Journal of Economic Dynamics & Control 177 (2025) 105133

Contents lists available at ScienceDirect

Journal of Economic Dynamics and Control

journal homepage: www.elsevier.com/locate/jedc

Expectation formation in financial markets: Heterogeneity and sentiment

Bart Frijns [a], Thanh Huynh [b], Remco C.J. Zwinkels [c,d,*]

[a] *Auckland University of Technology, New Zealand*
[b] *Monash University, Australia*
[c] *Vrije Universiteit (VU) Amsterdam, Netherlands*
[d] *Tinbergen Institute, Netherlands*

ARTICLE INFO

JEL classification:
G12
G14
G41

Keywords:
Expectation formation
Investor sentiment
Heterogeneity

ABSTRACT

We set up an endowment based asset pricing model in which agents have heterogeneous expectations about future price levels. Expectations are a function of fundamentals or trends, both interacted with sentiment. Agents are able to switch between expectation formation functions based on past performance combined with sentiment. Estimation results on the S&P500 index as well as its constituents reveal that there is heterogeneity between agents, with substantial switching between groups. We find that sentiment has both a direct and an indirect effect on expectations. Specifically, heterogeneity between groups is increasing in sentiment, and higher sentiment reduces the frequency of switching between functions. Our results imply that the true expectation formation process is a dynamic process based on multiple information sources.

1. Introduction

Expectations about future risk and return take center stage in the asset pricing literature (Sharpe, 1964; Lintner, 1965; Cochrane, 2005). While the traditional approach is to assume that investors hold rational expectations (Muth, 1961), more recent empirical work indicates that individual expectations are not rational (Cavaglia et al., 1994; MacDonald, 2000; Bloomfield and Hales, 2002; Hommes et al., 2004; Greenwood and Shleifer, 2014). An open question is how individuals do form expectations if not rational. Several alternatives have been proposed, typically separate from each other. For example, the investor sentiment literature (De Long et al., 1990; Baker and Wurgler, 2006, 2007) suggests that investors have stochastic but, on average, positive biases in their expectations. The heterogeneous agent literature, on the other hand, assumes that investors use different heuristics in forming expectations and switch between those heuristics over time (Barberis et al., 1998; Barberis and Shleifer, 2003; Hommes and LeBaron, 2018; ter Ellen et al., 2019). In this paper, we develop an asset pricing model combining heterogeneity with sentiment. The combination between the two approaches yields insights into the interactions between them. Estimation results for the S&P500 and its constituents reveal that both sentiment and heterogeneity play an important role in the price formation process, and we document strong interactions between sentiment and heterogeneity. In addition, we find substantial variation in the expectation formation function across stocks. Our results imply that the true model of expectation formation is highly conditional.

* Corresponding author.
E-mail addresses: bart.frijns@ou.nl (B. Frijns), Thanh.Huynh@monash.edu (T. Huynh), r.zwinkels@vu.nl (R.C.J. Zwinkels).

https://doi.org/10.1016/j.jedc.2025.105133
Received 26 September 2024; Received in revised form 15 April 2025; Accepted 17 June 2025

Available online 23 June 2025
0165-1889/

Modeling non-rational expectation is essentially introduced in the literature through the notion of noise trader risk. Noise trader risk, as introduced by Shleifer and Vishny (1997), is modeled by De Long et al. (1990) as a stochastic bias with positive mean added to otherwise rational expectations. The most natural way to capture noise trader risk empirically, is through investor sentiment. The investor sentiment literature shows that sentiment, broadly defined, is positively associated with contemporaneous stock returns and negatively with lagged returns (Brown and Cliff, 2004; Baker and Wurgler, 2006, 2007; Chung et al., 2012). Investor sentiment has also been shown to have real effect, such as investments (Baker, 2009) and employment (Montone and Zwinkels, 2020).

Agent based models, or more specifically heterogeneous agent models (HAMs), on the other hand, assume that financial markets are populated by agents that use different heuristics to form expectations (Zeeman, 1974; Brock and Hommes, 1997; Barberis et al., 1998). Typically, these models include two types of agents: fundamentalists and chartists. Fundamentalists expect prices to revert to a (perceived) fundamental value. As such, they are closely related to the typical rational investor. Chartists, on the contrary, do not consider economic fundamentals but base their expectations on recent price trends. This is motivated by the ample, mainly experimental, evidence that people have a tendency to extrapolate trends when forming expectations (Bloomfield and Hales, 2002; Greenwood and Shleifer, 2014; Landier et al., 2018). An additional feature of these models is that agents are able to switch between heuristics. Typically, the switching between heuristics occurs based on past performance. A host of studies have found empirical support for this approach to expectation formation in all sorts of asset classes; see Lux and Zwinkels (2018) for an overview.

In this paper, we develop a HAM in which investor sentiment directly and indirectly affects the expectation formation processes of fundamentalists and chartists. We extend the model of Brock and Hommes (1998) by integrating sentiment in the expectation formation process and allow for interactions between sentiment and heterogeneity. Baker and Wurgler (2006) focus on the cross-sectional variation in sensitivity to sentiment-based demand shocks. We extend this line in our setting and introduce time-variation in sensitivity to sentiment. This is motivated by the time-variation in noise trader activity, as well as time variation in arbitrage opportunities; see Shleifer and Vishny (1997) and Brunnermeier and Pedersen (2009). De Long et al. (1990) introduce noise traders next to sophisticated investors, where noise traders are sensitive to sentiment. In additional analyses, they allow for time-variation in the proportion of noise traders, which introduces time-variation in market sensitivity to sentiment. Specifically to our model, we let the expectations of all agents depend on sentiment directly, separate from the information they incorporate (fundamental vs trends). As chartists are more akin to noise traders and fundamentalists more akin to rational arbitrageurs, we expect that chartists are more sensitive to sentiment.

Then, we allow the fundamentalist mean reversion coefficient and chartist extrapolation coefficient to be time-varying and conditional on investor sentiment. Investor sentiment might affect investor heterogeneity through overconfidence. With regard to the belief formation, overconfidence could result in an exaggerated view that stock prices will evolve according to a specific belief that investors may hold. For instance, in times of high sentiment a fundamentalist may become more confident about the mean-reversion of the stock price towards a fundamental value (Huang and Goo, 2008). Likewise, a chartist may become more confident about price-continuation and thus become more extreme in their belief, expecting a more extreme price continuation than they would in case of low sentiment. Hence, we expect that high sentiment leads to more extreme beliefs of the different agents, thus resulting in more heterogeneity in beliefs as in Scheinkman and Xiong (2003). By the same token, we expect sentiment to have an impact on the switching behavior of agents between types. Because of the overconfidence induced by high sentiment, agents may become less sensitive to past performance of a specific trading strategy. This is because overconfidence can lead to belief perseverance (Kahneman et al., 1982), i.e., an overreliance on private beliefs and an underreliance on public signals. This results in agents holding on to the belief that they have formed (either fundamentalist or chartist) and paying less attention to public signals (Barberis et al., 1998), in this case the past performance of a specific trading strategy. Hence, our expectation is that overconfidence, induced by high sentiment, leads to a reduction in the switching behavior of agents.[1]

In the empirical part of the paper, we estimate our model on the S&P500 index and its constituents with daily observations over the period 2003 to 2023. We measure sentiment using the Buckman et al. (2020) news sentiment index. We find strong support for the joint importance of both heterogeneity and sentiment as well as their interaction. Specifically, the empirical results are consistent with our model with time-varying heterogeneity, in which fundamentalists and chartists co-exist in dynamic proportions. We find that especially chartists are sensitive to sentiment; because of the time-varying proportions of fundamentalists and chartists, the sensitivity to sentiment of the market in general is also time-varying. Furthermore, investor sentiment interacts with the expectation formation process as modeled, generating more heterogeneity in times of high sentiment; high sentiment results in stronger mean-reversion for the fundamentalist, and stronger price extrapolation for the chartist. In addition, agents switch less between the various trading rules in times of high sentiment, in line with the notion that investors become overconfident in times of high sentiment and thus rely more on their private beliefs rather than performance signals they get from the market. For the individual constituents of the S&P500 we find, on average, similar results as for the index. There is, however, ample variation in the coefficients across stocks. The results are robust to the exact specification of the model, the definition of the fundamental value, and the exact definition of sentiment.

Our findings illustrate that two approaches to expectation formation, sentiment and heterogeneity, have important interactions and should therefore not be considered in isolation. Our results also illustrate that the discussion about a proper alternative to rational expectations has not settled. Whereas prospect theory by Kahneman and Tversky (1979) is a more realistic approach relative to expected utility theory on the preferences side, the alternative to rational expectations on the beliefs side is not clear yet. The

[1] A related study to ours is Kukacka and Barunik (2013). They evaluate the impact of behavioral breaks in heterogeneous agent models. Specifically, they address the question of whether HAMs can capture behavioral biases, such as herding, overconfidence, and market sentiment. Through a numerical analysis, they demonstrate that HAMs can indeed capture dynamics generated as a consequence of behavioral biases. Their work forms an important motivation for our empirical study.

consensus does appear to be that the alternative approach should have an element of trend extrapolation (Barberis et al., 2015). We confirm the importance of trend extrapolation, but our results show, however, that this leaves out important other dynamics over time as well as across assets.

