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EXCHANGE-TRADED FUNDS, HETEROGENEOUS AGENTS, AND FINANCIAL STABILITY

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Abstract: Exchange Traded Funds (ETFs), esp. index funds, have seen an enormous growth over the recent decades. We investigate the financial market effects of actively traded ETFs in a heterogeneous agent model which is calibrated to historical data. We consider four types of traders, namely fundamentalists and trend followers who either trade ETFs or the underlying individual assets. We find that the complex interactions of investment strategies and the availability of ETFs generate interesting nonlinearities for typical market metrics such as susceptibility for bubbles, asset price volatility, asset price correlations, and mispricing. Thus, the growing popularity of ETFs as an investment vehicle gives rise to considerable regulatory challenges.

Keywords: Exchange-traded Funds, Financial Stability, Agent-based Model.

JEL codes: C63, D01, G10, G11, G40

1. INTRODUCTION

As one of the most important novelties in financial markets in decades, Exchange-Traded Funds (ETFs) have become a very popular financial product. Although ETFs were originally designed to follow stock market indices such as the S&P 500 in an easy-to-understand, cost-efficient way, the spectrum of ETFs has widened considerably with respect to underlying assets, market significance, and – esp. – trading strategies (Gastineau 2010, IMF 2015, Wiandt and McClatchy 2001). At the end of 2021, globally more than 8500 ETFs

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had assets under management of around USD 10 trillion, which represents, exemplarily, more than double of the hedge fund sector. Still, investments in such basket funds account for only around 10% of global equities (for recent surveys see Lettau and Madhavan 2018, BlackRock 2017, ETFGI 2021).

Originally mainly used as a passive investment mechanism, ETFs are increasingly used by active traders, e.g., by institutional and retail investors (Kommer 2016, Bhattacharya *et al.* 2013, Stacey and Narine 2018, Vlastelica 2017, Rennison 2017, Schatzker 2017). As a consequence, researchers as well as regulators are interested in the effects of this development on financial market governance, quality, volatility, efficiency, and stability (see, e.g., Fichtner *et al.* 2017, Ivanov and Lenkey 2014, Ockenfels and Schmalz 2016, Cuoco and Kaniel 2011, Pan and Zeng 2017, Anadu *et al.* 2018). According to Ben-David *et al.* (2014), volatility and turnover of stocks increase with higher shares of ETFs. News are faster reflected when stocks are listed in an ETF(Glosten *et al.* 2016) and their returns co-move more closely (Da and Shive 2017).Since assets that are listed in an ETF are linked to each other, their returns tend to be more strongly in line while they lose some idiosyncratic dynamic (see Pagano *et al.* 2019). This happens because traders react more to information concerning the index (i.e. the country or industry) and less to news about the underlying assets. As a consequence, earnings announcements etc. of the underlying firms have less and delayed impact on their price movements (see also Sullivan and Xiong 2012, Israeli *et al.* 2017). Zhao *et al.* (2022) find in the case of the Chinese A-share market that ETFs decrease idiosyncratic volatility, while increasing systemic volatility resulting in an overall reduction in volatility.

A smaller analyst coverage of assets listed in ETFs, which goes hand in hand with delayed price formation, might negatively affect market efficiency (cf. Israeli *et al.* 2017 and alsoBradley and Litan 2010, 2011). Other downsides of ETF investments come from an increased impact of traders' beliefs as well as short-sighted, highly correlated noise traders (see Da *et al.* 2015, Broman 2016).

In related research a number of studies analyze how ETFs might transmit noise to the underlying assets. ETF traders tend to bet more on the directions of short-time price changes, lowering efficiency, scaring long-horizontraders, and exacerbating price drops in bearish times (cf.Ben-David *et al.* 2014, Stratmann and Welborn 2012, Cella *et al.* 2013). When prices of individual assets change, the mechanical rebalancing requirements of ETFs may cause severe rebalancing cascades, which amplify the genuine signal (Chinco and Fos 2016).

A broad IMF study analyzes which processes in the asset management sector might create risks and how products that are thought to be innocuous, such as ETFs, could contribute to systemic risk (IMF 2015). They emphasize that systemic risk is strongly influenced by the type of trader who invests in ETFs and not so much by the volume of these products per se.

The European Systemic Risk Board (Pagano *et al.* 2019) also addresses ETF related system risks. It emphasizes that the financial market effects of ETFs become particularly relevant in times of financial stress. For example, a possible stronger co-movement of asset prices might raise stability problems as it becomes more likely that many traderslose money simultaneously, which might lead to waves of bankruptcies and fire sales.

Thus, when ETFs are available, shocks are likely to be larger and price developments might become unstable. One reason for this is that banks behave as market makers, which could reduce equity and, in turn, liquidity. Hence, it is an important research question how ETFs and the specific strategies of traders contribute to and affect risk resp. financial market instability (cf. Sushko and Turner 2018, D'Hondt *et al.* 2021).

We contribute to the literature by analyzing the mutual influences of ETFs and their underlying assets. This is particularly important for market regulators and policy makers due to ETFs' enormous increase in volume which is likely to continue in the future.

We consider two types of asset classes, namely stock indices and the underlying individual stocks, and two types of traders, namely fundamentalists and chartists. Fundamentalists invest if they believe that a specific asset or the index is undervalued, i.e., if the price is below its fundamental value, and disinvest if they believe them to be overvalued. Accordingly, fundamentalists' actions are typically thought to have a stabilizing effect (cf. Baumann *et al.*, 2019). Trend-following chartists invest if they face increasing prices and disinvest in the opposite case. Hence, they are often assumed to destabilize market dynamics.

Our study investigates the complex interactions between

- Fundamentalist vs. chartist and
- Individual stock vs. index investment strategies.

In a simulation study based on a heterogeneous agent model calibrated to historical data we examine how changes in the relative importance of these strategies affect standard asset market metrics such as

1. Assets' vulnerability to price bubbles,
2. Asset price volatility,
3. Correlation patterns between assets' and index's prices and fundamentals, as well as, more generally,
4. Mispricing.

While we find some of these effects of a greater use of ETFs and chartist strategies rather straight forward, e.g., that the prices of an index and the underlying assets co-move more closely, there is also evidence of wide-spread non-linearities due to complex interactions, e.g., in the case of the volatility of individual assets. This has important implications for regulators and financial market observers, as with an ongoing spread of ETFs, future developments cannot be simply extrapolated from the past but have to be monitored with great care.

The remainder of the paper is organized as follows. Section 2 introduces the theoretical model while Section 3 presents the simulation analysis. More specifically, Section 3.1 discusses the effects of ETFs and trend following resp. fundamental investments and develops working hypotheses on how these effects might interact. Section 3.2 presents the market metrics we are interested in, Section 3.3 introduces the model calibration, and Section3.4 depicts the technical simulation setup. In Section4 the simulation results are presented and interpretations are given. While Section5 gives ideas for possible future research directions, Section6 concludes the paper. In Appendices A and B additional information, e.g., robustness checks as well as alternative market metrics and graphs, are given.

2. THE MODEL

Building on the seminal work by Beja and Goldman (1980), market maker models populated with heterogeneous agents are widely used to analyze the effects of active trading strategies (see also Day and Huang 1990). Such so-called heterogeneous agent models (HAMs) usually focus on an easy to implement replication of the behavior of asset markets rather than of incorporating the specific mechanics of the pricing process. We follow this approach and (i) illustrate the basic ideas of the HAM pricing procedure for the case of a single asset market, (ii) discuss several limitations of the conventional HAM approach to model fundamentalist traders, and (iii) generalize the model so that markets with ETFs and multiple underlying assets can be analyzed.

2.1. Basic HAM for a Single Asset Market

As common in the HAM approach we assume that the change in the log price p^1 is linear in the sum of the excess demands D_l^1 of all traders l:

$$\dot{p}^1(t) = M^{-1} \sum_l D_l^1(t)$$

with $M > 0$ as a scaling parameter for trading volume and price sensitivity, i.e. the sensitivity of the asset price with respect to actions of the traders. The asset price increases when demand exceeds supply, i.e., when $\Sigma_l D_l^1(t) > 0$, and vice versa. Note that we use the superscript "1" to indicate the single-asset market case. When we generalize the model subsequently, parameters without a superscript refer to an index consisting of several assets.

We follow the literature and introduce a market maker who sets the asset price to clear the market. Assets are bought and sold by two types of traders, namely trend followers (which are simple chartists), denoted by *C*, and fundamentalists, denoted by *F* (Day and Huang 1990). Obviously, in real markets there are more trading strategies present. As is common in the HAM literature, we do not intend to rebuild all real trading rules. Rather the aim of HAMs is to find some simple and representative rules that, when combined, reproduce stylized market facts and real dynamics adequately well. For our purpose, this is achieved by chartists and fundamentalists. Traders that use both fundamental and chartists' rules can be thought to be split into two pure traders.

Again, we follow the literature and specifically model trend followers' excess demand to be linear in the change of the log price p^1 via

$$D_C^1(t) = W_C(p^1(t) - p^1(t - h_C))\, 1_{e \geq h_C},$$

Where W_C is a parameter of the chartists' strength (see Day and Huang 1990), i.e., it captures how sensitively chartists react to buying/selling signals, while $h_C > 0$ is a trader specific lag (or delay) parameter. The indicator function is necessary for technical reasons since $p^1(t–h_C)$ would not be well-defined if the time axis starts in $t_0 = 0$. Under $W_C > 0$, trader type *C* is a trend follower, i.e., *C* buys when the price rises and sells when it falls (i.e., when it rose or fell from $t – h_C$ to t). In the case of $W_C < 0$, this trader type could be characterized as a countercyclical trend follower or anti-trend follower, which we do not consider further. Analogously the fundamentalist's demand function is given via

$$D_F^1(t) = W_F(f^1(t + h_F) - p^1(t)),$$

Where f^1 is the log-fundamental-value of the asset. It is an open question in the literature, how fundamental asset values should be defined, e.g., as the expected sum of all future discounted cash flows, the balance sheet value or the resale value of the underlying firm divided by the total number of shares, and how traders should compute or estimate these values. Thus, we follow the HAM literature and assume that the fundamental value is exogenously given and that all traders, more specifically all fundamentalists, have got the same information on its future development and, hence, calculate the same expectation, which we label $f^e(t+h_F)$. Fundamentalists buy if the future expected fundamental value (in point of time $t + h_F > t$) is higher than the current price, i.e., if the asset is considered to be undervalued, and vice versa. Thus, their strength, i.e. their sensitivity to signals, is positive. In summary, fundamentalists expect the price to get close to the fundamental value in the long run, while trend followers expect a current trend to continue. Accordingly, chartists have been labelled backward-oriented, simple traders while fundamentalists have been characterized as forward-looking, sophisticated agents. The parameters $h_C > 0$ and $h_F > 0$ specify the degree to which chartists and fundamentalists are backward- respectively forward-looking. For simplicity, we assume that $h_C = h_F$ and that there are no cash flows, i.e., there are no dividends, incomes, or yields paid.

To be able to analyze financial market features such as mispricing, HAMs allow prices to deviate from fundamentals at any point of time. Thus, it is quite natural to ask why no one uses these arbitrage opportunities. The answer is twofold: First, as discussed, fundamentals in HAMs should not be understood as the real expected discounted future cash flows. Rather, the fundamental value function is a signal for fundamentalists (typical research questions are of the type: if the fundamentalists believe the asset to be undervalued, what happens?). Second, on real markets it holds that only because prices deviate from fundamentals this does not necessarily mean that there is an arbitrage opportunity. If the costs for discovering the mispricing (and for trading the asset) are higher than the possible mispricing, profits would vanish. Since an increasing use of ETFs tends to lower the analyst coverage (esp. of small firms), these costs might be high. Note that indices are often driven by big players.

2.2. Implicit Discretization of the Single Asset Market

As the simulation analysis can obviously not be conducted in continuous time, the model has to be transformed to discrete time with mesh size $h > 0$ (Day and Huang 1990). However, a straightforward discretization using an explicit Euler scheme for fundamentalists can lead to instability artifacts (Baumann *et* *al.* 2022) so that we partially discretize the model by use of an implicit Euler scheme (Baumann *et al.* 2022). With this discretization approach we get

$$p^1(t+h) = \chi_1(t+h) + (W_C h(p^1(t) - p^1(t-h_C))1_{t\geq hC})/M,$$

where $\chi^1(t+h)$ is the price equation's solution for the fundamentalist strategy

$$\chi^1(t + h) = \mathrm{p1(t)} + \mathrm{WFh}(f^1(t+h_F) - \chi^1(t + h))/M.$$

For simplicity we set the mesh size $h = h_C = h_F$ and assume the new log price $p^1(t + h)$ to be at least ln (0.01).

This market model is discussed in greater detail in Baumann *et al.* 2022. With respect to our market metrics in such a single-asset market,

1. A high share of fundamentalists implies a zero or at least very low bubble rate while a high share of trend-following chartists increases the likelihood of bubbles.
2. In the case of asset price volatility, a higher share of chartists has an ambiguous effect, as two opposing mechanisms are at work. When more chartists enter the market, asset prices are likely to overshoot, which might increase the volatility. If the chartists' share increases further such that they dominate the market, distinct price trends with low volatility could appear. However, rising asset prices in combination with a high share and strength of chartists might lead to exponentially growing prices, which increases volatility (cf. Baumann 2015).
3. Concerning the correlation between prices and fundamentals it is straight forward that a higher share of fundamentalists increases the co-movements.
4. Chartists lead to overshooting prices, bubbles, or prices that deviate from their fundamentals. All these effects should increase the degree of mispricing.

2.3. The Multi Asset Market

In order to analyze the ramifications of ETFs on financial markets we generalize our model and allow for traders that invest in an index ETF as well as for traders that invest in the underlying assets directly. There are $m \in \mathbb{N}$ assets with log prices $p^i(t)$, $i = 1, \ldots, m$, $t = 0, h, 2h, \ldots, y \cdot T$, listed in an index with log price $p(t) = \ln \Sigma \mathrm{i} \exp p^i(t)$. The number of trading days per year is defined as T and the number of years under investigation as y.

