0.064</td>
<td>-0.583</td>
<td>4.093</td>
<td>0.082</td>
<td>-0.103</td>
</tr>
<tr>
<td>$n = 5$</td>
<td>0.058</td>
<td>-0.723</td>
<td>4.074</td>
<td>0.074</td>
<td>0.179</td>
</tr>
<tr>
<td>$n = 6$</td>
<td>0.053</td>
<td>-0.808</td>
<td>4.069</td>
<td>0.068</td>
<td>0.233</td>
</tr>
<tr>
<td>$n = 8$</td>
<td>0.045</td>
<td>-0.914</td>
<td>4.065</td>
<td>0.057</td>
<td>-0.301</td>
</tr>
</tbody>
</table>

Table XI. Volatility Clustering – Availability through News

This table illustrates the autocorrelation in absolute return deviations for different availability bias parameters $m$ and news parameters $f$. For higher news parameter values $f$, the autocorrelation is more stable between models with different numbers of generations. For the simulation, I focus on non-Bayesian learning and exclude the first 100 periods from the calculation. I choose a mean dividend of $\delta = 0.04$ and a variance of $\Sigma = (0.01)^2$. The risk-free rate is $r_f = 0.01$. The availability bias parameter equals $m = 0.2$. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>$m = 0.2, f = 0$</th>
<th>n-Generations Model</th>
<th>$m = 0.1, f = 0.1$</th>
<th>n-Generations Model</th>
<th>$m = 0, f = 0.2$</th>
<th>n-Generations Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lag 1</td>
<td>lag 2</td>
<td>lag 3</td>
<td>lag 1</td>
<td>lag 2</td>
</tr>
<tr>
<td>$n = 2$</td>
<td>0.221</td>
<td>0.000</td>
<td>0.000</td>
<td>0.129</td>
<td>0.008</td>
</tr>
<tr>
<td>$n = 3$</td>
<td>0.082</td>
<td>0.037</td>
<td>0.000</td>
<td>0.074</td>
<td>0.036</td>
</tr>
<tr>
<td>$n = 4$</td>
<td>0.064</td>
<td>0.018</td>
<td>0.014</td>
<td>0.066</td>
<td>0.027</td>
</tr>
<tr>
<td>$n = 5$</td>
<td>0.057</td>
<td>0.015</td>
<td>0.008</td>
<td>0.064</td>
<td>0.025</td>
</tr>
<tr>
<td>$n = 6$</td>
<td>0.052</td>
<td>0.014</td>
<td>0.007</td>
<td>0.063</td>
<td>0.024</td>
</tr>
<tr>
<td>$n = 8$</td>
<td>0.045</td>
<td>0.013</td>
<td>0.006</td>
<td>0.061</td>
<td>0.021</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$m = 0.1, f = 0.1$</th>
<th>n-Generations Model</th>
<th>$m = 0, f = 0.2$</th>
<th>n-Generations Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lag 1</td>
<td>lag 2</td>
<td>lag 3</td>
</tr>
<tr>
<td>$n = 2$</td>
<td>0.129</td>
<td>0.008</td>
<td>0.006</td>
</tr>
<tr>
<td>$n = 3$</td>
<td>0.074</td>
<td>0.036</td>
<td>0.006</td>
</tr>
<tr>
<td>$n = 4$</td>
<td>0.066</td>
<td>0.027</td>
<td>0.006</td>
</tr>
<tr>
<td>$n = 5$</td>
<td>0.064</td>
<td>0.025</td>
<td>0.006</td>
</tr>
<tr>
<td>$n = 6$</td>
<td>0.063</td>
<td>0.024</td>
<td>0.006</td>
</tr>
<tr>
<td>$n = 8$</td>
<td>0.061</td>
<td>0.021</td>
<td>0.006</td>
</tr>
</tbody>
</table>
Table XII. Decomposition of Market Participants in an Environment with Money Managers

This table illustrates the percentage of self-directed agents and the decomposition of that group around a negative dividend shock (two standard deviations below the mean). The numbers are generated from an eight-generations model. After a negative shock the number of self-directed agents decreases. The remaining self-directed agents are young on average. For the simulation, I focus on non-Bayesian learning and choose a mean dividend $\delta$ of 0.04 and a standard deviation of 0.01. The availability bias parameter $m$ equals 0.2. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Percentage of Decomposition of Self-directed Agents</th>
<th>Before Shock</th>
<th>At Shock</th>
<th>After 1 period</th>
<th>After 2 periods</th>
<th>After 4 periods</th>
<th>After 6 periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-directed Agents belong to Generation</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Before Shock</td>
<td>77%</td>
<td>16%</td>
<td>15%</td>
<td>14%</td>
<td>13%</td>
<td>12%</td>
</tr>
<tr>
<td>At Shock</td>
<td>49%</td>
<td>26%</td>
<td>13%</td>
<td>12%</td>
<td>11%</td>
<td>10%</td>
</tr>
<tr>
<td>After 1 period</td>
<td>54%</td>
<td>23%</td>
<td>21%</td>
<td>11%</td>
<td>10%</td>
<td>9%</td>
</tr>
<tr>
<td>After 2 periods</td>
<td>59%</td>
<td>21%</td>
<td>20%</td>
<td>18%</td>
<td>9%</td>
<td>9%</td>
</tr>
<tr>
<td>After 4 periods</td>
<td>67%</td>
<td>19%</td>
<td>17%</td>
<td>16%</td>
<td>15%</td>
<td>13%</td>
</tr>
<tr>
<td>After 6 periods</td>
<td>74%</td>
<td>17%</td>
<td>16%</td>
<td>14%</td>
<td>13%</td>
<td>12%</td>
</tr>
</tbody>
</table>