The remainder of the paper is organized as follows. In Section 2 we present the heterogeneous agent model with sentiment and Section 3 contains the description of the data and empirical methods. Section 4 presents the results, Section 5 shows results of various robustness tests, and Section 6 concludes.

2. Model

We use a modified version of the Brock and Hommes (1998) model as the basis of our model. Assume an economy with a risk-free asset and a single risky asset with price p_t that pays a stochastic dividend y_t. Wealth then evolves according to:

$$W_{t+1} = RW_t + (p_{t+1} + y_{t+1} - Rp_t)z_t, \tag{1}$$

where R is the risk free rate and z_t the demand for the risky asset.

Investors are mean-variance optimizers such that their demand for the risky asset solves:

$$Max_z \left\{ E_{ht}(W_{t+1}) - (a/2)\sigma^2_{ht}(W_{t+1}) \right\}, \tag{2}$$

in which $E_{ht}(W_{t+1})$ is the expectation that investors of type $h = \{1, \dots, H\}$ at time t has about next period wealth W_{t+1}, a is the risk aversion parameter and $\sigma^2_{ht}(W_{t+1})$ the variance of wealth. We assume that the variance of wealth is time invariant and homogeneous across investor types, i.e. $\sigma^2_{ht}(W_{t+1}) = \sigma^2$. Solving yields the optimal demand for the risky asset, z_{ht}, i.e.:

$$z_{ht} = E_{ht}(p_{t+1} + y_{t+1} - Rp_t)/a\sigma^2. \tag{3}$$

Given that there are H groups of investors, we define n_{ht} as the fraction of type h investors in period t with $\sum n_{ht} = 1\,\forall t$ and $n_{ht} \geq 0$. Total demand for the risky asset is then given by:

$$\sum_{h=1}^{H} n_{ht} \left\{ E_{ht}(p_{t+1} + y_{t+1} - Rp_t)/a\sigma^2 \right\}. \tag{4}$$

Without loss of generality, we can set the outside supply of the risky asset to zero, such that the market clearing equation is given by:

$$\sum_{h=1}^{H} n_{ht} \left\{ E_{ht}(p_{t+1} + y_{t+1} - Rp_t)/a\sigma^2 \right\} = 0, \tag{5}$$

and:

$$Rp_t = \sum_{h=1}^{H} n_{ht} E_{ht}(p_{t+1} + y_{t+1}). \tag{6}$$

Now assume that a fundamental price is given by p^*_t. It is then convenient to write the model in terms of deviations from the fundamental, $x_t = p_t - p^*_t$. We make the assumption that all beliefs of the groups in H are of the form:

$$E_{ht}(p_{t+1} + y_{t+1}) = E_t(p^*_{t+1} + y_{t+1}) + f_h(x_{t-1}, \dots, x_{t-L}), \tag{7}$$

such that expectations are given by the fundamental expectation plus a function $f()$ of past price deviations from the fundamental.

Equation (6) can be written as:

$$Rx_t = \sum n_{ht} f_{h,t}(x_{t-1}, \dots, x_{t-L}). \tag{8}$$

Consistent with the literature on heterogeneous agents, we assume two types of traders with different beliefs, fundamentalists and chartists; $H = F, C$. Up to this point, our model is consistent with the original Brock and Hommes (1998) model. We now deviate from this model by allowing both fundamentalist and chartist beliefs to be conditional on sentiment, both directly and indirectly. The fundamentalists expect the price level to converge to the fundamental value, and thus x_t to converge to zero. We let the speed of convergence, however, to be conditional on market sentiment. Hence:

$$f_{F,t} = \left[(\phi^1_F + \phi^2_F S_t)x_{t-1} + \phi^3_F S_t \right], \tag{9}$$

where S_t is market sentiment. Note that agents take the observable information from the previous period, x_{t-1}. Agents are affected by their own contemporaneous sentiment when forming expectations. Therefore, we take sentiment in period t, so S_t. In accordance with a fundamentalist belief, we expect $0 < \phi^1_F < 1$, i.e., a deviation from the fundamental price will mean-revert towards zero in the subsequent period. Whereas in some models it is assumed that fundamentalists expect complete mean reversion in one period, i.e., $\phi^1_F = 0$, such as in Hommes and Lustenhouwer (2019), we let the data decide how fast mean reversion takes place. In addition, we expect $\phi^2_F < 0$, i.e., the higher the market sentiment, the stronger the belief of the fundamentalist in mean-reversion (Huang and

Goo, 2008). This negative expectation for ϕ_F^2 is in line with (over)optimism resulting in a stronger fundamentalist belief. Finally, we expect $\phi_F^3 > 0$, as expectations respond positively to sentiment (Baker and Wurgler, 2006).

Chartists, on the other hand, are destabilizing and expect the deviation between price and fundamental to increase. Hence:

$$f_{C,t} = \left[(\phi_C^1 + \phi_C^2 S_t)x_{t-1} + \phi_C^3 S_t\right], \tag{10}$$

with $\phi_C^1 > 1$, i.e., according to the chartist belief, a price discrepancy observed in the past is expected to increase in subsequent periods. In line with the expectation that this belief will get stronger in periods of high sentiment (due to (over)optimism), we expect $\phi_C^2 > 0$. Finally, we expect $\phi_C^3 > 0$ and $\phi_C^3 > \phi_F^3$ meaning that we expect chartists to be more sensitive to sentiment than fundamentalists.

Given these functional forms, we can rewrite Equation (8) as:

$$Rx_t = n_{F,t}\left[(\phi_F^1 + \phi_F^2 S_t)x_{t-1} + \phi_F^3 S_t\right] + n_{C,t}\left[(\phi_C^1 + \phi_C^2 S_t)x_{t-1} + \phi_C^3 S_t\right]. \tag{11}$$

Agents are able to switch between groups conditional on the relative performance of the groups. In other words, n_{ht} is endogenously determined by means of:

$$n_{h,t} = \exp\left(\beta_t \frac{\pi_{h,t}}{\pi_{F,t} + \pi_{C,t}}\right)/Z_t, \tag{12}$$
$$Z_t = \sum_h \exp\left(\beta_t \frac{\pi_{h,t}}{\pi_{F,t} + \pi_{C,t}}\right),$$

which simplifies to:

$$n_{F,t} = \left(1 + \exp\left(\beta_t \frac{\pi_{F,t} - \pi_{C,t}}{\pi_{F,t} + \pi_{C,t}}\right)\right)^{-1}, \tag{13}$$
$$n_{C,t} = 1 - n_{F,t} = \left(1 + \exp\left(\beta_t \frac{\pi_{C,t} - \pi_{F,t}}{\pi_{F,t} + \pi_{C,t}}\right)\right)^{-1},$$

in which $\pi_{F,t}$ and $\pi_{C,t}$ is the performance of fundamentalists and chartists, respectively.

The intensity of choice parameter, β_t, varies over time conditional on sentiment. Specifically:

$$\beta_t = \bar{\beta} + \psi S_t, \tag{14}$$

where $\bar{\beta}$ captures the degree of switching when sentiment is equal to zero, and ψ captures the impact of sentiment on switching behavior.

A positive value of β_t implies that agents switch towards the investment belief that has yielded the highest performance in the recent past (i.e., they follow a positive feedback trading strategy), while a negative value of β_t implies that agents switch towards the investment belief that has yielded the lowest performance in the recent past (i.e., they follow a negative feedback or contrarian trading strategy). When ψ takes on the same sign as $\bar{\beta}$, sentiment intensifies the switching behavior, while when ψ takes on the opposite sign of $\bar{\beta}$, sentiment mitigates the switching behavior. In line with the notion that high sentiment results in (over)optimism and overconfidence, ψ can be interpreted as the degree of belief perseverance (Kahneman et al., 1982) and thus to take on the opposite sign of $\bar{\beta}$ as agents would rely more on their private beliefs than public signals (which in this case is the past performance of the different trading strategies).

To complete the model, we need to define the performance measure $\pi_{h,t}$. We assume that agents base their choice on the relative ability of the groups to forecast x_t over the previous I periods. Specifically:

$$\pi_{ht} = \sum_{i=1}^{I} \left|x_{t-i} - f_{h,t-i}\right|, \tag{15}$$

in which I is set to five in the benchmark case; sensitivity to this choice is checked later in the paper.