Further, we introduce a total number of traders $\mathrm{N} \in \mathbb{N}$, which splits up into the four types of traders. We define $q_F \in [0,1]$ as the share of traders using a fundamental strategy and, independently, $q_E \in [0,1]$ as the share of traders investing in ETFs. Additionally, we have $q_C = 1 - q_F$ as the share of traders using a chartist strategy and, independently, $q_S = 1 - q_E$ as the share of traders investing in single stocks. Combining these elements, we get

- $N_q F q_S$ fundamentalists investing in individual stocks,
- $Nq_C q_S$ chartists investing in individual stocks,
- $Nq_F q_E$ fundamentalists investing in the index directly, and
- $Nq_C q_E$ Chartists investing in the index directly.

We introduce weights $w_F = W_F Nq_F q_S/M$, $w_C = W_C Nq_C q_S/M$, wFE = W_{FE} $Nq_F q_E/M$, and $w_{CE} = W_{CE}\, Nq_C q_E/M$ to simplify the notation, with $W_{FE} > 0$ and $W_{CE} > 0$ as the strength parameters of ETF fundamentalists and ETF chartists, respectively. These parameters specify how sensitively the specific trader types react to their respective buying or selling signals.

We specify the excess demand functions of the ETF traders if they are fundamentalists as

$$D_{FE}(t) = mW_{FE}\left(\ln \sum_i \exp f^i(t+h) - \ln \sum_i \exp p^i(t)\right)$$

$$= mW_{FE}\,(f(t+h) - p(t))$$

and if they are chartists as

$$D_{CE}(t) = mW_{CE}\left(\ln \sum_i \exp p^i(t) - \ln \sum_i \exp p^i(t-h)\right)1_{t\geq h}$$

$$= mWCE\,(p(t) - p(t-h))1_{t\geq h},$$

Where $f(t+h) = \ln \Sigma_i \exp f^i\,(t+h)$ is the log-fundamental of the index.

As the index consists of m different assets, the excess demand functions of the ETF traders have to be modified by multiplying with m to guarantee that the traders' investment volume does not depend on whether they invest in ETFs or in the individual underlying assets.

According to the construction principle of ETFs, an ETF traders' demand is allocated among the individual assets according to the relative weight of the assets in the index. We assume the index to be a price index, so that the relative weight of the assets is determined by the price of these assets relative to the price of the index, i.e.,

$$D^i_{EF}(t) = \pi^i(t)\,D_{EF}(t)$$

resp.

$$D^i_{EC}(t) = \pi^i(t)\,D_{EC}(t)$$

with $\pi^i(t) = \exp(p^i(t)) / \exp(p(t))$ (cf. Lettau and Madhavan 2018).

Taken together, the following system of nonlinear equations describes the asset price dynamics:

$$\{p^i(t+h) = \chi^i(t+h) + w_C h(p^i(t) - p^i(t-h))1_{t\geq h}$$
$$+ mw_{CE}\pi^i(t)(p(t) - p(t-h))1_{t\geq h}\}_{i=1,\dots m}$$

$\{\chi^i(t+h)\}_{i=1,\dots,m}$ being the solution of

$$\{\chi^i(t+h) = p^i(t) + w_F h(f^i(t+h) - \chi^i(t+h))$$
$$+ mw_{FE}\pi^i(t)(f(t+h) - \chi(t+h)\}_{i=1,\dots m},$$

with $t = 0, h, 2h, \dots, y \,.\, T$, using a suitable non-linear solving algorithm and with $\chi(t) = \ln \chi^i \exp \chi^i(t)$. Then $p(t+h)$ is calculated and, as in the single asset case for computational and economical reasons, p^i is minimally set to ln (0.01) and, analogously, p is minimally set to ln $(0.01m)$. That means, starting with given/initial values $p^i(0), f^i(t)$ $(i = 1, \dots, m; t = h, 2h, \dots, yT)$, we calculate $\chi^i(h) = p^i(h)$ (due to the indicator functions 1 in D_C and D_{CE}) and then successively $\chi^i(2h), p^i(2h), \chi^i(3h), p^i(3h), \dots, p^i(y \,.\, T)$ for all i (and with it p and χ). The intermediate step of calculating the χ^i is – as in the single asset case – necessary to avoid instability artifacts (Baumann *et al.* 2022).

2.4. Stochastic Fundamentals

To determine the demand of the (ETF) fundamentalists we have to define f^i resp. f. Up to now, the market model is fully deterministic. A widely used option to introduce stochastic elements into a pricing model is via the fundamental values (see Hommes2006).

Accordingly, we specify the fundamental values ϕ^i via stochastic differential equations $d\phi^i(t) = \mu\phi^i(t)\,dt + \sigma\phi^i(t)\,dB^i(t)$. The ϕ^i are geometric Brownian motions with trend $\mu \in \mathbb{R}$, volatility $\sigma > 0$ independent of i, resp., and constant for all assets, and stochastically independent Brownian motions (i.e. Wiener processes) B^i. With this, we define $f^i(t) = \ln(\phi^i(t))$. Note that prices do not have to follow geometric Brownian motions.

3. SIMULATION

In the subsequent Monte Carlo simulation, we investigate how the spread of index ETFs changes the structure of financial markets as measured by different market metrics and how these effects depend on the specific investment strategies. In particular, we account for two dimensions, namely,

(i) The relative weight of ETF vs. individual asset investors and

(ii) The relative weight of fundamentalist vs. chartist investment strategies.

As these two dimensions interact with each other, complex non-linearities might arise. In a first step we formulate working hypotheses how changes along these two dimensions are likely to affect different features of financial markets such as, e.g., the likelihood of asset price bubbles. In a second step, we define specific market metrics to measure these features, discuss the calibration of model parameters, and outline the simulation setup.

3.1. Working Hypotheses

Based on our previous discussions on the effects of ETFs and the role of investment strategies we generate several working hypotheses how these developments might change the structure of financial markets as measured by alternative market metrics. In some cases, these effects enforce each other, in other cases they work in opposite directions.

1. Likelihood of bubbles: We hypothesize that a rising weight of chartists relative to fundamentalists unambiguously increases the likelihood of bubbles as price trends are reinforced and overshooting prices become more likely. The effects of ETF investors might differ depending on the relative importance of chartist investors in the market – a first example of non-linearities associated with the presence of ETFs. With only few chartist traders in the market, we do not expect an increasing share of ETF-based investors to affect the likelihood of bubbles. However, with a high share of chartists, we conjecture that ETFs can make a difference leaving asset markets more susceptible to asset price bubbles. In chartist-dominated asset markets an increase in ETF traders enforces the effect that prices of individual assets become more aligned, hence, the index price is more likely to overshoot. At the same time, we expect the increasing use of ETFs to have an averaging effect: as effects of the index price start to dominate, bubbles in individual asset markets may become less likely.

2. Asset price volatility: An increase in chartist trading might on average lead to higher volatility, although this pattern is likely to be non-linear or even non-monotonic. Higher shares of ETF traders can increase the volatility of the individual asset prices since traders are affected by the movements of the index's price or fundamental, which are possibly higher than those of a specific individual asset. However, for high shares of chartists, it is not clear whether this effect dominates or whether aligned prices lead to lower volatilities.

3. Correlation of asset prices, index price, and fundamentals: With an increasing weight of chartists, we conjecture correlations between the prices of individual assets and the index to increase. Also a higher share of ETF traders is believed to imply higher correlations between the prices of assets and the index. These two effects are expected to reinforce each other. Further, with a higher share of chartists, correlations between individual prices and their fundamentals should decline. When there are almost only ETF traders in the market, this correlation is likely to be very low. However, if there are sufficiently many chartists, an increase in ETFs might have opposite effects. Firstly, asset prices are likely to become more independent from their fundamentals, but, secondly, with fewer single-asset chartists the correlations of asset prices and their fundamentals might increase. It is not clear which of these effects dominates. The correlation between the index's fundamental and the individual asset prices might increase with both a higher share of fundamentalists and ETF traders with both effects reinforcing each other. The effect of ETF trading on the correlation of the index's price and fundamentals (both single-assets and index) might be low, while chartists are likely to decline these values.

4. Mispricing: We hypothesize that mispricing is more prevalent on the level of the individual assets if more investors follow a chartist investment strategy as price trends should become more important relative to fundamentals and also if investors switch to ETF-based investments due to the concomitant averaging effect. Mispricing on the level of the index might also increase with the shift to chartist strategies while in the case of an increased use of ETFs as an investment vehicle the overall effect is likely to depend on the relative weight of chartists in the market. With few chartists an increasing use of ETFs might have little effect while at a high level of chartists again two opposing effects could be at work as discussed in the case of asset price bubbles.

3.2. Market Metrics

As discussed above, changes in the relative importance of ETFs and alternative investment strategies are likely to affect financial markets along different dimensions. In the following we define the specific metrics how we measure these market features.

1. We define an **asset price bubble** as a situation in which for at least one of the individual assets or for the index itself the respective price is more than four times its corresponding fundamental value.As this value is chosen somewhat arbitrarily, we complement our analysis by a sensitivity analysis with

alternative values, see Appendix B.If a bubble occurs in one of our Monte Carlo runs, we abort this run and all subsequent computations. Consequently, we compute the other market indicators only for the non-bubble runs.

2. We measure the **volatility of the index and the individual asset prices** based on the concept of historical volatility. The historical volatility bases on the following idea: if the price was a geometric Brownian motion, it would be most plausible that the historical volatility was the underlying volatility of the respective stochastic differential equation. Thus, we used the assumption of geometric Brownian motions (GBMs) for the prices. Alternatives to the historical volatility are the implicit volatility or the standard deviation. While implicit volatilities use even more assumptions (those of Black Scholes), the standard deviation uses less. The latter approach is typically harder to interpret. As our HAM does in general not lead to GBM price paths (see Baumann 2015), it is a priori not clear whether the historical volatility is a meaningful tradeoff – however, it turns out that it is.A comparison with the standard deviation of the returns of the index resp. of the returns of the assets shows that the historical volatility is meaningful. See Appendix A for this complementing robustness check.

3. As a measure for the **correlations between the prices of the individual assets, their fundamentals, the index, and its fundamental** we compute the easy to interpret Pearson correlation. It seems to be a natural choice as it measures linear dependencies and our model is for the limiting case of only single asset fundamentalists linear in log-prices and, hence, approximately in the returns, too.As we cannot rule out non-linearities in the model for other parameter values, additionally, we compute Kendall's τ as a robustness check. When there are monotone but non-linear dependencies, Kendall's τ as a metric for monotone dependencies (i.e.rank correlations) will indicate them – in contrast to the Pearson correlation, see Appendix A.

Note that for all the correlations, we consider the returns of the processes. To get one correlation value for the several individual assets, we calculate the mean of the correlations for the stocks. Then, we average these means over the different Monte Carlo runs in which no bubble occurred. The same is done for the assets' unique counterpart, the index.

4. As a measure for **mispricing,** we calculate the mean squared deviation of a stock's (respectively the indexes) price from its respective fundamental value. Here, we do not use log-prices or log-fundamentals but the nominal level values. The asset prices' deviations from their fundamentals are averaged

over all assets and all indicators are averaged over the number of non-bubble runs.

3.3. Parameter Values

We conduct the simulation for $y = 5$ years consisting of $T = 250$ trading days each. The initial log-fundamental-value of each asset is $f(0) = 0$, which is also the starting log-price of each asset ($f^i(0) = p^i(0) = 0$). Trend and volatility of the fundamental of each asset are set to $\mu = 0.05\%$ and $\sigma = 2.25\%$ resp. How these values are chosen is explained in the next paragraph. The parameters modeling the strength of the traders are set to $W_F = W_{FE} = 1$ and $W_C = W_{CE} = 0.25$. The particular values of the strength parameters do not have a specific interpretation per se (cf. Beja and Goldman 1980, Day and Huang 1990, and Huang and Day 1993). Rather the parameter values are chosen so that the model replicates basic stylized financial market facts like asset volatility, non-vanishing prices/indices, and unpredictable returns for most combinations of trader types. Our simulation results suggest that moderately alternative parameter values have similar qualitative effects. As the scaling parameter $M > 0$ and the total number of traders $N \in \mathbb{N}_0$ are always paired as $N/M > 0$, we set $N/M = 4.1$ as a single parameter in our application (see also the next paragraph).

For calibrating the model, we use a grid search method. For estimating the three parameters μ (trend of the fundamental values), σ (volatility of the fundamental values), and N/M (price elasticity), we conduct 1,000 Monte Carlo runs of our model with varying values of μ, σ, and N/M and compare the price trend and price volatility of the resulting price developments with real world data, as further explained below. In these simulations – which use the same 1,000 underlying random walks for each parameter combination – we have to specify fixed values for the share of the ETF traders and (independently) for the share of the chartists. As discussed in the literature, cf., e.g., Oberlechner (2001), Menkhoff (2010), or Nti *et al.* (2020), most traders seem to (possibly) combine elements of fundamental and chartist strategies. We split these mixed rules into the chartist part and the fundamental part, leading to our two basic rules. While the potential range of chartist strategies is quite large, a 20% share seems to be a plausible initial value (cf. the discussion in Section5). For the share of ETF traders, we also use 20% as discussed in the literature (despite of other opinions, cf. Kommer 2016). Additionally, we assume that our index consists of $m = 30$ stocks.

As can be seen in the literature, there is no clear finding concerning the shares of trading rules used on markets – and the opinions about that differ strongly. This concerns active/passive/ETF/etc. as well as chartist/fundamentalist/noise/liquidity/etc. and all the countless subtypes. As a tradeoff which seems to us to be not completely contradictory to the literature we use, as mentioned above, 20% chartists and 20% ETF traders for calibrating. It is very important to note that the exact values are not that important: All results have to be understood in a qualitative sense and not in a quantitative one. That means our findings are of the form "If the share of ETF tradersincreases moderately from a very low level while the share of chartists stays very high, the frequency of bubbles to occur in our simulation rises" and not of the form "If the share of ETF traders increases from 10% to 60% while the share of chartists is constant 97.5% the likelihood of bubbles to occur in real markets increases from 0% by at least 33*pp*." Thus, the results are qualitative and not quantitative simulation outcomes relative to the calibration point and give, hence, qualitative und relative hints for real markets.