Table XIII. Trading Volume of Self-Directed Agents in an Environment with Money Managers

This table illustrates the average absolute trading of self-directed agents after generation $j$ in the case of additional opportunity to consult a money manager. The percentage of persons in a generation that consult a money manager depends on the number of bad dividend observations throughout their life ($d_t \leq \bar{d} - \sqrt{\Sigma}$). The exact function of the remaining self-directed agents is given by Equation (38). Trading volume $TV_j$ is defined as in Equation (32). For the simulation, I focus on non-Bayesian learning and choose the basic parametrization i.e., a mean dividend of $\delta$ = 0.04 and a variance of $\Sigma = (0.01)^2$. The availability bias parameter equals $m = 0.2$. The risk-free rate is $r_f = 0.01$. Risk aversion parameters are chosen to normalize prices to 1.

<table>
<thead>
<tr>
<th>Trading after Period</th>
<th>n = 2</th>
<th>n = 3</th>
<th>n = 4</th>
<th>n = 5</th>
<th>n = 6</th>
<th>n = 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.20</td>
<td>2.98</td>
<td>3.02</td>
<td>3.11</td>
<td>3.18</td>
<td>3.40</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>1.37</td>
<td>1.63</td>
<td>1.82</td>
<td>1.94</td>
<td>2.18</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.75</td>
<td>0.73</td>
<td>0.74</td>
<td>0.87</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
<td>0.62</td>
<td>0.54</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.75</td>
<td>0.54</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.63</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.72</td>
</tr>
</tbody>
</table>
Figure 2. Simulation of Price Process. This figure illustrates the average price reaction to an extraordinary low dividend (two standard deviations below the mean). The average is from $p = 1000$ simulations and after period 100. For the simulation, I focus on non-Bayesian learning and choose a mean dividend $\delta$ of 0.04 and a standard deviation of 0.01. The availability bias parameter $m$ equals 0.2. Risk aversion parameters are chosen to normalize prices to 1.
Figure 3. Return Probability Density Function. This figure shows the variation in the return probability density function for varying generations and varying availability bias parameters. In Subplot a), varying generations are simulated with an availability bias parameter of $m = 0.2$. In Subplot b), the effect of the availability bias parameter is simulated for four generations. In the simulation, I focus on non-Bayesian learning and simulate the dividend stream using a mean of 0.04 and a standard deviation of 0.01. The risk aversion parameters are chosen such that the prices normalize to 1.
Figure 4. Multiple Assets – Asymmetric Change in Dividend Expectations. This figure shows the average dividend expectations of a generation that observed a low/high dividend (two standard deviations astride the mean) in its first period after market entrance. It illustrates that positive shocks fade faster than negative shocks. The parameter $\varepsilon$ equals 10. In the simulation, I focus on non-Bayesian learning and simulate the dividend stream using a mean of 0.04 and a standard deviation of 0.01. Risk aversion parameters are chosen so that the prices normalize to 1.
Figure 5. Multiple Assets – Effect of Learning from Portfolio Performance on Prices. This figure illustrates the average effect of one positive dividend shock (two standard deviations above the mean) on the price process. In the first scenario, the second asset experiences a positive shock. In the second scenario, the second asset is subject to a negative shock. Subplot a) shows the effect in a four-generations model, and Subplot b) treats the eight-generations model. If the other (second) asset has a negative shock and, thus, is less attractive for investment, the influence of the dividend shock fades faster. The parameter $\varepsilon$ equals 10. In the simulation, I focus on non-Bayesian learning and simulate the dividend stream using a mean of 0.04 and a standard deviation of 0.01. Risk aversion parameters are chosen such that prices normalize to 1.
Figure 6. Effect of Dividend Smoothing on Prices. This figure shows the effect of dividend smoothing on the average price process after a dividend shock of two standard deviations below the mean. The price process is shown for different lengths of the smoothing period. I observe that dividend smoothing leads to a reduction in the short-term overreaction. Under dividend smoothing the price remains closer to the rational price and is less volatile. However, it leaves medium-term and long-term effects almost unchanged. In the simulation, I focus on non-Bayesian learning and simulate the dividend stream using a mean of 0.04 and a standard deviation of 0.01. Risk aversion parameters are chosen such that prices normalize to 1.