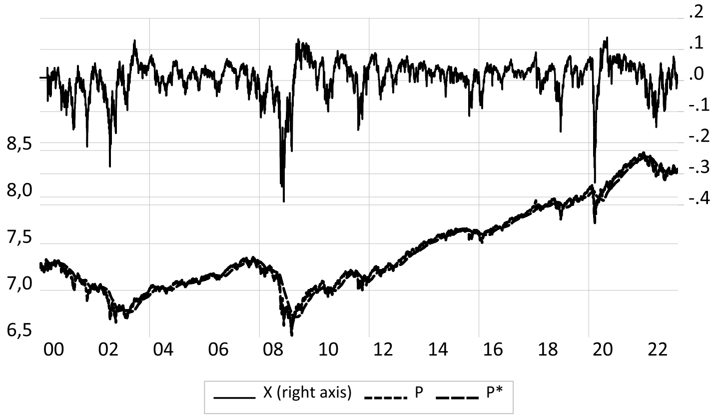
3. Data and methods

To estimate our heterogeneous agent model, we obtain daily data on dividend yield, price-earnings ratio, and the total return index on S&P500 from Thomson Reuters Datastream. Our final sample contains 6,064 daily observations over the period 03 January 2000 to 30 March 2023. Using these data, we first need to obtain a proxy the fundamental value p^*. Similar to Boswijk et al. (2007) we compute the fundamental value based on the Gordon growth model:

$$p_t^* = \frac{1+g}{r-g} y_t, \tag{16}$$

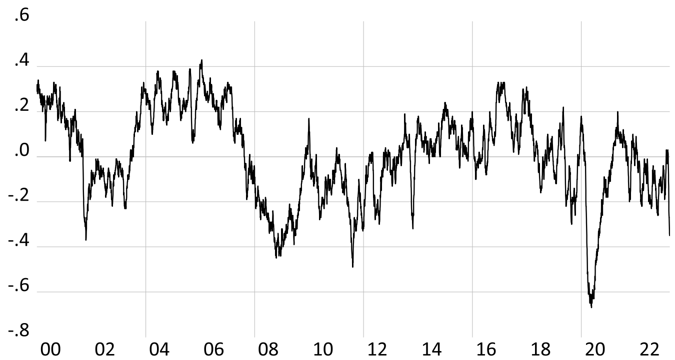
in which g is the growth rate of dividends y_t and r the required return.

Assuming that the long-run growth in prices is equal to the long-run growth in dividends (Fama and French, 2002), we get that $r - g = y/p$. Hence:



Notes: This figure presents the log fundamental value estimate p^* based on Equation (17) using 100 days moving average, the log market price p, and the deviation of the market price from fundamental, $x_t = p_t - p_t^*$.

Fig. 1. Price, fundamental price, and deviation.



Notes: This figure presents the sentiment measure S, which is the Buckman et al. (2020) daily news sentiment index.

Fig. 2. Investor sentiment.

$$p_t^* = \frac{1+g}{E(y/p)} y_t, \tag{17}$$

where $E(y/p)$ is the expected dividend yield. In the benchmark setting, we assume that agents take a 100-day historical rolling average to calculate g and $E(y/p)$.[2] Note that we take logs of all values. Fig. 1 presents the evolution of p_t, p_t^*, and x_t for the S&P500, and Table 1 the descriptive statistics.

Both Fig. 1 and Table 1 show that our measure of a fundamental value behaves as one would expect from a fundamental value estimate. On average, the fundamental value is roughly equal to the market value. Furthermore, the market value is more volatile than the fundamental value, consistent with the findings of Shiller (1981).

To measure sentiment, we employ daily news sentiment measure of Buckman et al. (2020). This index is a high frequency measure of economic sentiment based on lexical analysis of economics-related news articles. The advantage of this measure is that it is available at the daily frequency over a long period, and measures sentiment at large, not only for investors.

Apart from the S&P500 index itself, we also estimate the model on its constituents. Because the fundamental value calculation requires companies to pay dividends, we only include companies that pay dividends throughout the period. Furthermore, as the nonlinear model requires a high number of observations, we only include firms with daily observations throughout the full sample period. This leaves us with 184 unique companies. This is clearly not a representative sample of all listed U.S. companies, but contains a bias towards older, larger, and more successful companies. However, it does provide a first insight into the cross-sectional variation in heterogeneity, sensitivity to sentiment, and switching behavior. It is a large enough sample for cross-sectional analyses, although we need to be careful generalizing the results to the full population of companies.

Daily stock prices (closing prices, adjusted for splits and spinoffs) and dividend yields are obtained through Factset (FG_Price and FG_DIV_YLD). These are used to calculate x and average return Ret (daily log returns). To calculate average company characteristics,

[2] In the empirical section we study the robustness of the results to this choice.

Table 1
Descriptive statistics S&P500.

	x_t	p_t	p_t^*	S_t
Mean	0.009	7.433	7.426	0.004
Median	0.020	7.270	7.273	0.010
Maximum	0.139	8.476	8.430	0.430
Minimum	-0.390	6.517	6.715	-0.670
Std. Dev.	0.056	0.462	0.457	0.199
Observations	6,064	6,064	5,993	6,064

Notes: This table presents the descriptive statistics of the market and sentiment data. p_t represents the log-S&P500 index; p_t^* the fundamental value based on Equation (17); $x_t = p_t - p_t^*$. Sentiment is the daily news sentiment index from Buckman et al. (2020).

Table 2
Descriptive statistics stocks.

	x_avg	ret_avg	dy_avg	Size	BtM
Mean	0.016	0.000	2.406	40,494	0.427
Median	0.015	0.000	2.194	18,183	0.391
Maximum	0.037	0.001	6.160	343,960	1.213
Minimum	-0.005	0.000	0.094	3,912	-0.022
Std. Dev.	0.009	0.000	1.240	55,707	0.239
Observations	184	184	184	184	184

Notes: This table presents the descriptive statistics of the included individual stocks. $x_t = p_t - p_t^*$, and x_avg is the average x_t over the included companies; ret_avg is the average return; dy_avg the average dividend yield; Size is the market capitalization (in millions); and BtM is the average book-to-market value.

we obtain annual data from the CRSP-compustat merged database through WRDS. Specifically, we calculate Size by multiplying closing price (PRCC_C) with the number of common stocks outstanding (CSHO, in millions). We calculate book-to-market by dividing book value per share (BKVLPS) by closing price (PRCC_C). Table 2 presents the descriptive statistics of the stock-level data. The numbers represent average statistics over the 184 individual stocks.[3]

We estimate the model given by the empirical version of Equation (11), including an intercept and residual term, by means of maximum likelihood. We build up the analysis by first estimating a restricted model with no switching ($\bar{\beta} = 0$) and no sentiment interaction ($\phi_h^2 = 0$). We then build towards the full model by first introducing switching, and then sentiment. At each step, we use the estimated coefficients of the previous step as starting values. Otherwise, we did not apply parameter restrictions.

4. Results

In this section, we present the estimation results for the model developed in Section 2. We first present the results for the S&P500 index, and subsequently the results per individual stock. Then, we look into the cross-section of estimation results across stocks. Finally, we show various parameterizations of the model and document the results for several robustness tests.

4.1. Index results

In Table 3 we present the estimation results for the S&P500. We start with the estimation of a homogeneous agent model, where we do not allow for heterogeneous beliefs and do not consider the impact of sentiment. We then build up the full model by introducing additional elements step by step.

The estimation results for the homogeneous agent model (1) in Table 3 indicate that x_t is mean-reverting, with a highly significant AR(1) coefficient of 0.947.[4] Model (2) only includes sentiment, and we confirm earlier literature that shows a positive contemporaneous relation between sentiment and returns (Baker and Wurgler, 2006, 2007). Model (3) includes sentiment in the homogeneous agent model and reveals that sentiment does not have an indirect (ϕ_F^2) nor a direct (ϕ_F^3) effect on x when not considering heterogeneity. The LLR-1 statistic, which is the likelihood ratio test comparing the fit of model 3 to model 1, also indicates that the model fit does not increase significantly after introducing sentiment to the homogeneous agent model. Model (4) introduces heterogeneity to Model (1), but still excludes sentiment. Results show that there is significant heterogeneity in S&P500 return expectations: fundamentalists expect mean reversion ($\phi_F^1 < 1$) whereas chartists expect the mispricing to increase ($\phi_C^1 > 1$). The switching parameter $\bar{\beta}$ is negative, meaning that agents switch away from the strategy that performed well in the previous five periods, i.e. they follow a negative feedback trading strategy. The LLR-1 statistic indicates that allowing for heterogeneity significantly increases the fit of

[3] E.g., $\overline{Ret}$ is calculated by first taking the time-series average per stock over the full sample period, and subsequently calculating the mean, median, etc. over the 184 stocks.

[4] Indeed, the Augmented Dickey-Fuller unit root test rejects the null of a unit root in x_t with p = 0.000; results not shown.

Table 3
Estimation results: index.