In an extensive grid search we look for the parameter values of the fundamentals and the price elasticity, namely, μ, σ, and N/M, that best replicate features of real-world financial markets. As benchmarks we use the Dow Jones Industrial Average, the European index EURO STOXX 50, as well as the German index DAX – all from 2016 to 2020. We use the following target values in our parameter search, which are the 5-year trend per day resp. the 5-year volatility per day (cf. square-root-t formula):

$\mu_{DowJones} = 0.00042$

$\mu_{EUROSTOXX50} = 0.00022$

$\mu_{DAX} = 0.00020$

$\sigma_{DowJones} = 0.01764$

$\phi_{EUROSTOXX50} = 0.01774$

$\sigma_{DAX} = 0.01801$

(Grüne 2017, Refinitiv Eikon/Datastream). Note that these values are calculated with the methods used in this work. Based on our grid search we select $\mu = 0.0005$, $\sigma = 0.0225$, and $N/M = 4.1$ as the parameter values for the fundamentals and the price elasticityand yield $\mu_{MonteCarlo} = 0.00025$ and $\sigma_{MonteCarlo} = 0.01789$ the averaged values for price trend and volatility.

For a share of ETF traders and chartists of 20% each, $\mu_{MonteCarlo}$ and $\sigma_{MonteCarlo}$

lie in the range spanned by the historic market data (with $h = 1$, $y = 5$, $T = 250$, and the other values as mentioned above). In Figure 1 it is depicted how we calibrate our models to three markets at once. Via an extensive grid search we found values for the parameters of the fundamentals and price elasticity such that under the assumption of 20% chartists and 20% ETF traders the resulting price trends and volatilities lie in the span of the historic data.

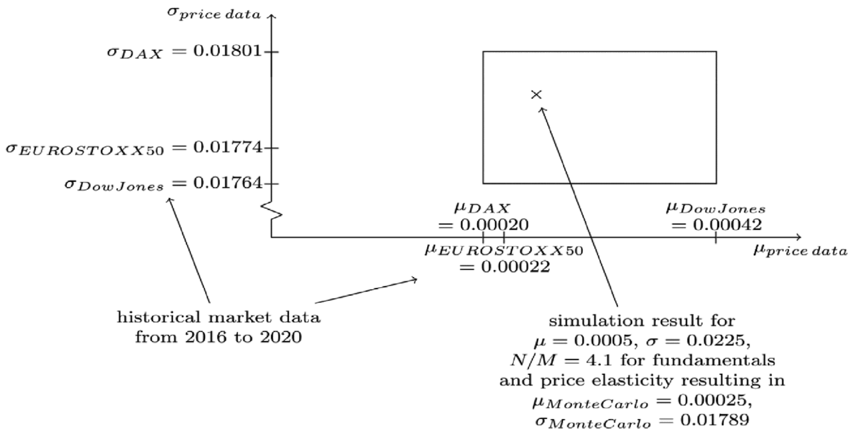


Figure 1: Estimated trends and volatilities for historical market data and for our simulation with 20% chartists and 20% ETF traders

3.4. Simulation Setup

To simulate the market model with alternative weights for ETF investors and chartist traders, we discretize the parameter space (qC, qE) ∈ $[0,1)^2$ into $(q_C, q_E) \in \{0,0.025,0.05, ..., 0.975\}^2$. Note that the cases $q_C = 1$ and $q_E = 1$ are excluded since in both cases there are no market forces that would push the price back to its fundamental, leaving fundamentals meaningless. Since our market model consists of m = 30 stocks, we simulate 30 . 100 = 3,000 fundamental value paths for the Monte Carlo study (each being of length 250) and use these fundamental paths for all points $(q_C, q_E) \in \{0,0.025,0.05, ..., 0.975\}^2$. This leads to 1,600 market developments with a total of 48,000 asset price paths. As a further parameter for the simulation, we set a seed to make the results replicable.

4. RESULTS

In the following we discuss how changes in the share of ETF traders and/ or chartist traders affect the market structure as measured by the alternative market metrics. 1.) Figure 2 depicts how varying shares of chartists (horizontal axis) and ETF traders (vertical axis) affect the likelihood of **asset price bubbles** (number between zero and 100). For every grid point, the number of bubbles is indicated by a color ranging from dark/violet (low number of bubbles) to light/yellow (high number of bubbles). Bubbles occur only for a very high share of chartist and a share of ETF traders between roughly 25% and 90%. A growing share of chartists unambiguously increases the likelihood of bubbles, as their trading strategy strengthens price trends and, thus, possibly overshooting prices. In contrast, the effect of ETFs is ambiguous and, thus, a first example of the non-linearities associated with the presence of ETFs. With only few chartist traders in the market, an increasing share of ETF-based investors does not affect the likelihood of bubbles. However, if many chartists are present in the market changing shares of ETFs can make a difference. Starting at a low level an increase in ETF trading makes the asset markets more susceptible to asset price bubbles: With more chartists both as investors in individual assets and in ETFs, longer-lasting price trends become more common with two opposing effects. As more traders invest via ETFs the prices of the individual assets become more aligned and at the same time the index price tends to overshoot to a larger degree. Thus, the index becomes via this ETF channel an additional driver for overshooting prices in the case of individual assets and bubbles become more likely. Once a (very) high level of ETF trading is reached a further increase tends to lower the likelihood of bubbles as the averaging effect of the index price starts to dominate making bubbles in individual asset markets less likely, i.e., the share of chartists investing in individual assets becomes so small that the purchase signals via the ETF channel do not cause bubbles in the single assets anymore.

Put differently, under a (very) high share of ETF traders asset prices can move far (above their fundamentals), so that chartists of individual assets might increase their investments (see also the discussion on "mispricing" further below). If there are no single asset fundamentalists to stabilize, these extensive asset purchases might lead to bubbles. However, if the share of ETF traders is very high, there are not enough chartists investing in single assets left in the markets to cause bubbles. Taken together, the common hypothesis that ETFs per se make financial markets more unstable, has to be put into question.

2. The **asset price volatility** depends strongly on both the share of chartists and the share of ETF traders whereas the **volatility of the index** mainly

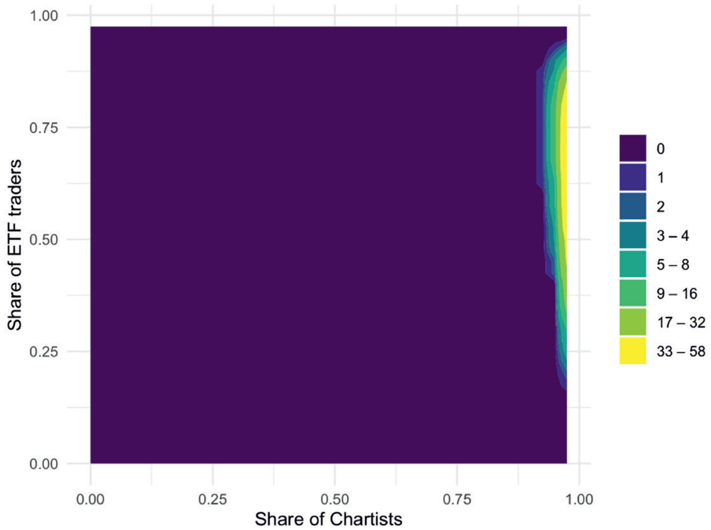
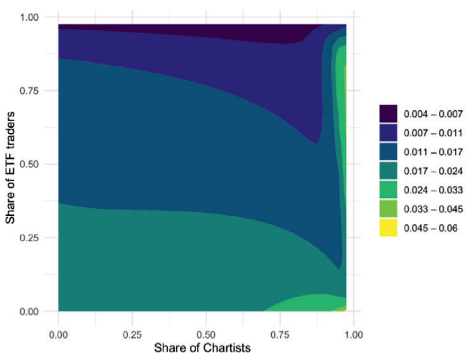


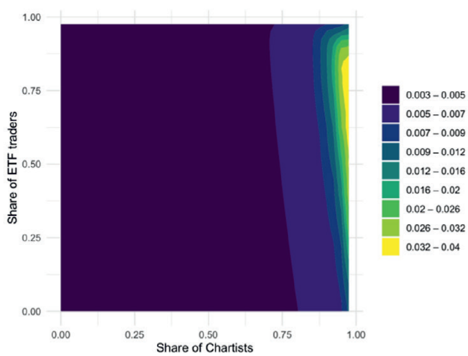
Figure 2: Number of bubbles

depends on the share of chartists, see Figure 3. The standard deviation gives similar results as the so-called historical volatility, see Figure A3 in Appendix A.

Chartists affect the volatility of individual asset prices in a complex and interesting way. Again, two effects can be observed, which overlap and have different strengths and are of opposite directions: On the one hand, many chartists can lead to long-lasting trends, which lowers volatility. That means, they are smoothing the volatile fundamental signals. On the other hand, if there are enough buy or sell signals in the market, they amplify price trends, which increases volatility and thus might also cause bubbles. The latter effects are also mirrored in the volatility of the index.



(a) Volatility of the stocks

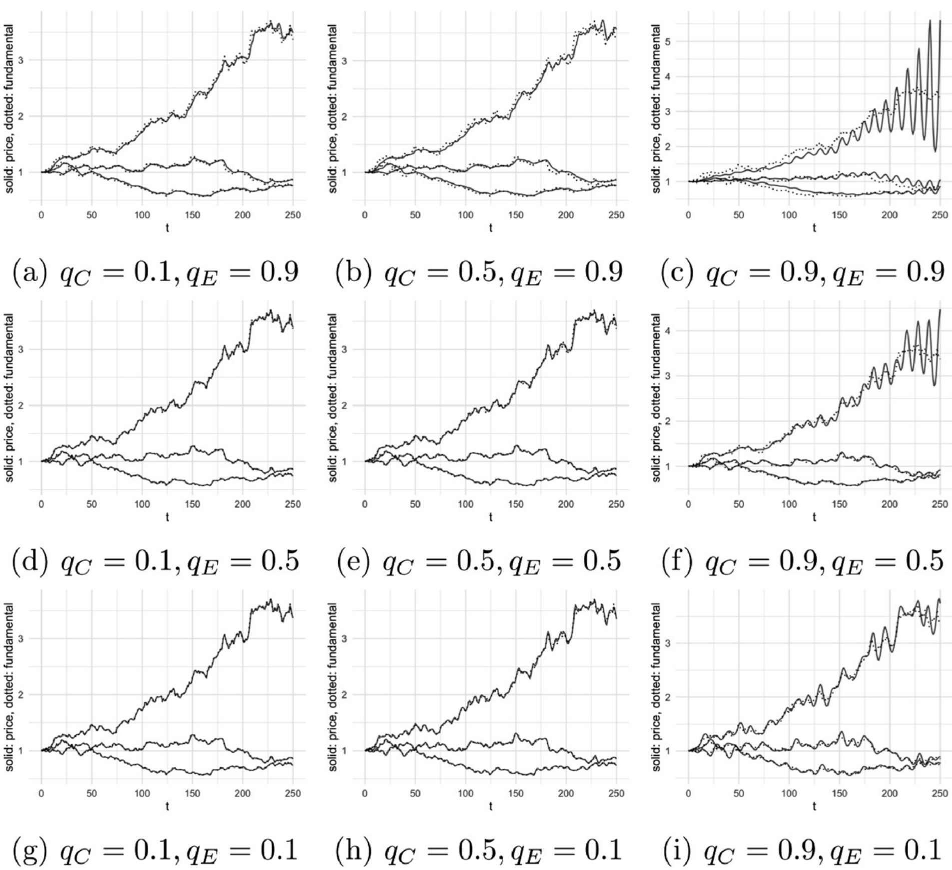


(b) Volatility of the index

Figure 3: Volatility level plots

More ETF traders basically decrease market volatility because traders react less to changes in the fundamentals and prices on the level of the individual assets and more to the index's averaged fundamental value change resp. to the averaged change of the index's price. The share of ETF traders has little influence on the volatility of the index since they only look at averaged values anyway.