	(1)	(2)	(3)	(4)	(5)	(6)
ϕ_F^1	0.977***		0.980***	0.774***	0.961***	0.883***
	(676.286)		(288.377)	(37.327)	(59.456)	(34.357)
ϕ_F^2			0.013		-0.396***	-0.550***
			(1.419)		(-7.577)	(-7.867)
ϕ_F^3		0.080***	-0.000		0.015***	0.015***
		(23.644)	(-0.525)		(3.478)	(3.607)
ϕ_C^1				1.195***	1.006***	1.086***
				(56.449)	(64.351)	(42.014)
ϕ_C^2					0.411***	0.570***
					(8.011)	(8.072)
ϕ_C^3					-0.017***	-0.017***
					(-4.148)	(-4.806)
$\overline{\beta}$				-0.657***	-1.506***	-0.812***
				(-8.907)	(-9.682)	(-3.673)
ψ						2.455***
						(4.372)
c	0.000	0.009***	0.000	0.000	0.000	0.000
	(1.098)	(9.669)	(0.702)	(1.272)	(0.651)	(0.826)
#obs	5,965	5,965	5,965	5,965	5,965	5,965
LL	17,885.7	8,880.5	17,886.3	17,901.6	17,914.8	17,919.1
LLR-1			1.180	31.700		
LLR-3					56.940	
LLR-4					26.420	
LLR-5						8.700

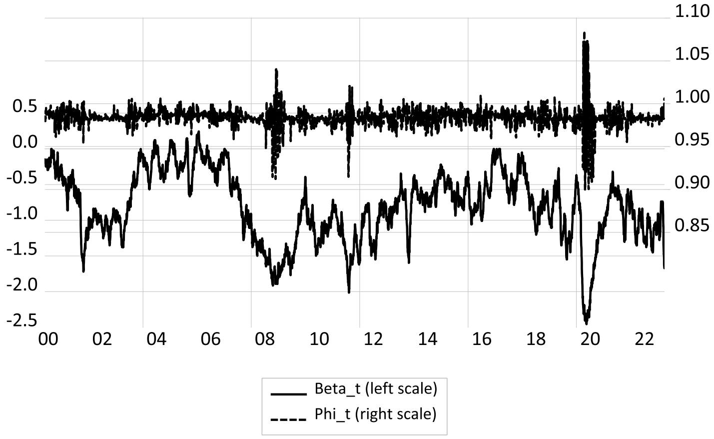
Notes: This table presents the estimation results of the model given by Equation (11). LL is the likelihood; LLR-1, LLR-3, and LLR-5 represent outcomes of the likelihood ratio test with model 1, 3, and 5 as the restricted models, respectively. Robust t-values in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

the homogeneous agent model (1). These findings corroborate earlier estimation efforts on the S&P500 from Boswijk et al. (2007), Chiarella et al. (2014), and ter Ellen et al. (2021).

Model (5) introduces sentiment in the fundamentalist and chartist expectation formation functions. Sentiment has a direct effect on both the chartist and the fundamentalist expectation formation. First, we observe that both chartists' and fundamentalists' expectations are directly sensitive to sentiment; both ϕ_C^3 and ϕ_F^3 are significantly different from zero, and their absolute values are directly comparable. Whereas fundamentalists are positively sensitive to sentiment, chartists expectation react negatively to sentiment shocks. Their opposing signs explain why the direct effect of sentiment in Model (3) is insignificant. Regarding the interaction effects of sentiment, we find for chartists $\phi_C^2 > 0$, implying that chartists extrapolate (even) stronger in times of high sentiment. In other words, they become 'more chartist' in reaction to sentiment shocks. Fundamentalists, on the other hand, expect greater mean reversion in times of high sentiment ($\phi_F^2 < 0$). These findings imply that agents becoming more optimistic about their specific trading strategy in times of high sentiment, and imply that sentiment is positively related to heterogeneity. The switching coefficient, $\bar{\beta}$, remains negative and significant. The LLR-3 statistic for model (5) shows that adding sentiment to the expectation formation functions significantly contributes to the explanatory power of the model.

Finally, model (6) is the full model with heterogeneity, switching, and sentiment in both the switching and the expectation formation functions. Overall, the findings of Model (5) remain. Furthermore, sentiment has a negative effect on the switching tendency; $\psi > 0$ whereas $\overline{\beta} < 0$. This implies that investors tend to stick to their investment strategy more (less) in terms of high (low) sentiment. The estimated coefficients imply that there is no switching when sentiment is $1.602/25.952 = 0.062$ and turns positive for higher levels of sentiment, which is true in 6% of the days in the sample. Compared to Model (5), we observe that introducing sentiment in the switching function adds to the explanatory power of the model; the LLR-5 statistic for Model (6) is significant. This suggests that sentiment has a significant moderating role on switching behavior, which is in line with belief perseverance where agents rely more on their private beliefs rather than public signals (Baumeister, 2007).

To demonstrate the impact of sentiment on switching behavior over time, Fig. 3 presents the evolution of β_t over time, as well as the time-varying AR(1) coefficient from Equation (11), given by $n_{Ft} * (\phi_F^1 + \phi_F^2 * S_t) + n_{Ct} * (\phi_C^1 + \phi_C^2 * S_t)$. The time-varying intensity of choice β_t is negative, on average, indicating that investors tend to switch away from the better performing strategy. This could be driven by expectations of mean reversion in strategy performance. On a number of occasions, especially between 2004 and 2007, the intensity of choice turns positive. When looking at this period in Fig. 1, it seems to coincide with a relatively tranquil episode with small deviation of price from fundamental, presumably because there are not large price swings towards and from the fundamental, causing agents to switch between groups. Otherwise, the movements of β_t follow those of sentiment as seen in Fig. 2. The average AR(1) coefficient $n_{Ft} * \phi_F + n_{Ct} * \phi_C$ is below unity, on average, implying a globally stable system. Hence, the market price reverts to its fundamental value in the long-run; i.e., x_t goes to zero. There are, however, periods in which chartists dominate, pushing the weighted average AR(1) coefficient above unity, causing a locally unstable market environment. We especially observe unstable behavior surrounding market turmoil, such as the Global Financial Crisis in 2008/2009, the sovereign debt crisis in 2010 and the COVID crisis in 2020.



Notes: This figure presents the time-varying intensity of choice $\beta_t = \overline{\beta} + \psi * S_t$ together with the aggregate time-varying mean reversion parameter $\phi_t = n_{F,t}(\phi_F^1 + \phi_F^2 S_t) + n_{C,t}(\phi_C^1 + \phi_C^2 S_t)$.

Fig. 3. Time-varying intensity of choice.

Table 4
Estimation results: stocks.

	(1)	(2)	(3)	(4)	(5)	(6)
ϕ_F^1	0.973***		0.978***	0.648***	0.669***	0.643***
	(515.787)		(2911.911)	(25.041)	(16.013)	(14.537)
ϕ_F^2			0.017***		-1.049***	-1.257***
			(13.235)		(-8.521)	(-8.741)
ϕ_F^3		0.106***	0.000**		-0.014	-0.023**
		(23.819)	(2.309)		(-1.573)	(-2.027)
ϕ_C^1				1.310***	1.293***	1.318***
				(50.360)	(30.912)	(29.802)
ϕ_C^2					1.076***	1.274***
					(8.736)	(8.842)
ϕ_C^3					0.015	0.023**
					(1.646)	(2.033)
$\overline{\beta}$				0.284*	-0.359***	-0.181**
				(1.792)	(-4.413)	(-2.328)
ψ						1.163***
						(10.096)

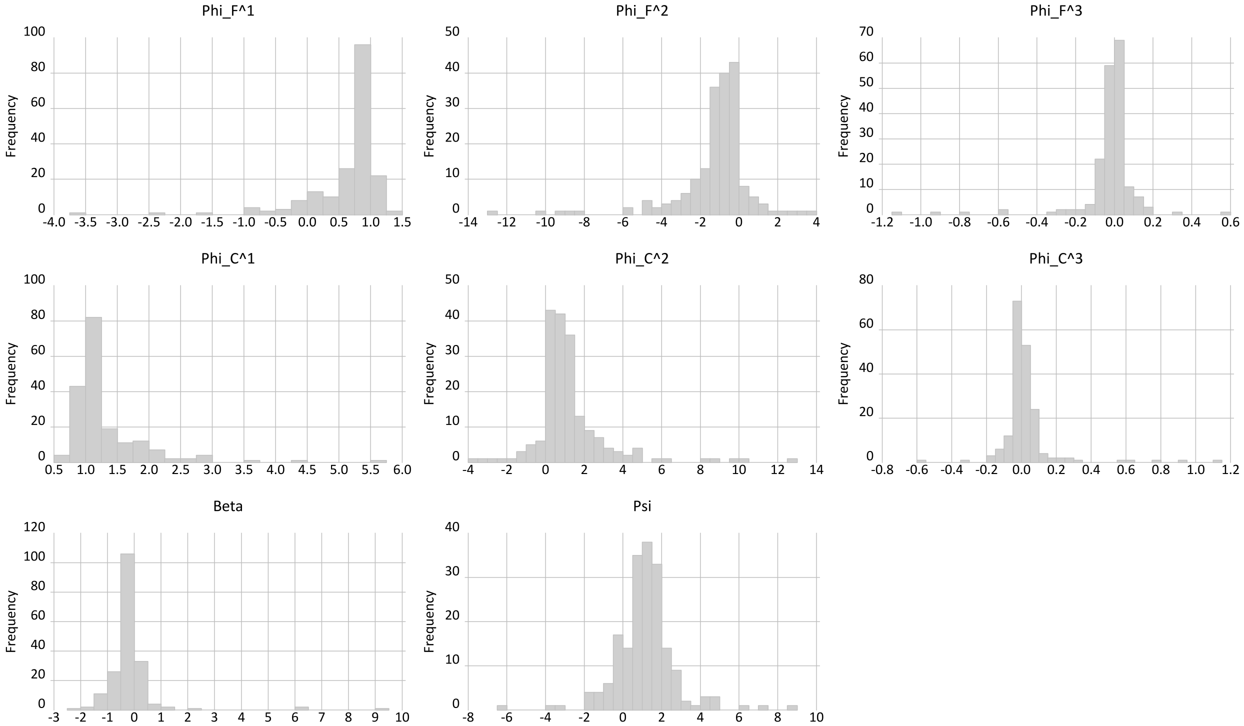
Notes: This table presents the average estimation results of the model given by Equation (11) on each of the constituents of the S&P500. T-values are calculated across the cross-section of stocks and given in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

4.2. Individual stocks results

4.2.1. Model estimates

In the previous subsection, we presented the estimation results of our heterogeneous agent model on the S&P500 index. In this subsection, we proceed by estimating the model individually for each of the 184 constituents of the S&P500 index for which sufficient data is available. The average estimation results and the cross-sectional standard errors across the stocks are presented in Table 4.

Table 4 is built up equivalently to Table 3; first, we estimate the most restricted model excluding both heterogeneity and sentiment, and increase the flexibility of the model step by step from Model (1) through Model (6). Overall, the estimation results per stock are highly comparable to those for the full index in the sense that the average stock displays heterogeneity, switching, and sensitivity to sentiment in both the expectation formation rules as well as the switching function. In Model (1), we observe that the average AR(1) coefficient is high but below unity. In Model (2), we see that the average stock's price deviation x_t has a positive unconditional exposure to sentiment. In the estimation results for Model (3) we observe some difference with the estimation results for the index: whereas ϕ_F^2 and ϕ_F^3 were insignificant for the index, they are significant on average over the individual stocks. Specifically, $\phi_F^2 > 0$, implying that mean-reversion slows down in times of high sentiment. $\phi_F^3 > 0$ as well, confirming the positive unconditional effect of sentiment on equity markets. The fundamentalist and chartist coefficients in Model (4) are comparable to those in Table 3, with $\phi_F^1 < 1 < \phi_C^1$. The switching parameter $\overline{\beta}$, however, is positive for the average stock whereas it was negative for the index. In Model (5), after introducing sentiment in the expectation formation rules, we again observe heterogeneity and switching. Different from



Notes: This figure presents the distributions of the coefficient estimates of the model given by Equation (11), estimated on 184 stocks from the S&P500 index.

Fig. 4. Estimated coefficients per stock.

Table 3, the direct effects of sentiment on fundamentalists and chartists captured by ϕ_F^3 and ϕ_C^3 are now (marginally) insignificant. Different from Model (4), the intensity of choice $\overline{\beta}$ is now negative again. Finally, the estimation results of the full model in Model (6) show that, different from before, fundamentalists have a negative direct sensitivity to sentiment ($\phi_F^3 < 0$), whereas chartists have a positive direct sensitivity to sentiment ($\phi_C^3 > 0$).

Whereas Table 4 presents the average estimation results over the 184 stocks, in Fig. 4 we present the distributions of the estimated coefficients.

The first row of Fig. 4 displays the distributions of the estimated fundamentalist expectation formation rules. The distribution of ϕ_F^1 in the top left figure shows that for the majority of stocks the coefficient is just below unity. There is a left tail in the distribution, indicating that for a number of stocks the fundamentalists expect slower mean reversion. For a small proportion of stocks, the coefficient is below zero. This implies that for average sentiment (i.e., $S = 0$), fundamentalists expect prices to mean-revert oscillating. The distribution of ϕ_F^2 in the top middle figure shows that for the majority of stocks the indirect effect of sentiment on the mean reversion parameter is negative, as we found for the index in Table 3. For ϕ_F^3, the direct effect of sentiment on fundamentalist expectations, the estimates are clustered around zero with a number of outliers in the left tail. This explains the sign flip from Models (2) and (3) to (5) and (6) in Table 4.

The middle row of Fig. 4 displays the distribution of the estimated chartists expectation formation rules. The chartist extrapolation coefficient ϕ_C^1 is between 1.0 and 1.5 for the far majority of stocks. There is a right tail with very high coefficients, but these cannot be interpreted without the interaction with sentiment. The middle figure in the middle row shows the distribution of ϕ_C^2. Clearly, almost all numbers are above zero, indicating that for most stocks the chartist extrapolation becomes stronger with sentiment. The figure on the right hand side of the middle row, depicting ϕ_C^3, shows a more dispersed image. Hence, as we observed for ϕ_F^3, the sign of the direct effect of sentiment on the chartist expectation formation rule is not so uniform.

The bottom row of Fig. 4, finally, shows the distribution of the coefficients governing the switching function, $\overline{\beta}$ and ψ. As for the index, for the majority of stocks we observe a small negative intensity of choice $\overline{\beta}$, implying that agents switch towards the expectation formation rule that performed worse in the previous five periods. The sensitivity of the intensity of choice parameter to sentiment, captured by ψ, is positive for the majority of stocks. Hence, as for the index, for most stocks the switching between groups decreases in sentiment, consistent with beliefs perseverance.

Hence, for most coefficients the findings for the individual stocks are in line with those for the index. The exceptions are the direct effects of sentiment on the fundamentalists and chartists rules, ϕ_F^3 and ϕ_C^3, which are more spread out above and below zero.

Whereas the previous analyses focused on the average stock and the distribution of stocks, we now proceed to study the cross-section of stocks. Specifically, we test whether the estimated coefficient of our heterogeneous agent model correlates with specific company characteristics. Baker and Wurgler (2006) and Baker and Wurgler (2007) study how the sensitivity to investor sentiment

Table 5
Cross-sectional results.

Dependent:	M1 - ϕ	M2 - ϕ^3	M3 - ϕ^2	M4 - β	M5 - ϕ_F^2	M5 - ϕ_C^2	M6 - ψ
ret_avg	-3.103*	-3.245***	-7.158	1010.2**	702.05	-710.3	-218.36
	(-1.709)	(12.201)	(-0.966)	(2.294)	(0.937)	(-0.951)	(-0.328)
ret_stdev	0.419***	-1.245***	-0.018	-17.285	-28.116	28.006	-11.001
	(6.542)	(12.739)	(-0.066)	(-1.054)	(-0.871)	(0.867)	(-0.470)
x_avg	0.001	10.609	-0.216	16.803*	9.290	-9.549	-5.689
	(0.022)	(0.270)	(-1.362)	(1.697)	(0.594)	(-0.613)	(-0.380)
x_stdev	0.114***	6.217	-0.108**	-7.175***	-5.884	5.713	0.811
	(12.850)	(-1.587)	(-2.266)	(-2.553)	(-1.101)	(1.068)	(0.206)
x_abs	0.171***	10.277	-0.189***	-10.189**	-8.322	8.032	2.903
	(13.442)	(0.000)	(-2.759)	(-2.505)	(-1.077)	(1.039)	(0.507)
dy_avg	-0.001**	0.001	0.005***	-0.018	-0.039	0.048	-0.079
	(-2.283)	(0.000)	(5.485)	(-0.227)	(-0.393)	(0.479)	(-0.975)
dy_stdev	0.001***	0.032	0.004**	-0.014	-0.093	0.099	0.024
	(3.566)	(0.000)	(2.345)	(-0.137)	(-0.660)	(0.697)	(0.193)
Size	0.000	-0.007	0.000	-0.046	0.301**	-0.301**	0.128
	(-1.026)	(0.000)	(-0.064)	(-0.507)	(2.316)	(-2.322)	(1.129)
BtM	0.003***	0.143	0.024***	-0.453	-0.409	0.451	-0.153
	(3.025)	(0.000)	(5.195)	(-1.163)	(-0.604)	(0.664)	(-0.288)

Notes: This table presents the estimation results of univariate cross-sectional regressions of company characteristics on the estimated coefficients of the heterogeneous agent model. T-statistics in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

varies over the cross-section of stock returns, and argue that especially stocks that are either sensitive to sentiment-based demand shocks and/or experience large limits to arbitrage are sensitive to sentiment. Here, we study to what extent such stocks also show higher sensitivity to sentiment in our model. To do so, we regress a set of company characteristics on the estimated coefficients from Equation (11). The estimation results are given in Table 5.[5]

4.2.2. Cross-sectional patterns

The results in Fig. 4 show that there is ample variation in heterogeneity between stocks. Therefore, here we study whether there are any patterns in the cross-section of parameter estimates. We regress a number of company characteristics on the parameter estimates from models (1) to (6) in Table 4. Specifically, for each of the six empirical models from Table 4, we choose the defining parameter, so the parameter that is added to the model relative to the model before. These are indicated on top of Table 5. Hence, the equation is given by:

$$\begin{aligned} y_i = \alpha &+ \beta_1 ret\_avg_i + \beta_2 ret\_stdev_i + \beta_3 x\_avg_i + \beta_4 x\_stdev_i + \beta_5 x\_abs_i \\ &+ \beta_6 dy\_avg_i + \beta_7 dy\_stdev_i + \beta_8 Size_i + \beta_9 BtM_i + \varepsilon_i, \end{aligned} \tag{18}$$

in which ret_avg is average return; ret_stdev the standard deviation of return; x_avg the average x; x_stdev the standard deviation of x, x_abs the average absolute value of x; dy_avg the average dividend yield; dy_stdev the standard deviation of dividend yield; Size the log-market capitalization; and BtM the average book-to-market value. For y_i we take a number of coefficients, one-by-one, taken from models (1) to (6) in Table 4. Table 5 presents the estimation results.