To give further insights in the price behavior of individual stocks and their fundamentals, Figure 4 exemplarily depicts the price paths of three stocks and Figure 5 of the index consisting of these three and the remaining 27 other stocks for nine different trader constellations, namely all combinations of $q_C \in \{0.1, 0.5, 0.9\}$ and $q_E \in \{0.1, 0.5, 0.9\}$. The nine graphs for the stocks and the index appear at those positions in Figures 4 and 5 where they are roughly

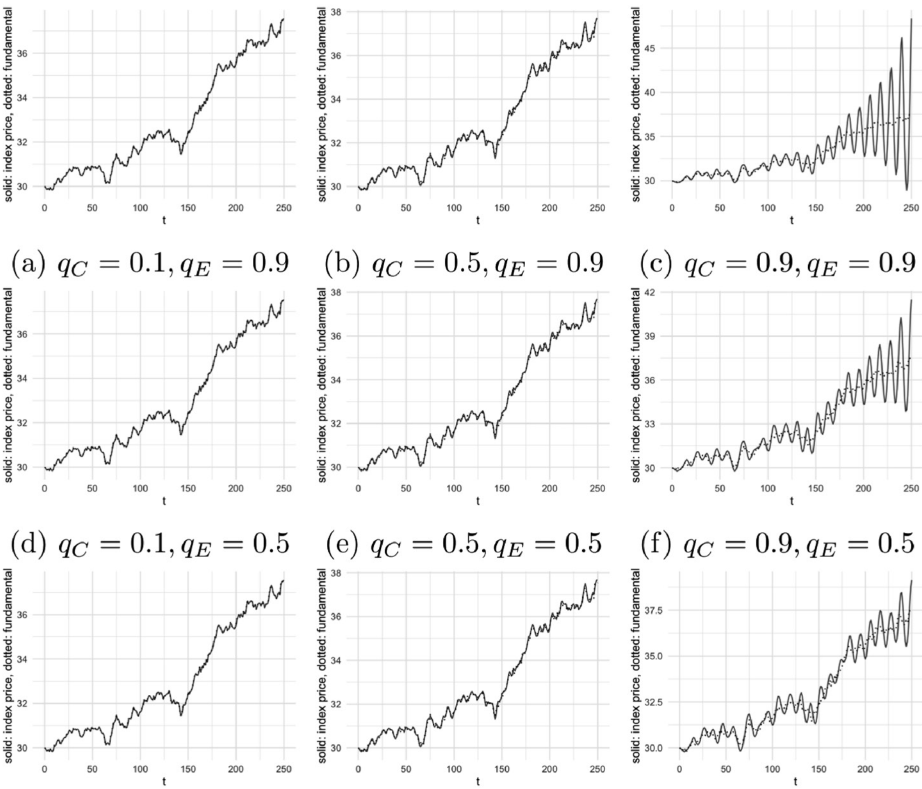


(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure 4: Price paths and fundamental paths for three exemplary stocks with the respective share of chartists q_C and share of ETF traders q_E



(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

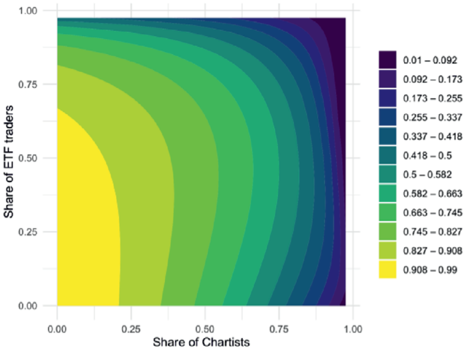
(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

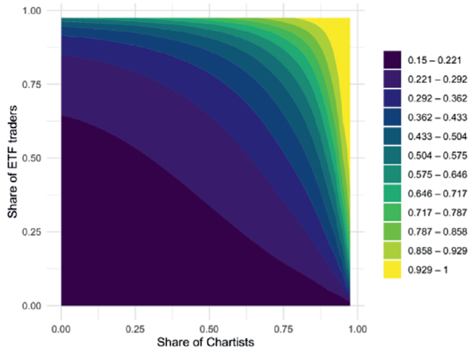
Figure 5: Price path and fundamental path for the index with the respective share of chartists q_C and share of ETF traders q_E

located in the level plots.Additionally, Figure A5 in Appendix Adepicts the price paths of all 30 stocks.

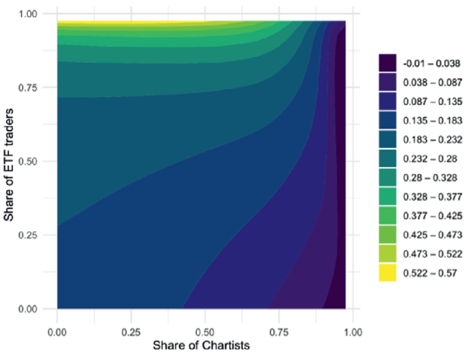
The price paths are the solid lines and the fundamental paths the dotted ones. Evidently, a higher share of chartists amplifies the price movements of the stocks and the index, leading to oscillation patterns. Note that only non-bubble paths are shown here, meaning that more chartists could also lead to more bubbles. However, since the path selection is from the non-bubble paths, we see oscillations here as prices return to their fundamental values. While an increase in ETF traders drives prices of stocks away from their fundamental values, it may basically reduce the distance between the index and its fundamental value. However, a delay effect caused by ETF trading and oscillation effects caused by chartists mutually amplify each other on the level of individual stocks, which then of course also affects the index.



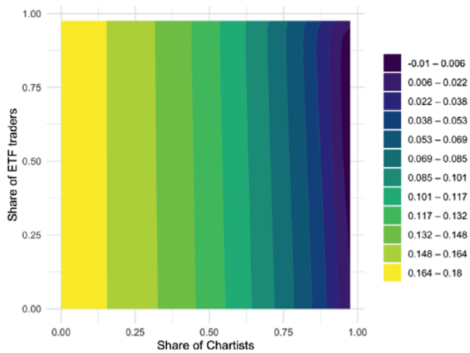
(a) Correlation between assets prices and their fundamental values



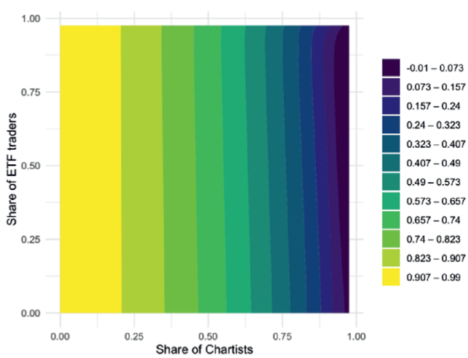
(b) Correlation between asset prices and the price of index



(c) Correlation between asset prices and the fundamental value of the index



(d) Correlation between the index price and the assets' fundamental values



(e) Correlation between index price and its fundamental value

Figure 6: Correlation level plots

3) The **correlations** between the returns of individual assets, their respective fundamental values, the index, and its fundamental value are important indicators for the efficiency of financial markets. Figure 6depicts our simulation results for the Pearson correlation. Qualitatively similar results for Kendall's τ are shown in Appendix A (see Figure A4). Obviously, the correlation between the fundamentals of the assets and of the index does not depend on the trading strategies. The value is $cor_{fi,f} = 0.1759006$ and can be used as a benchmark. The corresponding value for Kendall's τ is $\tau_{fi,f} = 0.1127749$.***

Not surprisingly, the correlation between the prices and the fundamentals of the assets increases with the weight of fundamentalists in the market (see Figure 6a). Additionally, for a minimum share of fundamentalists (i.e. in the left part of Figure 6a), the correlation also decreases with the share of ETF traders, which is of course due to the fact that the ETF fundamentalists consider the index and the index's fundamental value for their trades and not the individual assets and their fundamentals. However, when there are more chartists in the market, there is again a non-linearity observable: namely in the correlation between the price and the fundamental value of the assets. We observe that at first the correlation increases with the share of ETF traders and decreases when the share of ETF traders increases further (at an ETF traders' share of about 20-60% in our example).

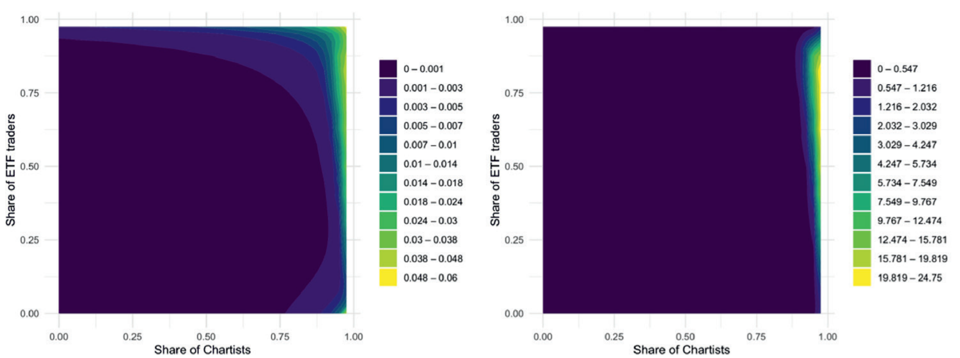
Chartists use a different calculus than fundamentalists: they relate to price trends rather than fundamentals. Thus, it is not surprising that more chartists lead to less correlation between asset prices and fundamental values since their decisions do not directly depend on fundamental values. When we have more ETF traders, the correlation of asset prices and fundamental values decreases when there are few chartists because ETF traders also use a different calculus and refer to the index rather than (directly) to the fundamental value of individual stocks. Overshooting prices caused by chartists are possibly more disconnected from fundamentals, so the correlation decreases. With a few ETF traders in the market this overshooting effect is mitigated, which increases the correlation. But as the number of ETF traders further increases at some point the 'index effect' of the ETF traders dominates and the correlation decreases – as explained above.

Put differently, as chartists basically reinforce asset price movements, it seems that these amplifications are so high that prices overshoot when there are only few ETF traders active in the market. With a moderate share of ETF traders, the activities of the single asset fundamentalists are too weak to align the movements of fundamentals and asset prices. However, when there are some chartists that strengthen the signals sent by the fundamentalists, the amplified actions are strong enough to increase correlations. When there are a lot of ETF traders in the market, their price signals dominate those of the single asset fundamentalists. Thus, the chartists do not reinforce the signals of the single asset fundamentalists anymore. Rather the ETF-based signals are strengthened and the correlation declines.

Regarding the correlation between the prices of the assets and the index, our hypothesis that the correlation increases with the weight of ETF traders is confirmed since their calculus is based on the index (see Figure 6b). Additionally, we see that the correlation of asset prices and index prices also increases with the number of chartists. As the number of chartists increases, they cause stronger price trends which are also visible in the index data.

Concerning the correlation between the stocks and the fundamental value of the index a growing number of ETF traders yields a higher correlation as expected. Also, as more chartists trade in the market, asset prices become more disconnected from their fundamentals – and also from the fundamentals of the index. This effect can also be seen in Figures 6dand 6e, but here no strong effect of ETF traders is visible since the index's return is under investigation.

4. The **mispricing** of assets and the index calculated as the mean (over the time) squared deviation of a price from its respective fundamental is depicted in Figure 7. The evidence fits the above discussion since mispricing is more prevalent when prices overshoot (and bubbles are likely to occur). Note that with regard to the mispricing of individual stocks, the extend of mispricing also increases for very high shares of ETF traders and chartists – opposite to the number of



(a) Mispricing of the stocks (b) Mispricing of the index

Figure 7: Mispricing level plots

bubbles. However, for the mispricing of the index this is not true – in accordance with the bubble plot. It fits to our working hypotheses that the mispricing of the single assets is high also for very high numbers of both chartists and ETF traders since ETF traders look at the index rather than at the single assets.

5. ONGOING RESEARCH

While changes in the ratio of ETF traders to single asset traders can be observed relatively easily, it is still an open question how to adequately detect the ratio of chartist to fundamentalist traders. The latter one must be understood in an idealized way, that is, mixed strategies have to be separated into their chartist and their fundamental parts. Other parts of such strategies like noisy ones or those driven by liquidity needs have also to be kept in mind.

The most interesting question is obvious: it concerns the policy recommendations. We recall that our simulation was calibrated to both 20% chartists and 20% ETF traders. All findings are qualitative (and not quantitative). Thus, if a policy maker observes a change in the ETF/single asset ratio and/or in the chartist/fundamentalist ratio, how can this policy maker estimate where exactly in the figures the actual state of the market lies? If one knows this, it is easy to see together with the direction of the changes of the ratios how market metrics may change. However, it is not clear which concrete policy measures are needed to keep markets stable.

Additionally, robustness checks concerning the calibration would be interesting: other markets like other geographical regions, industry sectors, years – and bear instead of bull markets. Concerning the preceding paragraph: would policy recommendations alter in bear markets? Further, it is of interest whether a wider spread of ETFs makes chartist rules more profitable (which would lead to a wider spread of those strategies as well), see Appendix A.

6. CONCLUSION

Exchange-Traded Funds are an interesting, cost-efficient, and liquid financial product to rebuild index performances and, thus, track asset markets resp. industries. Since ETFs have seen enormous growth over the last decades, financial market regulators have become increasingly concerned about potential risks for financial stability caused by ETFs. In our analysis we take a broader perspective and do not only investigate the market effects of ETFs' growth per se, but also the role of the trading strategies ETF investors follows. While ETFs are still seen by many researchers as an instrument to passively invest in an index resp. market, i.e. like a buy and hold strategy, they are evermore used in active investment strategies.

We build a heterogenous agent model to analyze the implications of the growing popularity of ETFs as an investment vehicle and their use in active investment strategies. We allow for investors

(i) Who either invest in ETFs or in the underlying assets and

(ii) Who follow fundamentalist or chartist trading strategies?

The model is calibrated to mirror stylized facts of real-world asset markets. We emphasize the idea that an adequate evaluation of ETFs should not only look at ETFs' growth, but it also has to include the specific trading strategies of ETF investors. Due to the complex interactions between the relative weight of ETFs in financial markets and the investment strategies, nonlinearities are likely to occur.

Typically, fundamentalists are thought to stabilize markets while trend followers are generally thought to be destabilizing. In the single asset HAM of Section 2.1 it is easy to see where these labels come from. Due to the single-asset price equation and the excess demand functions, fundamentalists push prices back to their fundamentals while trend followers strengthen the current trend. Both strategies could therefore be characterized as self-fulfilling prophecies. In a single-asset market, if fundamentalists' trading dominates, prices stay in a close neighborhood of the fundamental, i.e., they are stable, however, if chartists' trading dominates, trends are enforced, leading prices to permanently stay (far) away from fundamentals and in the extreme leading to an asset price bubble. We show that the labels "stabilizing" for fundamentalists and "destabilizing" for chartists do not necessarily have to be true when traders have the possibility to invest in an index of assets.

Concerning the correlation between prices and fundamental values of assets and the respective ETF we confirm, e.g., that an increasing weight of ETF traders tends to lower the correlation between prices of assets and their idiosyncratic fundamentals. However, this effect is not independent of the trading strategies in the market. With relatively more chartists in the market, an increasing number or ETF traders at first increases the co-movement of asset prices and their fundamental values and then lowers the correlation. In a similar fashion, we find that bubbles and the degree of the index's mispricing are relatively independent of the number of ETF traders except for a widespread use of chartists trading strategies. In this case, financial instability first increases with more ETF traders in the market and then decreases. So, while we find that fundamentalists investing in single assets as well as in ETFs often reduce mispricing it would be "naive" to assume ETF fundamentalists to always stabilize markets, let alone to follow the perception that ETFs per se are stabilizing.

Based on these findings, ETFs should not be considered as a risk to financial stability per se. Instead, an adequate evaluation of stability effects must take into account other factors as well, in particular, the investment strategies that use ETFs. Our findings also imply that due to non-linearities market regulators cannot simply extrapolate when evaluating ETFs. Due to the complex interactions of ETFs with, among others, the used trading rules, a so far seemingly stable development might be disrupted. Thus, while ETFs up to now did not seem to have been bad for financial health, a continued growth of ETFs asks for a continued close scrutiny of potential destabilizing effects.

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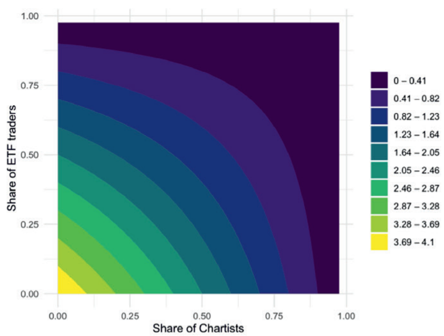
Appendix A. Additional Metrics and Figures

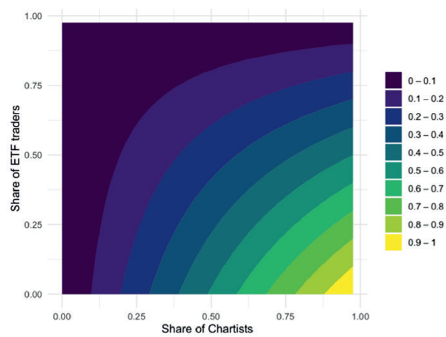
In this section we provide some additional information which is not needed to understand the main body of this paper. However, it may provide further insights to the interested reader.

A.1 Weights and Gains

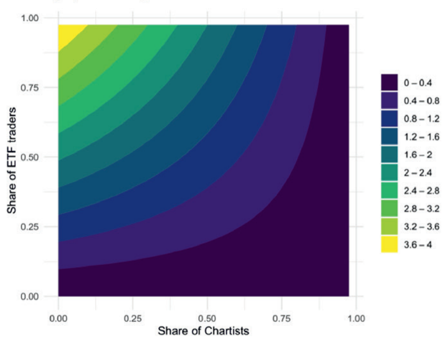
We show the weights of the traders and calculate the gain of one trader (of each type), i.e., the cumulated period gains, which are calculated by means of the returns of the prices of the stocks resp. of the index and via the net asset positions of the trader types. That means, we accumulated the excess demands of the trader types. Note that we use undiscounted and averaged values. Since it may be convenient for the reader, the level plots for the weights of all four trader types are depicted in Figure A1. So, in the other level plots it is easy to see which type of trader causes which effect.



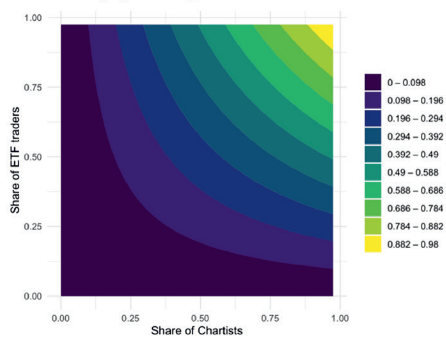
(a) Weight of fundamentalists



(b) Weight of chartists



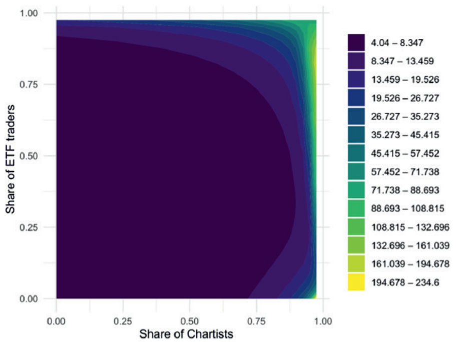
(c) Weight of ETF fundamentalists



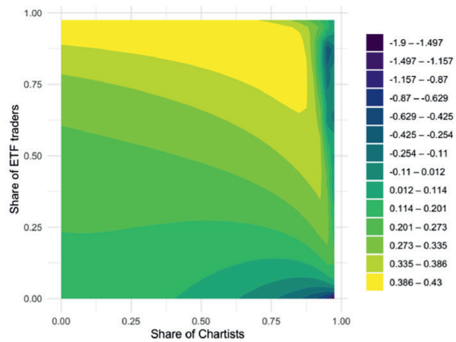
(d) Weight of ETF chartists

Figure A1: Weights level plots. Please note that the model is calibrated to the calibration point (q_C, q_E) = (0.2, 0.2), i.e., when interpreting the following plots, we have to take the point of view from this calibration point

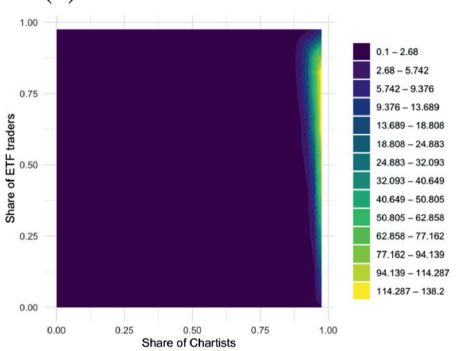
We provide pictures for the gains of one trader of each type in Figure A2. At this point we note that our model – as usual for market maker models – is not a zero sum game: possible excess gains or losses are taken by the market maker, who clears the market. As mentioned above, HAMs are constructed to replicate stylized market facts, not mechanics. Unfortunately, for the computation of "real" gains, mechanics are needed (like order books). Thus, the gain levels must be understood in a relative way, meaning that we can observe for which trader constellation which trader type is in the model more profitable – but we cannot observe their real gain in an absolute way. We see that (ETF) fundamentalist strategies are more profitable when the mispricing of the ETF resp. stocks is high. As can be seen in the plots, chartists lose money in the bubble areas. This is quite counterintuitive and caused by the fact that the gain is only depicted for the non-bubble cases. That means, in the bubble cases, the chartists clearly make a lot of money when the bubble occurs. (Clearly, on real markets it is questionable if such chartist could ever realize these 'bubble gains' since a buyer would have to be found.) However,



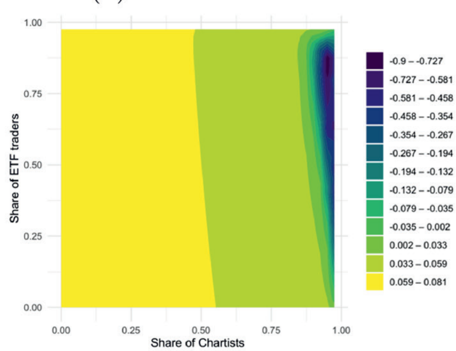
(a) Gain of one fundamentalist



(b) Gain of one chartist



(c) Gain of one ETF fundamentalist



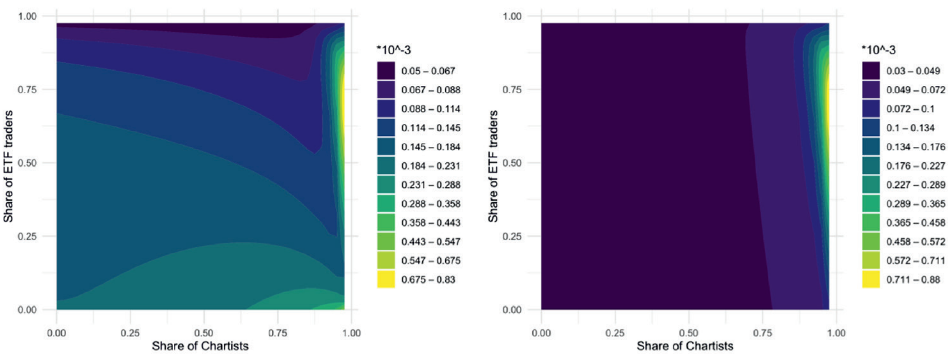
(d) Gain of one ETF chartist

Figure A2: Gains level plots – for the non-bubble cases only

due to comparison and computational reasons we had to abort these runs. Thus, one must read this level plot – and similar all other level plots except the bubble plot – like this: average gains of each trader type if there occurs no bubble. We emphasize again that the gain plots are misleading because only the non-bubble paths are included. In all bubble paths, the chartists make a lot of profit, and the fundamentalists make a high loss. But these paths are aborted. Interestingly, normal chartists perform well when there is a high share of ETF traders, which might implicate that growing numbers of ETF investments lead to higher profitability (and in turn to a higher number) of chartist strategies.

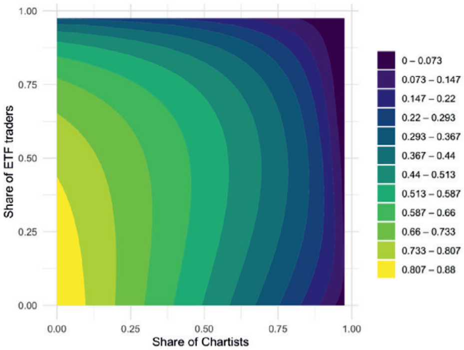
A.2 Standard Deviation, Kendall's τ, and all Price Paths

Here, we show the plots for Kendall's τ (note: $\tau_{fi,f} = 0.1127749$), the standard deviation, and all price paths for completeness and robustness of results.

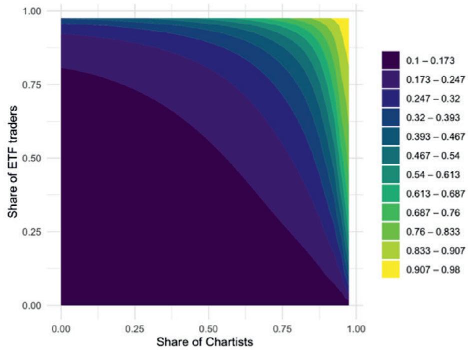


(a) Standard deviation of the stocks (b) Standard deviation of the index

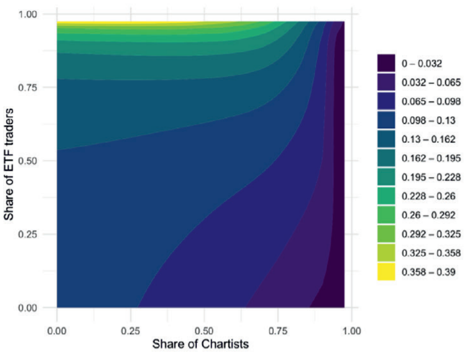
Figure A3: Standard deviation level plots



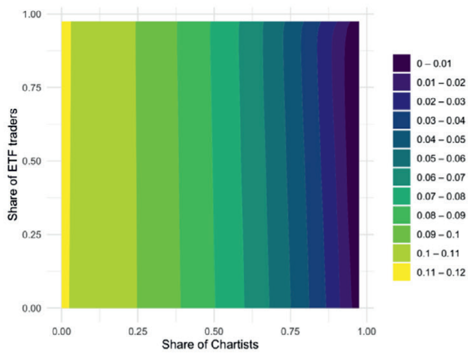
(a) Kendall's τ between stocks and their fundamental values



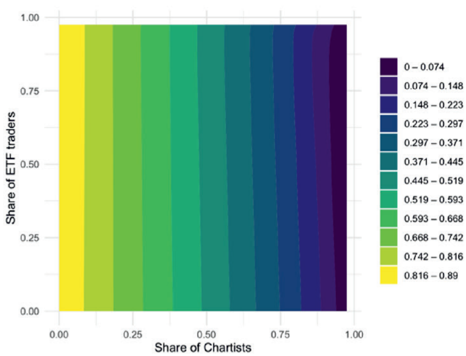
(b) Kendall's τ between stocks and the index



(c) Kendall's τ between stocks and the index's fundamental value

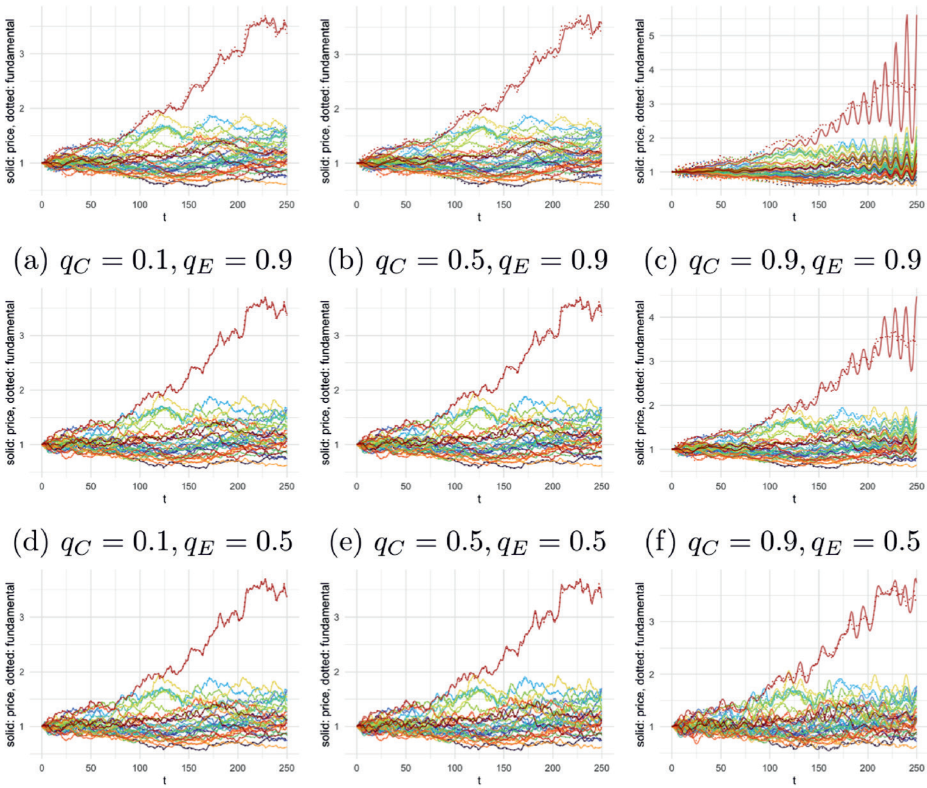


(d) Kendall's τ between the index and the stocks' fundamental values



(e) Kendall's τ between index and its fundamental value

Figure A4: Kendall's τ level plots



(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure A5: Price paths and fundamental paths for all stocks with the respective share of chartists q_C and share of ETF traders q_E

Appendix B: Robustness Checks for other Bubble Thresholds

Clearly, in HAMs it is not meaningful to define bubbles as prices that are unequal to their fundamentals since, possibly, in nearly all points in time prices deviate from the fundamentals. This property holds due to the stylized facts replicating construction of HAMs and is intended since these deviations shall be analyzed. Thus, another less restrictive bubble definition is needed. As noted on page 9, we define a bubble as a price path that is higher than four times its fundamental. However, this definition is somewhat arbitrary. For this reason, we include robustness checks here. In Appendix B.1 a stronger definition (with threshold two) and in Appendix B.2 a weaker definition (with threshold six) is applied. All in all, the results are robust against the bubble threshold, which can easily be observed when noting that the results only vary quantitatively, but not qualitatively.