The results in the first column (M1) reveal how the auto-regressive coefficient ϕ is related to company characteristics. Companies with a higher return volatility have a higher ϕ, implying faster reversion to the fundamental. Correspondingly, companies with a higher volatility in x have a higher ϕ. Companies that experience larger absolute deviation from the fundamental, a high $|x|$, also revert faster to the fundamental. The same holds for companies with a more volatile dividend yield. Finally, companies with a higher book-to-market have a higher ϕ. Then, in the second column (M2), we study the (univariate) sensitivity to sentiment, ϕ^3. Companies with higher return and higher volatility have a lower ϕ^3, indicating lower direct sensitivity to sentiment. The results in the third column (M3) indicate to what extent the autocorrelation parameter is sensitive to sentiment. Here we observe that it is especially the firms with a high and variable x, so deviation of price from fundamental, have a autocorrelation parameter that is less sensitive to sentiment. In the next column, M4, we test how the intensity of choice parameter β varies over firms. Recall that the average β is negative. Especially firms with a high variation in x have a more negative β, suggesting more sensitivity to performance differences and thus more switching between groups. Columns 5 and 6, both indicated by M5, show how the fundamentalist and chartist parameter differ in their sensitivity to sentiment. Interestingly, for fundamentalists we find a positive relation with size and

[5] Note that we estimate cross-sectional regressions on the 184 individual stocks in our sample. This is explicitly not a representative sample of the entire stock market because of the rather restrictive filters we had to apply to be able to estimate our model on the individual stock data.

for chartists a negative relation with size. The sensitivity of the intensity of choice to sentiment, ψ in M6, does not appear to be related to any of the company characteristics.

5. Robustness

In the empirical analyses we have made a number of choices. In this section, we will assess the robustness of the results to these choices. For the sake of brevity and lack of observations, we will focus on the index results alone. To be more specific, we test the robustness of the sentiment measure, the memory in the switching function I, and the fundamental value parametrization.

5.1. Sentiment measure

We next assess the robustness of our results by using alternative sentiment measures. Specifically, we replace the Buckman et al. (2020) with either of two complementary alternatives: Thomson Reuters News Analytics (TRNA) and the music sentiment measure from Edmans et al. (2022).

TRNA collects and analyzes firm-level news articles from major news outlets such as Down Jones Newswires, the Wall St Journal, Reuters, as well as local newspapers.[6] To measure the information content of each news article, it employs a proprietary algorithm of textual analysis and produces three quantitative scores that represent the probabilities that the news item has positive, negative, and neutral sentiment. TRNA also provides us with a score of how relevant the news item is for a given firm. As in Hendershott et al. (2015), we match news articles to a firm using NYSE trading days and hours. News stories appearing after 4 pm Eastern time will be assigned to the following trading day. To allow for the fact that a news item can be more relevant to one firm than another, we follow Hendershott et al. (2015) and scale the tone score by its relevance to the firm as follows:

$$tone_j = relevance_j \times (pos_j - neg_j) \tag{19}$$

where $relevance_j \in [0, 1]$ is the relevance score of the news item j to firm i; pos_j and neg_j are the probabilities that the news article j has positive and negative tone, respectively. For each firm, we compute the average tone of its news stories on a given day. Our measure of market-wide news sentiment on day t is then the simple average of firm-specific news tone across all firms in the market.

Second, we use the music sentiment measure from Edmans et al. (2022). Spotify, the leading online music platform, provides ample listening data. Spotify has an algorithm that classifies a song's valence, or positivity, trained on ratings of positivity by musical experts. We use the valence of the daily top-200 songs streamed on Spotify in the US as our second alternative measure sentiment.

Whereas the TRNA measure focuses specifically on news sentiment, the music measure picks up a more general sentiment level in society. Hence, we consider the two measures complementary. One drawback of both measures, is that their availability is lower compared to the Buckman et al. (2020) measure. The music sentiment measure is available to us from January 2017 to March 2023 (1,044 days) whereas the TRNA measure is available to us from 2003 to 2016 (3,357 days). The estimation results of the full model using the two alternative sentiment measures are given in Table 6.

The results in Table 6 reveal that the estimation results are slightly weaker for the alternative sentiment measures. The signs of all estimated coefficients are the same for both alternative sentiment measures as in the benchmark case using the Buckman et al. (2020) measure in Table 3. The significance of the estimated coefficients, however, is somewhat lower than in the benchmark case, especially for the music sentiment measure, which is explained by the lower number of available observations.

5.2. Memory

In the benchmark setting of the model, we set the memory parameter I equal to five. To study the sensitivity of the results to this choice, Fig. 5 presents the sensitivity of the results to the lookback period in the switching function Equation (13), I. Specifically, the figure presents the estimated coefficients of the full model with I varying from 1 to 250.

Results are largely robust to the choice of lookback period in the switching function in the sense that the signs and order of magnitude of the coefficients does not change, especially after somewhat more volatility for very low values of I. For the fundamentalist coefficients ϕ_F^1, ϕ_F^2, and ϕ_F^3 in the first row of Fig. 5 we observe that the first hovers between 0.6 and 0.9, the second moves between -2 and -3, and the third between -0.02 and -0.06. For the chartist coefficients ϕ_C^1, ϕ_C^2, and ϕ_C^2 in the second row of Fig. 5 we observe a similar stable pattern. The first varies between 1.0 and 1.4, the second between 1.8 and 3.2, and the third between 0.02 and 0.06. In other words, the expectation formation rules themselves are largely unaffected by the lookback period of the switching function.

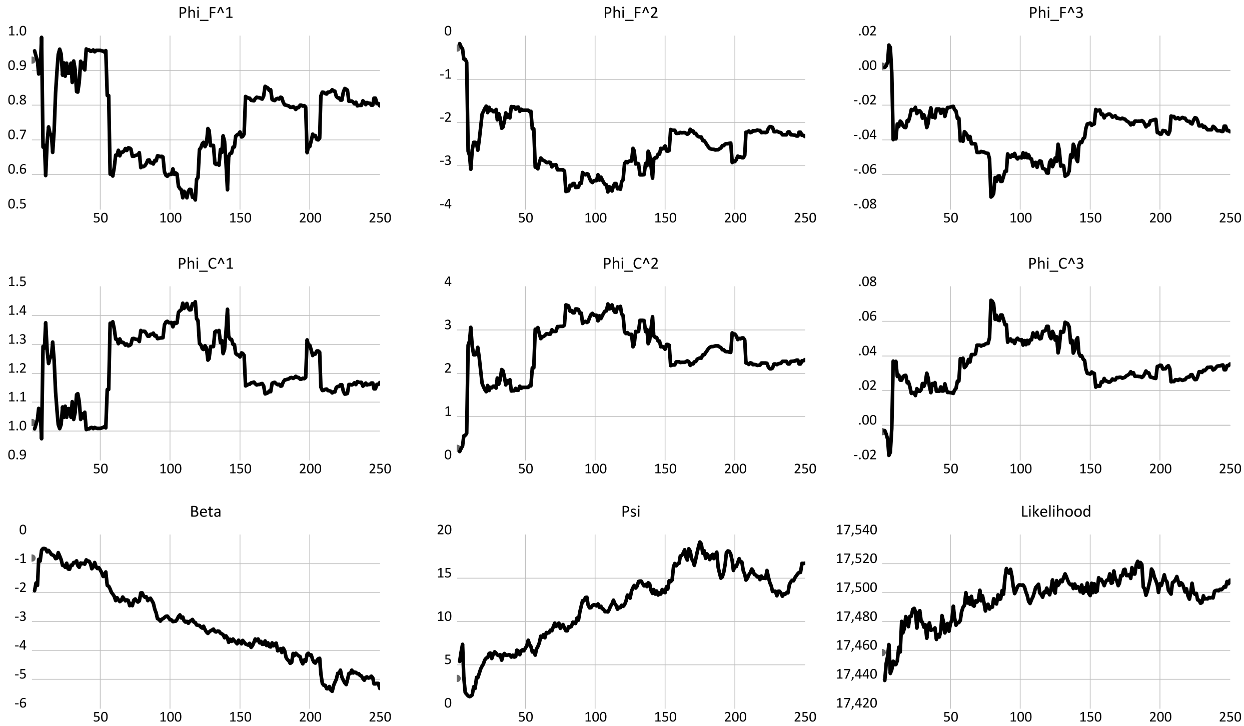
The third row displays the evolution of $\overline{\beta}$, ψ, and the likelihood for values of I. The intensity of choice parameter $\overline{\beta}$ becomes more negative as I increases. This implies that the model is looking for increased sensitivity to profit differences as the profitability becomes more stable with increasing I. The ψ parameter becomes more positive with increasing I meaning that the impact of sentiment on switching increases with I. The likelihood, finally, generally increases with I. In other words, the optimal lookback period of the agents in the market is longer than the benchmark of five.

[6] TRNA has increasingly become popular in academic research, as well as in the industry. For example, Hendershott et al. (2015) employ TRNA to examine whether financial institutions can predict the tone of firm-specific news. Heston and Sinha (2014) study the return predictability of TRNA's news sentiment in the U.S. market, while Smales (2016) examines the relation between TRNA's news sentiment and bank credit risk. Li et al. (2015) show that the coverage of TRNA is comprehensive and covers over 92% of Compustat's earnings announcements (the most common source of this information for the U.S. market). Mitra and Mitra (2011), Hendershott et al. (2015), Heston and Sinha (2014), and Li et al. (2015) provide detailed description of TRNA.

Table 6
Sentiment Measures.

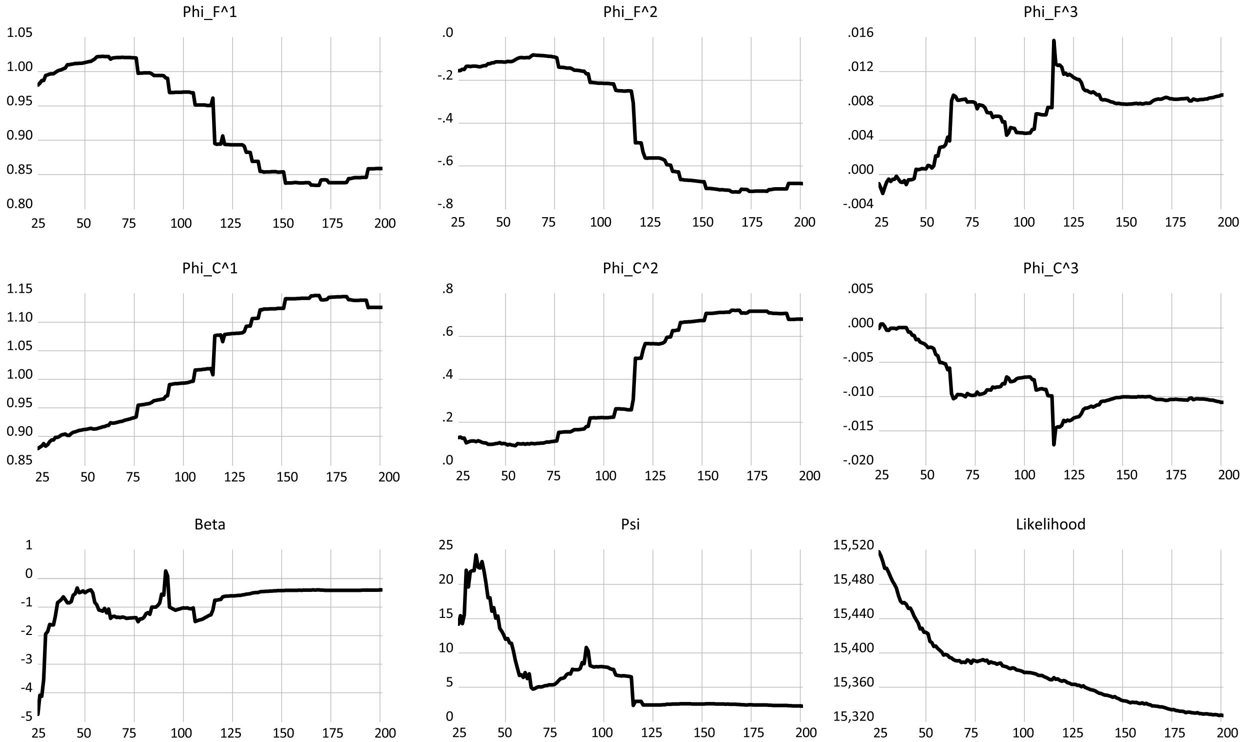
	TRNA	Spotify
ϕ_F^1	0.508***	0.612
	(14.118)	(1.125)
ϕ_F^2	-6.145***	-0.682
	(-12.741)	(-0.627)
ϕ_F^3	-0.049**	-0.079***
	(-2.556)	(-5.083)
ϕ_C^1	1.381***	1.525**
	(42.858)	(2.326)
ϕ_C^2	5.894***	0.265
	(13.455)	(0.201)
ϕ_C^3	0.103***	0.142***
	(7.266)	(6.195)
$\overline{\beta}$	-1.602***	-3.083***
	(-10.795)	(-2.311)
ψ	25.952***	4.677*
	(4.607)	(1.675)
c	0.001***	-0.020***
	(3.053)	(-5.163)
#obs	3,357	1,044

Notes: This table presents the estimation results of the model given by Equation (11) for two alternative empirical proxies of the sentiment measure S. Robust t-values in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.



Notes: This figure presents the sensitivity of the estimation results to the lookback period in the switching function I in Equation (15). The x-axis represents I, ranging from 1 to 250 days. In the benchmark case, we set $I = 5$.

Fig. 5. Sensitivity to Lookback Period in Switching Function.



Notes: This figure presents the sensitivity of the estimation results to the length of the moving average in Equation (17). The x-axis represents moving average period, ranging from 25 to 200 days. In the benchmark case, we take 100 days.

Fig. 6. Sensitivity to Fundamental Value Specification.

5.3. Fundamental value

Another choice in the benchmark model, was the calculation of the fundamental value in Equation (17). Fig. 6 presents the sensitivity of the results to the exact configuration of the fundamental value proxy. Specifically, we show the estimated coefficients of the full model when increasing the length of the moving average window from 25 to 200 days.

As for the lookback period I, results are also largely robust to the choice of fundamental value as all coefficients remain of the same sign and significant across the range. The fundamentalist coefficients ϕ_F^1 and ϕ_F^2 decrease as the window increases, with a pronounced drop around 110, and ϕ_F^3 in the first row of Fig. 6 increases. The increase in ϕ_F^1 is explained by the fact that the persistence in x increases as the moving average window increases. With a longer window, the effect of sentiment decreases, explaining the decreasing impact of sentiment. We observe the opposite patterns for the chartist coefficients in row two. ϕ_C^1 and ϕ_C^2 increase, whereas ϕ_C^3 decreases as the window increases.

The switching parameters $\overline{\beta}$ and ψ both decrease in absolute value as the moving average windows increases. Hence, switching becomes less intense and less sensitive to sentiment with a smoother fundamental value estimate. The likelihood, finally, decreases with increasing moving average window.

5.4. Functional form of switching

In the baseline switching function given by Equation (13), sentiment is included linearly. This choice, however, is not micro-founded making the model flexible enough to incorporate other functional forms. The optimal choice is then an empirical question. Therefore, in this subsection we run experiments with alternative ways to incorporate sentiment in the switching function.

In the baseline model, we let the intensity of choice β depend linearly on sentiment:

$$\beta_t = \bar{\beta} + \psi S_t. \tag{20}$$

Here, we consider three alternatives. First, we allow for agents to respond differently to positive than to negative sentiment through a piecewise linear function:

$$\beta_t = \bar{\beta} + \psi S_t + +\psi^- I_t S_t, \tag{21}$$

in which I_t is an indicator function equal to one when $S_t < 0$. In a second alternative, we allow the intensity of choice to depend on the absolute value of sentiment:

Table 7
Estimation results: sentiment form.

	(1)	(2)	(3)	(4)
ϕ_F^1	0.883***	0.838***	0.851***	0.845***
	(34.357)	(27.560)	(26.971)	(25.367)
ϕ_F^2	-0.550***	-0.632***	-0.615***	-0.615***
	(-7.867)	(-7.887)	(-7.389)	(-7.559)
ϕ_F^3	0.015***	0.016***	0.017***	0.016***
	(3.607)	(3.926)	(3.949)	(4.087)
ϕ_C^1	1.086***	1.131***	1.119***	1.125***
	(42.014)	(36.111)	(34.696)	(32.702)
ϕ_C^2	0.570***	0.658***	0.649***	0.644***
	(8.072)	(7.954)	(7.631)	(7.589)
ϕ_C^3	-0.017***	-0.018***	-0.018***	-0.018***
	(-4.806)	(-5.055)	(-4.881)	(-5.333)
$\overline{\beta}$	-0.812***	-0.203	0.072	-0.393*
	(-3.673)	(-0.599)	(0.237)	(-1.862)
ψ	2.455***	-1.042		1.143
	(4.372)	(-0.482)		(1.237)
ψ^-		5.183		
		(1.850)		
ψ^{abs}			-4.179***	
			(-4.803)	
ψ^2				-5.614**
				(-2.500)
c	0.000	0.000	0.000	0.000***
	(0.826)	(1.850)	(0.708)	(-2.500)
#obs	5,965	5,965	5,965	5,965
LL	17919.1	17920.23	17918.57	17920.5
LLR		2.240	-1.080	2.780

Notes: This table presents the average estimation results of the model given by Equation (11) on the S&P500 index, with varying configurations for the law of motion of the intensity of choice β given by Equations (21), (22), or (23). Robust T-statistics in parentheses; *, **, *** represents significance at the 10, 5, and 1% level, respectively.

$$\beta_t = \bar{\beta} + \psi |S_t|. \tag{22}$$

In this setup, the assumption is that switching is conditional on the magnitude of sentiment, regardless the sign. Hence, that agents might switch more if sentiment is extreme. The third and final alternative we consider, is a quadratic model:

$$\beta_t = \bar{\beta} + \psi S_t + \psi S_t^2, \tag{23}$$

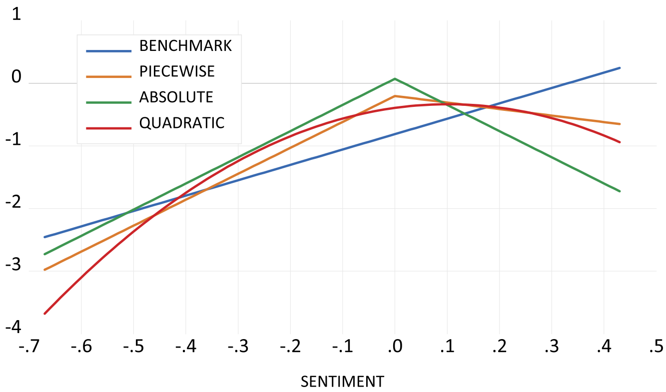
which allows for a nonlinear exponential relationship between sentiment and switching. The estimation results with these three alternative laws of motion for the intensity of choice β are given in Table 7.