B.1 Robustness Check with Stronger Bubble Definition

In this section, we apply a stronger bubble definition, i.e., a path may be called a bubble that is not called a bubble in the main body of this paper. We plot: the number of bubbles in Figure B1, the volatility in Figures B2 and B3, the correlations in Figures B4 and B5 (note: $cor_{fi,f} = 0.1759006$ and $\tau_{fi,f} = 0.1127749$, which are obviously the same as in the main part of this work since these values do not depend on the bubble definition), the mispricing in Figure B6, the gains in Figure B7 (please note the discussion on the gain plots in Appendix A: the gains are depicted for non-bubble paths only, which may cause misleading interpretations), and exemplary price paths in Figures B8, B9, and B10.

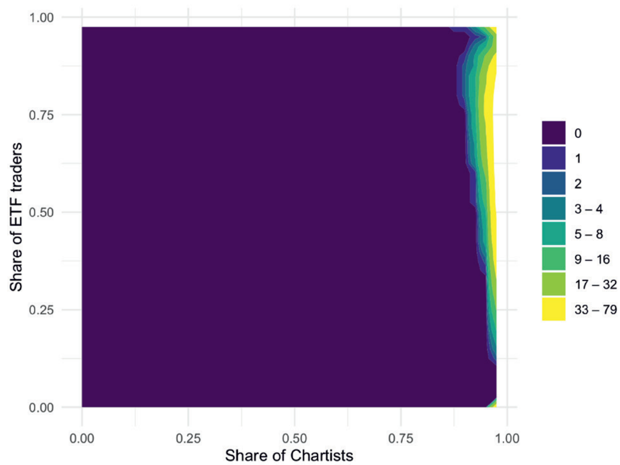
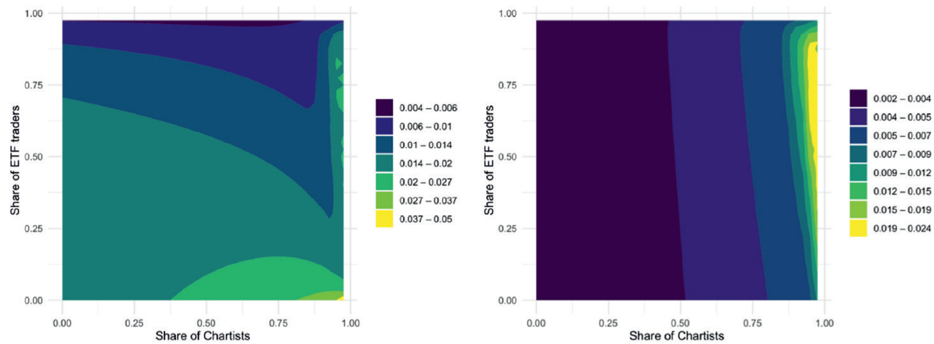
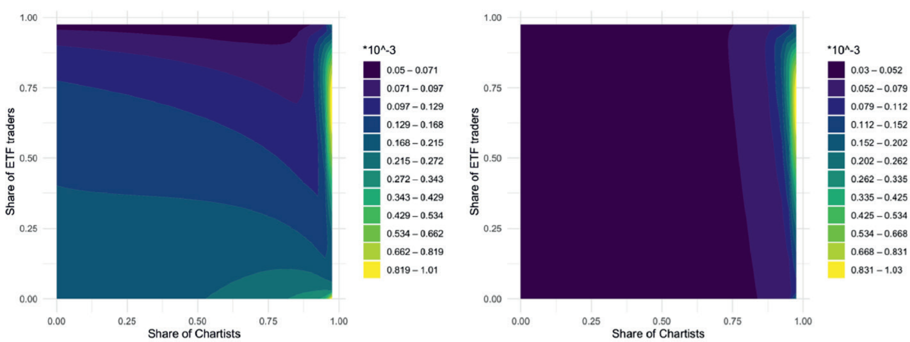


Figure B1: Number of bubbles



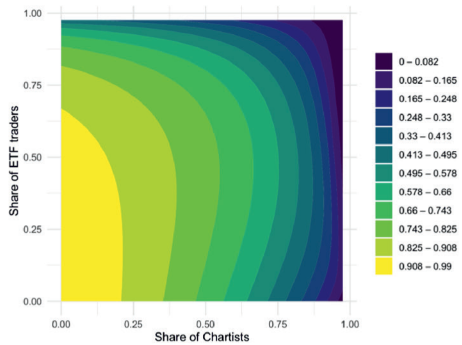
(a) Volatility of the stocks (b) Volatility of the index

Figure B2: Volatility level plots

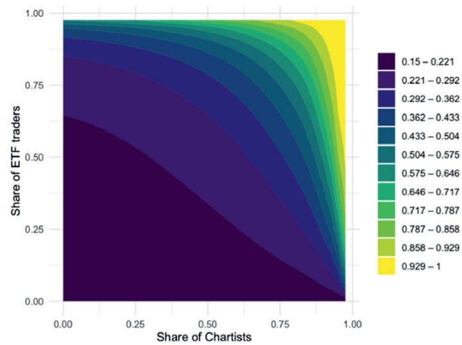


(a) Standard deviation of the stocks (b) Standard deviation of the index

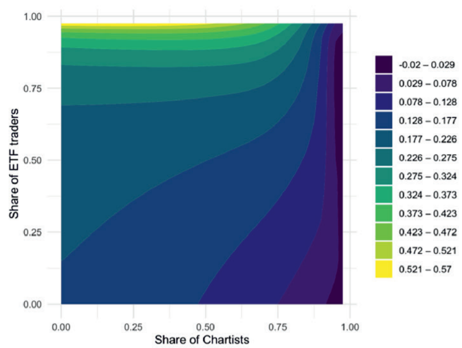
Figure B3: Standard deviation level plots



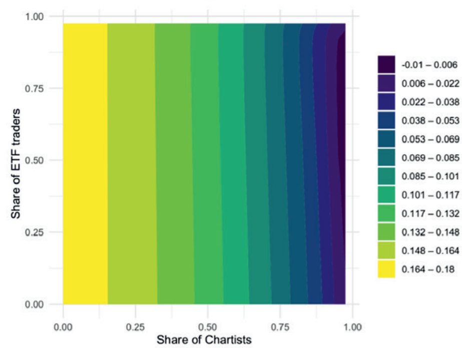
(a) Correlation between assets prices and their fundamental values



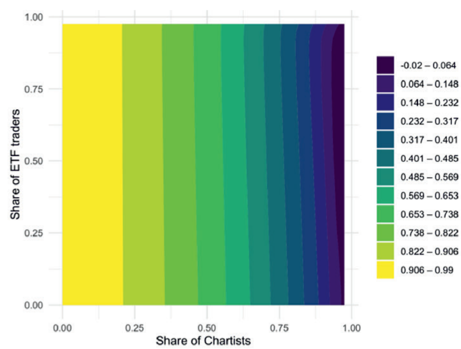
(b) Correlation between asset prices and the price of index



(c) Correlation between asset prices and the fundamental value of the index

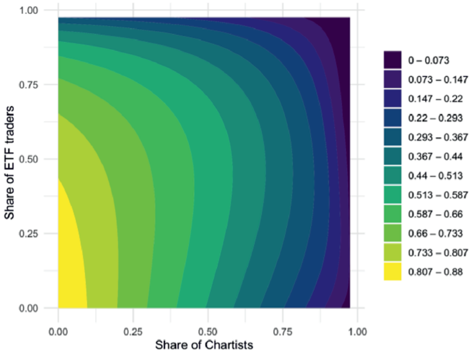


(d) Correlation between the index price and the assets' fundamental values

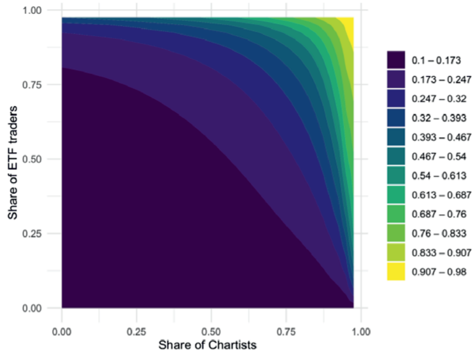


(e) Correlation between index price and its fundamental value

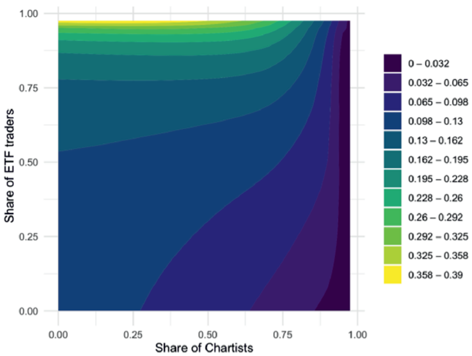
Figure B4: Correlation level plots



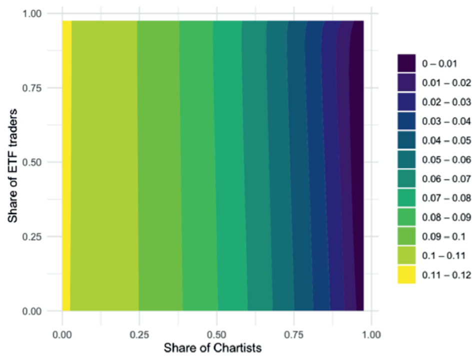
(a) Kendall's τ between stocks and their fundamental values



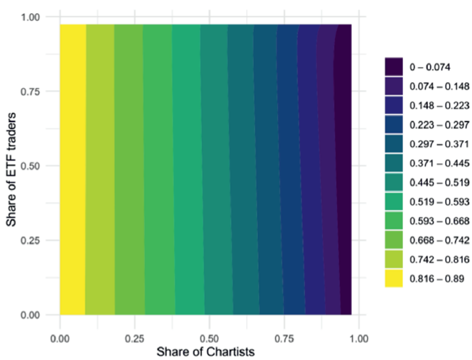
(b) Kendall's τ between stocks and the index



(c) Kendall's τ between stocks and the index's fundamental value

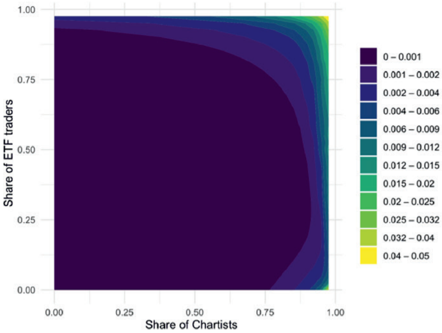


(d) Kendall's τ between the index and the stocks' fundamental values

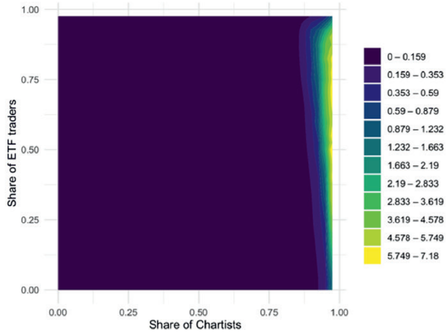


(e) Kendall's τ between index and its fundamental value

Figure B5: Kendall's τ level plots

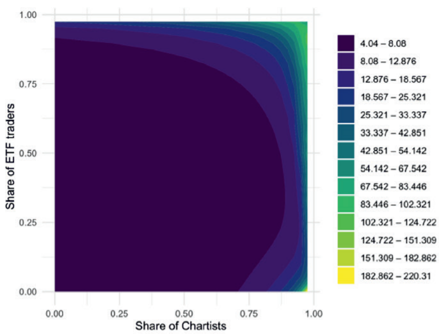


(a) Mispricing of the stocks

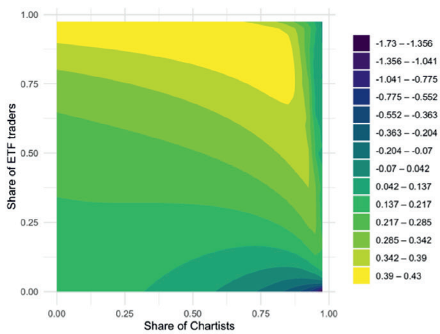


(b) Mispricing of the index

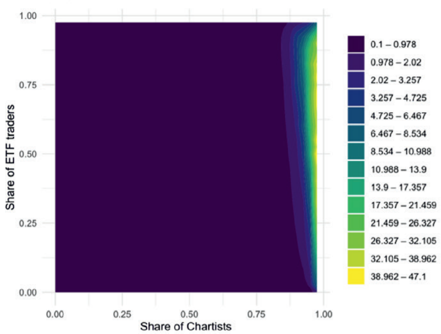
Figure B6: Mispricing level plots



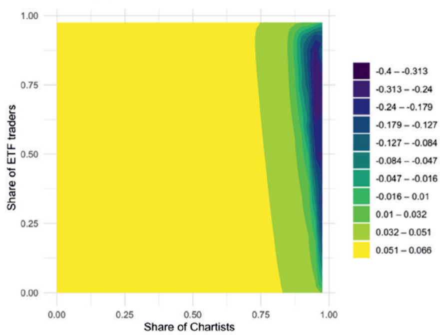
(a) Gain of one fundamentalist



(b) Gain of one chartist

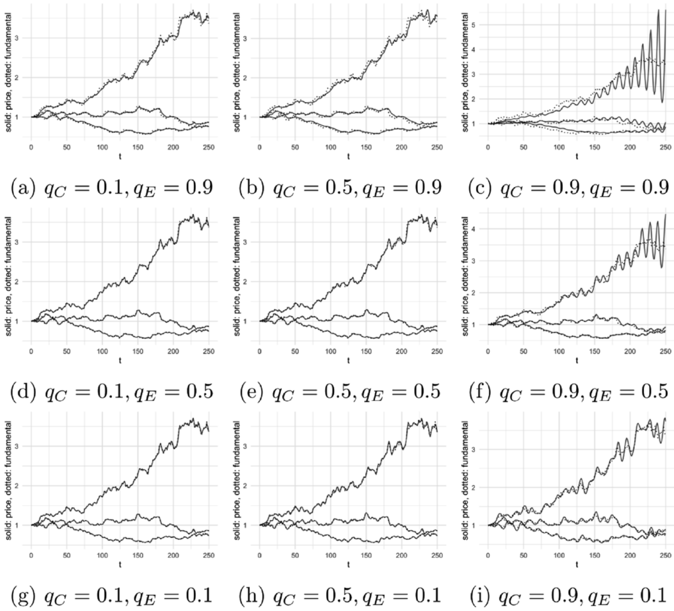


(c) Gain of one ETF fundamentalist



(d) Gain of one ETF chartist

Figure B7: Gains level plots – for the non-bubble cases only

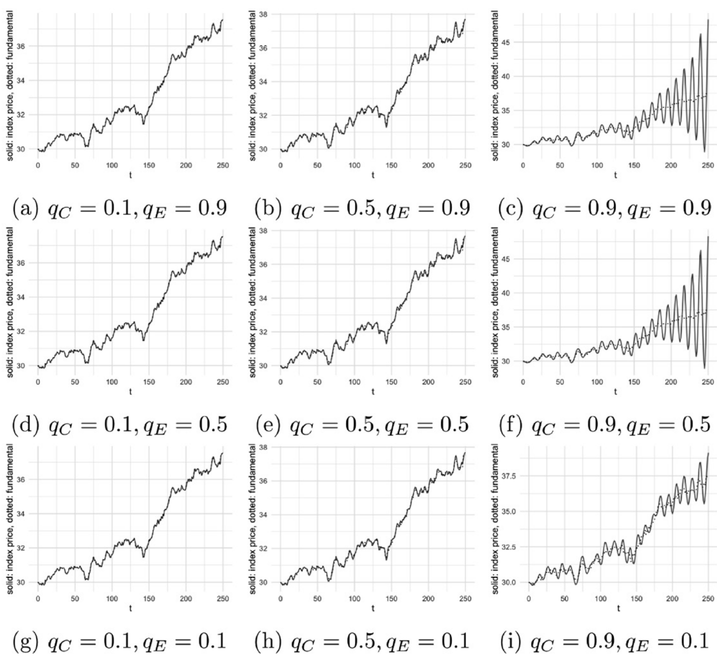


(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure B8: Price paths and fundamental paths for three exemplary stocks with the respective share of chartists q_C and share of ETF traders q_E

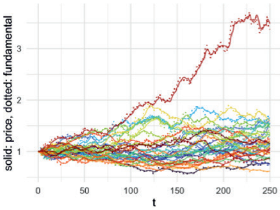


(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

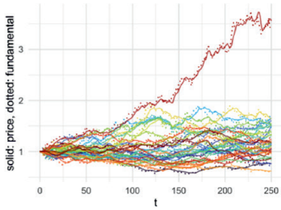
(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

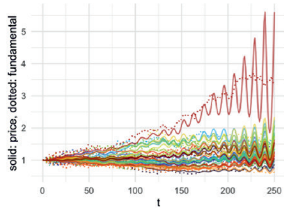
Figure B9: Price path and fundamental path for the index with the respective share of chartists q_C and share of ETF traders q_E



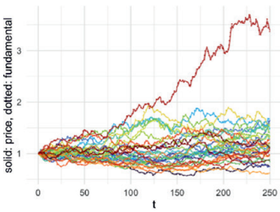
(a) $q_C = 0.1, q_E = 0.9$



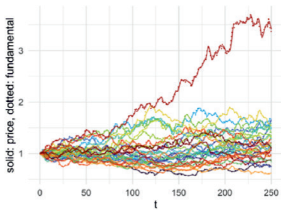
(b) $q_C = 0.5, q_E = 0.9$



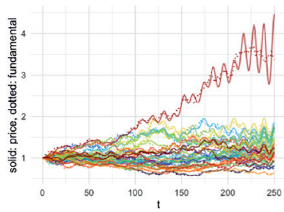
(c) $q_C = 0.9, q_E = 0.9$



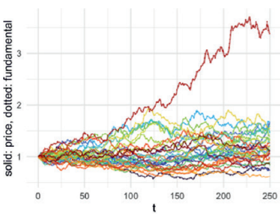
(d) $q_C = 0.1, q_E = 0.5$



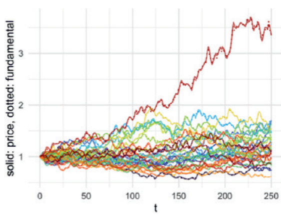
(e) $q_C = 0.5, q_E = 0.5$



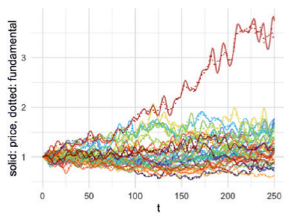
(f) $q_C = 0.9, q_E = 0.5$



(g) $q_C = 0.1, q_E = 0.1$



(h) $q_C = 0.5, q_E = 0.1$



(i) $q_C = 0.9, q_E = 0.1$

Figure B10: Price paths and fundamental paths for all stocks with the respective share of chartists q_C and share of ETF traders q_E

Appendix B.2: Robustness Check with Weaker Bubble Definition

In this section, we apply a weaker bubble definition, i.e., a path may not be called a bubble that is called a bubble in the main body of this paper. We plot: the number of bubbles in Figure C1, the volatility in Figures C2and C3, the correlations in Figures C4 and C5 (note: $cor_{\{fi,fi\}}$ = 0.1759006 and $\tau_{\{fi,fi\}}$ = 0.1127749, which are obviously the same as in the main part of this work since these values do not depend on the bubble definition), the mispricing in Figure C6, the gains in Figure C7 (please note the discussion on the gain plots in Appendix A: the gains are depicted for non-bubble paths only, which may cause misleading interpretations), and exemplary price paths in Figures C8, C9, and C10.

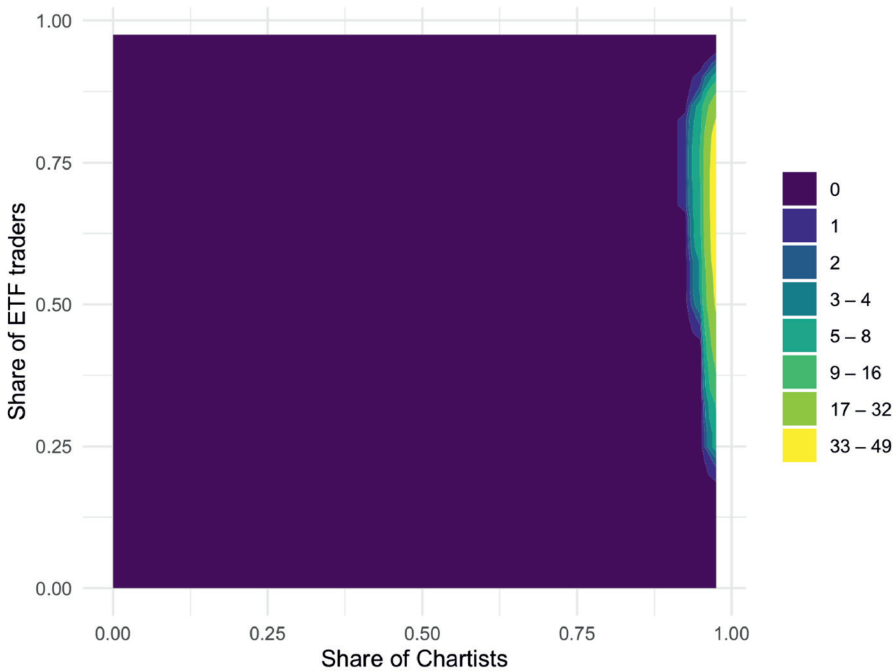
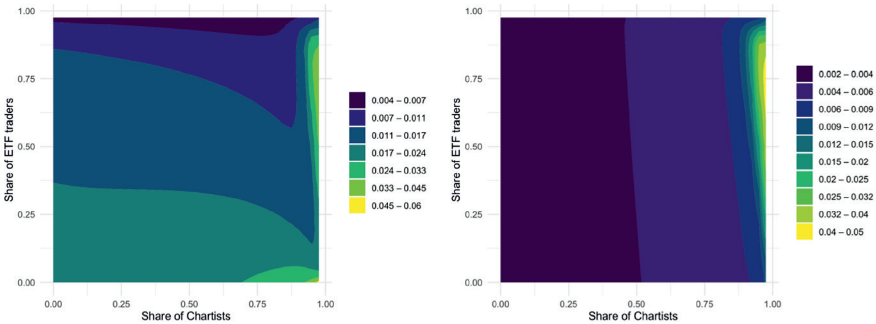
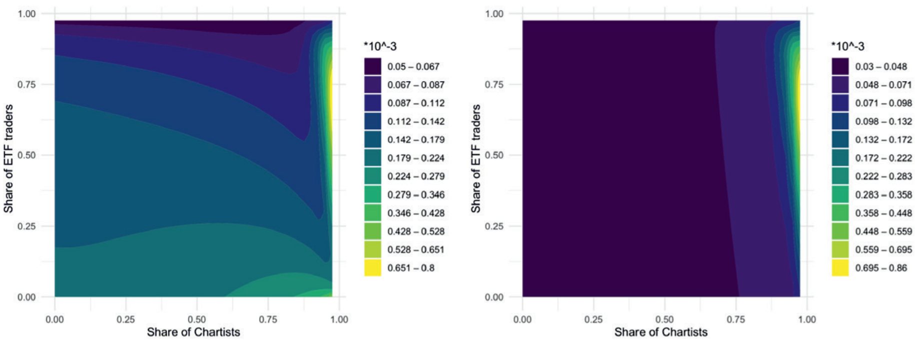


Figure C1: Number of bubbles



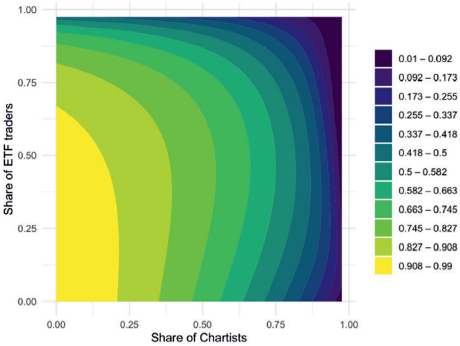
(a) Volatility of the stocks (b) Volatility of the index

Figure C2: Volatility level plots

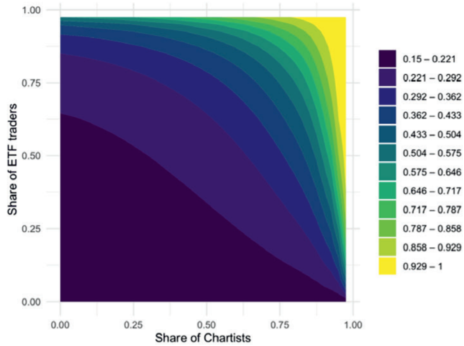


(a) Standard deviation of the stocks (b) Standard deviation of the index

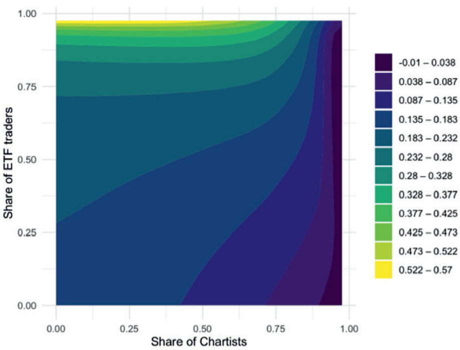
Figure C3: Standard deviation level plots



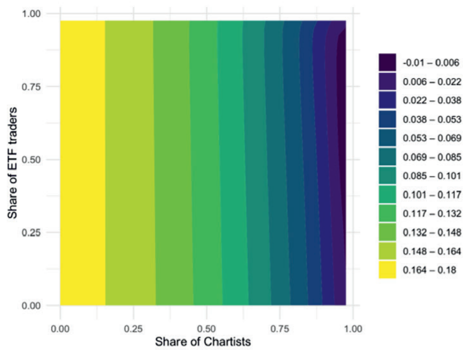
(a) Correlation between assets prices and their fundamental values



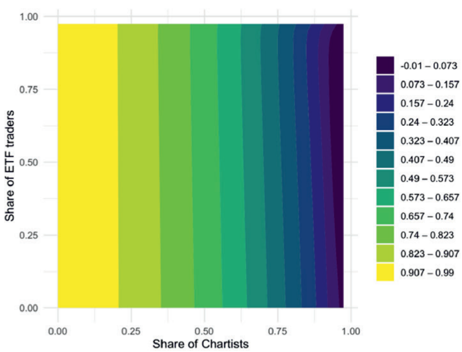
(b) Correlation between asset prices and the price of index