Column (1) of Table 7 contains the benchmark estimation results, equivalent to column (6) in Table 3. Column (2), then, displays the estimation results with the law of motion of the intensity of choice β_t given by Equation (21). We observe that the absolute value and significance of $\overline{\beta}$ and ψ drop substantially, whereas ψ^- becomes marginally significant and positive. The drop in significance is an indication that the model might be overfitted. The likelihood increases somewhat relative to the benchmark model, but not significantly so. In column (3) we use the law of motion of β_t give by Equation (22). In this case the model fit decreases compared to the benchmark model, indicating that the absolute sentiment is too restrictive to capture the market dynamics. In column (4), finally, we use the quadratic form given by Equation (23). Again, we observe a drop in significance. The coefficient on the quadratic turn is negative and significant at the 5% level. This suggests a concave relationship between sentiment and the intensity of choice. To be better able to interpret the differences in estimation results in Table 7, in Fig. 7 we visualize the relationship between sentiment and intensity of choice β over the range of empirically observed sentiment values (i.e., -0.67 to 0.43).

The four lines are fairly consistent with each other, in the sense that the dynamics are somewhat skewed towards negative values of sentiment. It is unclear, however, whether this is due to behavior or the fact that the sentiment data itself has somewhat more negative than positive observations over our sample period. Economically, therefore, there seems to be slight evidence that the switching is especially driven by episodes of negative sentiment but given the statistical limits we are reluctant to draw strong conclusions.

6. Conclusion

This paper integrates the literature on investor sentiment with that on heterogeneous expectations. We adapt a heterogeneous agent model by making both the expectation formation rules and the switching rule conditional on market sentiment. Estimation results on the S&P500 and its constituents reveal that sentiment has an important confounding effect on the expectation formation process of fundamentalists and chartists in an agent-based setting. Specifically, only chartists are unconditionally sensitive to sentiment; fundamentalists are not. As a result, the market's overall sensitivity to sentiment is also time-varying. Furthermore, funda-



Notes: This figure presents the relationship between sentiment S and intensity of choice for different version of the functional form. Sentiment ranges from -0.7 to +0.5, reflecting the empirically observed values. The models represent the linear benchmark model; the piecewise linear model, with a break at $S = 0$; the absolute model based on $|S|$, and the quadratic model including S^2.

Fig. 7. Sensitivity to functional form.

mentalists' expectation of the speed of mean reversion is increasing in sentiment. Chartists' degree of trend extrapolation is increasing in sentiment. Hence, heterogeneity is increasing in sentiment. Furthermore, switching is decreasing in sentiment; agents become less sensitive to profit differences as sentiment increases. This set of results points towards the general conclusion that agents become more certain about their expectations as sentiment is higher. More generally, it shows that both sentiment, heterogeneity, as well as their interaction are crucial components of an alternative model for expectation formation.

References

Baker, M., 2009. Capital market-driven corporate finance. Annu. Rev. Financ. Econ. 1 (1), 181–205.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680.
Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21 (2), 129–152.
Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2015. X-capm: an extrapolative capital asset pricing model. J. Financ. Econ. 115 (1), 1–24.
Barberis, N., Shleifer, A., 2003. Style investing. J. Financ. Econ. 68 (2), 161–199.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49 (3), 307–343.
Baumeister, R.F., 2007. Encyclopedia of Social Psychology, vol. 1. Sage.
Bloomfield, R., Hales, J., 2002. Predicting the next step of a random walk: experimental evidence of regime-shifting beliefs. J. Financ. Econ. 65 (3), 397–414.
Boswijk, H.P., Hommes, C.H., Manzan, S., 2007. Behavioral heterogeneity in stock prices. J. Econ. Dyn. Control 31 (6), 1938–1970.
Brock, W.A., Hommes, C.H., 1997. A rational route to randomness. Econometrica 65 (5), 1059–1095.
Brock, W.A., Hommes, C.H., 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model. J. Econ. Dyn. Control 22 (8–9), 1235–1274.
Brown, G.W., Cliff, M.T., 2004. Investor sentiment and the near-term stock market. J. Empir. Finance 11, 1–27.
Brunnermeier, M.K., Pedersen, L.H., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.
Buckman, S., Shapiro, A.H., Sudhof, M., Wilson, D., 2020. News sentiment in the time of COVID-19. FRBSF Econ. Lett. 2020 (08), 1–5.
Cavaglia, S.M.F.G., Verschoor, W.F.C., Wolff, C.C.P., 1994. On the biasedness of forward foreign exchange rates: irrationality or risk premia? J. Bus. 67 (3), 321.
Chiarella, C., He, X.-Z., Zwinkels, R.C.J., 2014. Heterogeneous expectations in asset pricing: empirical evidence from the S&P500. J. Econ. Behav. Organ. 105 (1), 1–16.
Chung, S.-L., Hung, C.-H., Yeh, C.-Y., 2012. When does investor sentiment predict stock returns? J. Empir. Finance 19, 217–240.
Cochrane, J.H., 2005. Asset Pricing. Princeton University Press.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial markets. J. Polit. Econ. 98 (4).
Edmans, A., Fernandez-Perez, A., Garel, A., Indriawan, I., 2022. Music sentiment and stock returns around the world. J. Financ. Econ. 145 (2, Part A), 234–254.
Fama, E.F., French, K.R., 2002. The equity premium. J. Finance 57 (2), 637–659.
Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27 (3), 714–746.
Hendershott, T., Livdan, D., Schürhoff, N., 2015. Are institutions informed about news? J. Financ. Econ. 117 (2), 249–287. cited by 35.
Heston, S.L., Sinha, N.R., 2014. News versus sentiment: comparing textual processing approaches for predicting stock returns. In: Robert H. Smith School Research Paper.
Hommes, C., Lustenhouwer, J., 2019. Inflation targeting and liquidity traps under endogenous credibility. J. Monet. Econ. 107, 48–62.
Hommes, C., Sonnemans, J., Tuinstra, J., van de Velden, H., 2004. Coordination of expectations in asset pricing experiments. Rev. Financ. Stud. 18 (3), 955–980.
Hommes, C.H., LeBaron, B., 2018. Handbook of Computational Economics, vol. 4. Elsevier.
Huang, C.-L., Goo, Y.-J., 2008. Are happy investors likely to be overconfident? Emerg. Mark. Financ. Trade 44 (4), 33–39.
Kahneman, D., Slovic, S.P., Slovic, P., Tversky, A., 1982. Judgment Under Uncertainty: Heuristics and Biases. Cambridge University Press.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47 (2), 263–291.
Kukacka, J., Barunik, J., 2013. Behavioural breaks in the heterogeneous agent model: the impact of herding, overconfidence and market sentiment. Phys. A 392, 5920–5938.
Landier, A., Ma, Y., Thesmar, D., 2018. New experimental evidence on expectations formation. Working paper.
Li, E., Ramesh, K., Shen, M., Wu, J., 2015. Do analyst stock recommendations piggyback on recent corporate news? An analysis of regular-hour and after-hours revisions. J. Account. Res. 53 (4), 821–861.
Lintner, J., 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Rev. Econ. Stat. 47 (1), 13–37.
Lux, T., Zwinkels, R.C.J., 2018. Empirical validation of agent-based models. In: LeBaron, B., Hommes, C.H. (Eds.), Handbook of Computational Economics, vol. 4. https://doi.org/10.1016/bs.hescom.2018.02.003.

MacDonald, R., 2000. Expectations formation and risk in three financial markets: surveying what the surveys say. J. Econ. Surv. 14 (1), 69–100.
Mitra, G., Mitra, L. (Eds.), 2011. The Handbook of News Analytics in Finance. John Wiley & Sons Ltd.
Montone, M., Zwinkels, R.C.J., 2020. Investor sentiment and employment. J. Financ. Quant. Anal. 55 (5), 1581–1618.
Muth, J., 1961. Rational expectations and the theory of price movements. Econometrica 29 (3), 315–335.
Scheinkman, J., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Polit. Econ. 111 (6), 1183–1220.
Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk*. J. Finance 19 (3), 425–442.
Shiller, R.J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? Am. Econ. Rev. 71 (3), 421–435.
Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. J. Finance 52 (1), 35–55.
Smales, L.A., 2016. News sentiment and bank credit risk. J. Empir. Finance 38, 37–61.
ter Ellen, S., Hommes, C., Zwinkels, R., 2021. Comparing behavioural heterogeneity across asset classes. J. Econ. Behav. Organ. 185, 747–769.
ter Ellen, S., Verschoor, W., Zwinkels, R., 2019. Agreeing on disagreement: heterogeneity or uncertainty? J. Financ. Mark. 44, 17–30.
Zeeman, E., 1974. On the unstable behaviour of stock exchanges. J. Math. Econ. 1, 39–49.