(c) Correlation between asset prices and the fundamental value of the index

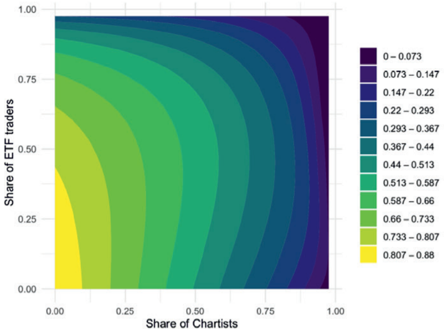


(d) Correlation between the index price and the assets' fundamental values

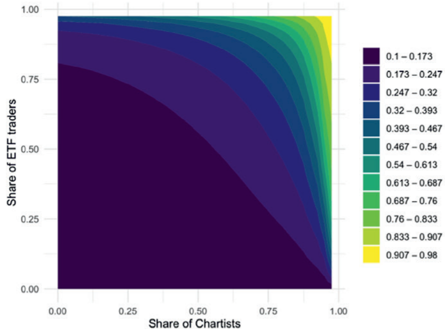


(e) Correlation between index price and its fundamental value

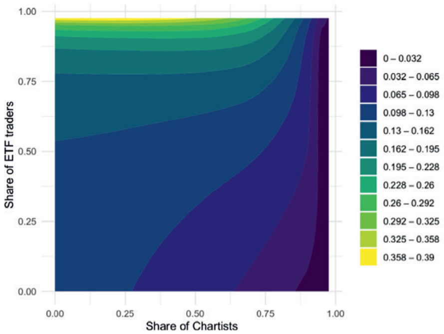
Figure C4: Correlation level plots



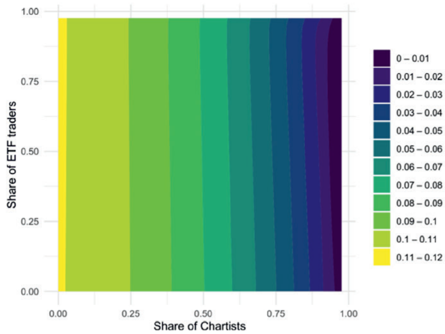
(a) Kendall's τ between stocks and their fundamental values



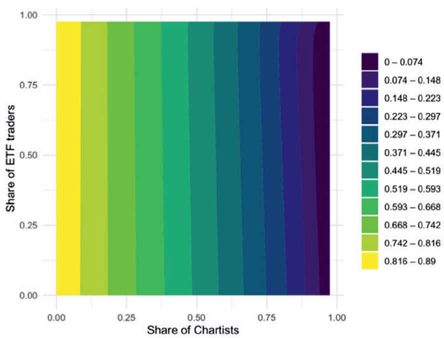
(b) Kendall's τ between stocks and the index



(c) Kendall's τ between stocks and the index's fundamental value

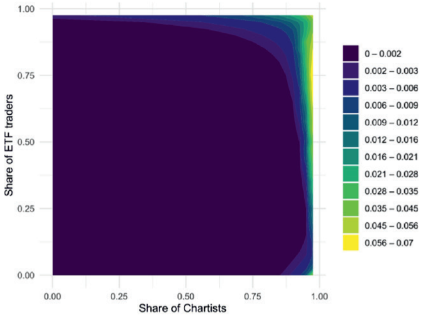


(d) Kendall's τ between the index and the stocks' fundamental values

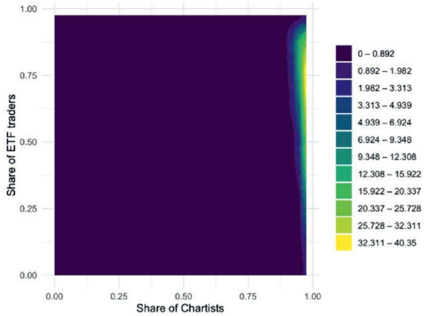


(e) Kendall's τ between index and its fundamental value

Figure C5: Kendall's τ level plots

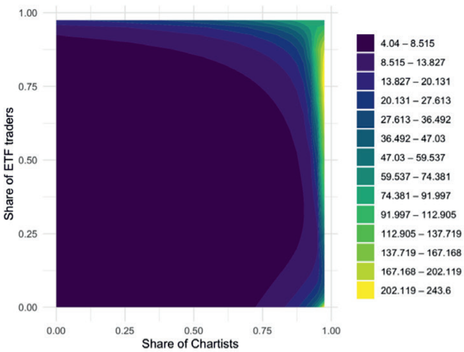


(a) Mispricing of the stocks

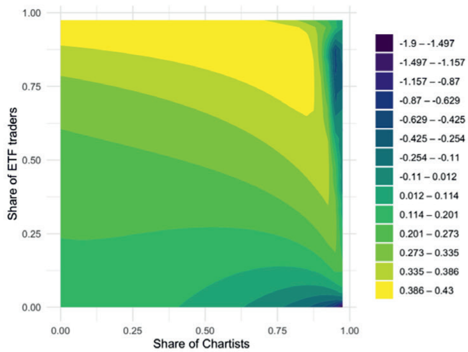


(b) Mispricing of the index

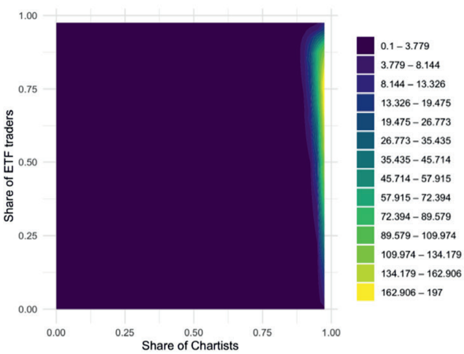
Figure C6: Mispricing level plots



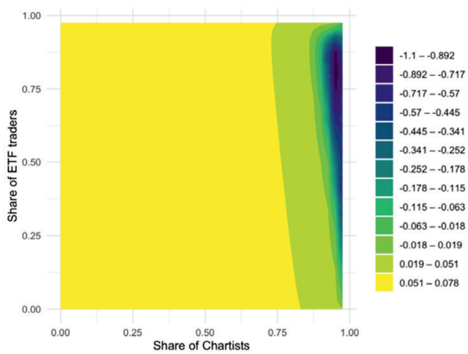
(a) Gain of one fundamentalist



(b) Gain of one chartist

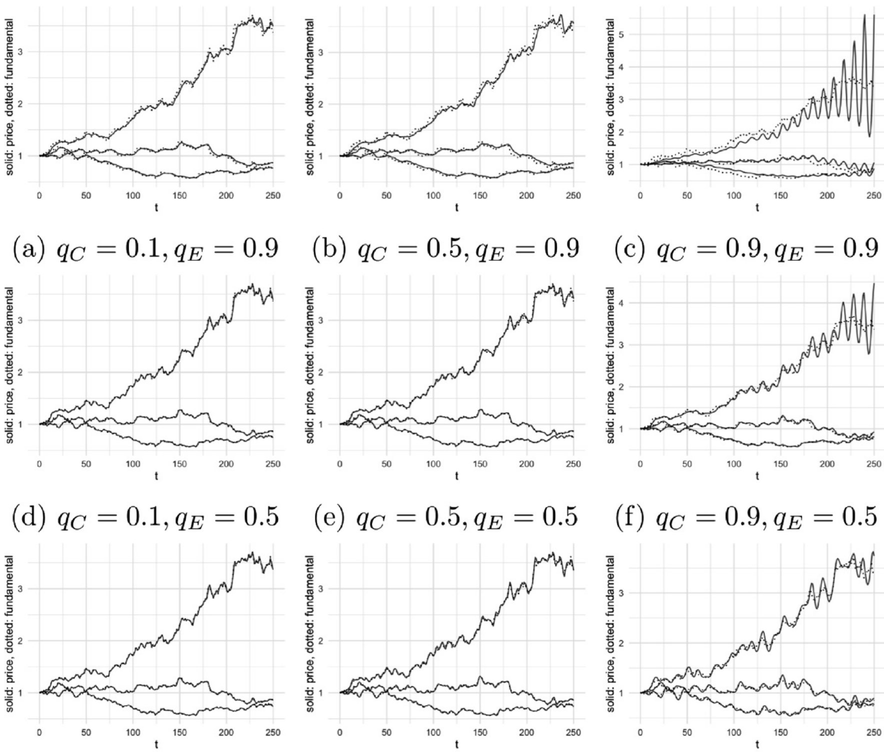


(c) Gain of one ETF fundamentalist



(d) Gain of one ETF chartist

Figure C7: Gains level plots – for the non-bubble cases only

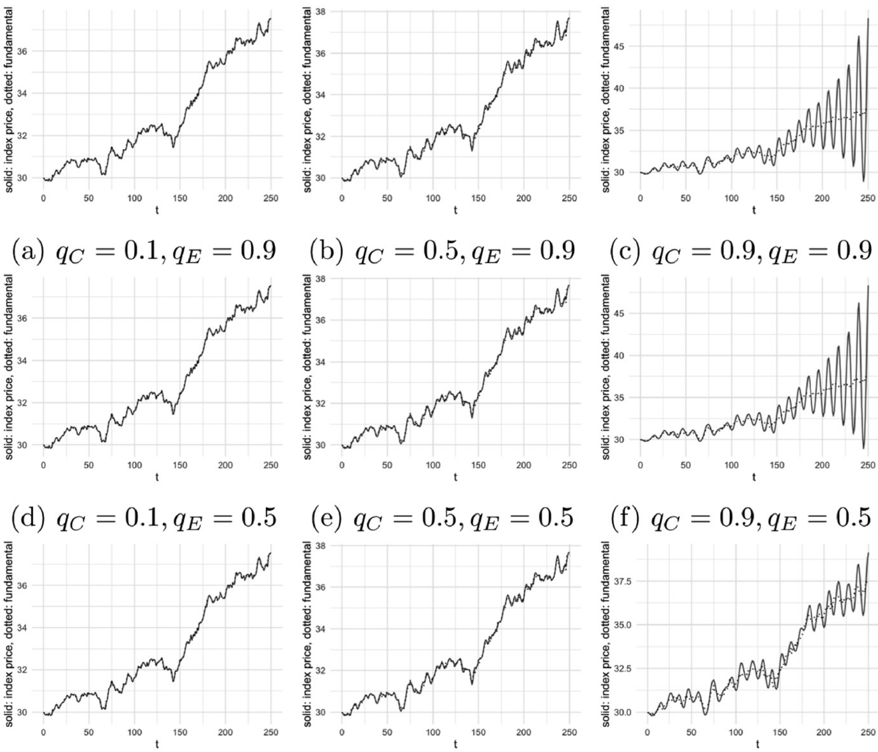


(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure C8: Price paths and fundamental paths for three exemplary stocks with the respective share of chartists q_C and share of ETF traders q_E

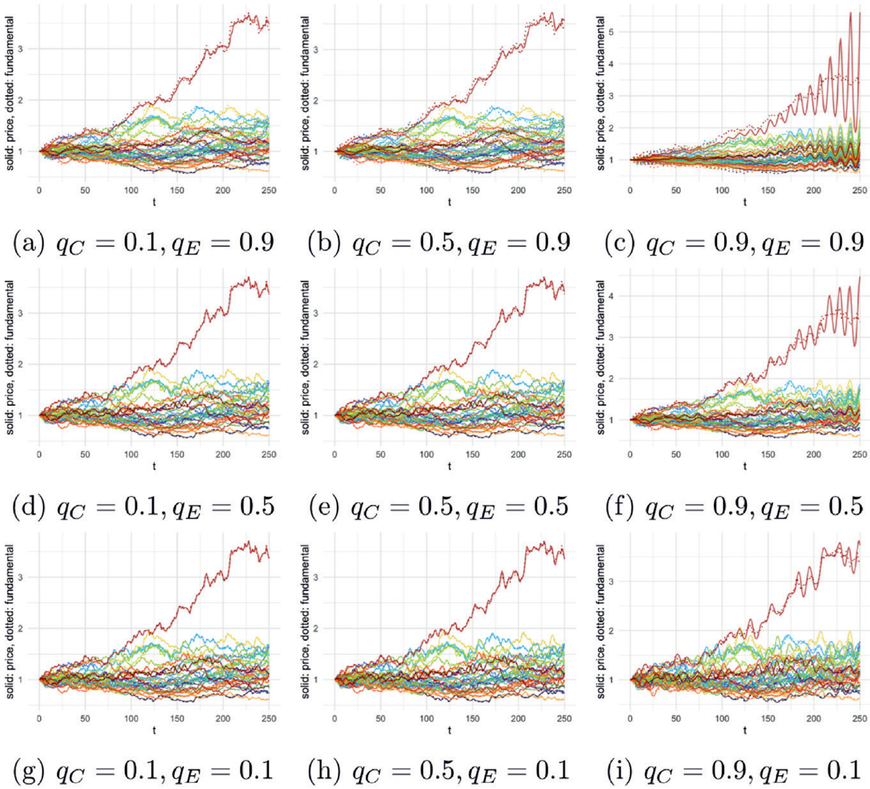


(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure C9: Price path and fundamental path for the index with the respective share of chartists q_C and share of ETF traders q_E



(a) $q_C = 0.1, q_E = 0.9$ (b) $q_C = 0.5, q_E = 0.9$ (c) $q_C = 0.9, q_E = 0.9$

(d) $q_C = 0.1, q_E = 0.5$ (e) $q_C = 0.5, q_E = 0.5$ (f) $q_C = 0.9, q_E = 0.5$

(g) $q_C = 0.1, q_E = 0.1$ (h) $q_C = 0.5, q_E = 0.1$ (i) $q_C = 0.9, q_E = 0.1$

Figure C10: Price paths and fundamental paths for all stocks with the respective share of chartists q_C and share of ETF traders q_E