Decoupled fundamentals in an agent-based stock-market model

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Abstract

In this paper, I explore whether a 'decoupling scenario', in which stock prices fluctuate around their fundamental value less frequently than behavioural models predict, is still consistent with the stylized facts of stock market returns: no autocorrelation, volatility clustering, long memory, and fat tails. Applying the method of simulated moments reveals that adding a mean-reversion component to the behavioural chartist-fundamentalist model allows it to jointly replicate the moments associated with decoupling as well as the stylized facts. A global sensitivity analysis on the relative popularity of trading strategies shows that this is largely a result of mean-reversion expectations replacing fundamentalist expectations.

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1 Introduction

This paper contributes to the ongoing debate about market efficiency. A key question is whether stock prices converge to the present value of future dividends - the fundamental value. There are two competing positions on this issue (Asness and Liew, 2014; Campbell, 2014). The Fama (1963) efficient market hypothesis states that stock prices equal fundamental value and the behavioural finance hypothesis predicts that prices fluctuates (frequently) around the fundamental value (Thaler, 2016).

Shiller (2014) modifies the behavioural hypothesis by stating that there might be longer market phases in which market prices deviate from the fundamental value. In these phases, stock prices do not mean-revert to their fundamental value. They can become decoupled from their fundamentals for extended periods of time because it might take successful fundamentalist investors many years to acquire enough wealth to bring the price back to its fundamental value. In the meantime, the market is dominated by ordinary traders. This would imply that stock prices fluctuate around their fundamental value far less frequently then behavioural models would predict. I name this scenario the 'decoupling scenario.'

This paper explores if the decoupling scenario consistent with the stylized facts of financial markets: low daily return predictability, (Samuelson, 1965; Cont, 2005; Stanley, Plerou, and Gabaix, 2008), excess volatility (fat tails) in the returns distribution (Shiller, 1981) (Gu, Chen, and Zhou, 2008), return predictability at longer time horizons (long memory) and returns volatility clustering (Cont, 2001; Gigerenzer and Selten, 2002; Gould et al., 2013). The behavioural chartist-fundamentalist model serves as my baseline because it can jointly replicate these stylized facts (Franke and Westerhoff, 2012; Bertella et al., 2014; Fischer and Riedler, 2014; Chiarella, Iori, and Perelló, 2009; Chiarella et al., 2017). However, because this model predicts that prices mean-revert to the fundamental value it needs to be extended.

Therefore, in this paper, I extend the behavioural model by introducing a new type of trading: mean-reversion trading. By adding mean-reversion trading to the standard trend-following strategy, the model now features the two main flavours of profitable technical trading strategies (Serban, 2010). Replacing some of the fundamentalist traders with mean-reversion traders allows the model to replicate a decoupling between price and fundamental while still being able to replicate the stylized facts.

Before formulating the model, I present the data from which I compute of the disconnect between prices and fundamentals along with the other stylized facts. Then, I explore the model dynamics through Monte-Carlo Simulations. I estimate the model parameters on empirical data and show that the inclusion of mean-reversion trading improves the models ability to jointly replicate decoupling and the stylized facts. By varying the relative popularity of trading strategies in a sensitivity analysis, I show that this result is primarily obtained by replacing the fundamentalist expectation component with the mean-reversion expectation component.

2 Computing fundamental value, prices decoupling and stylized facts: data and calculations

To judge the model's ability to produce a price decoupling from fundamentals while replicating the stylized facts, I quantify both empirically.

The data comes from three sources. The first source is daily data on nominal prices from the S&P500 starting on the 1st of August 2008 and ending on the 16th of August 2018 (2509 observations) from the Federal Reserve of St. Louis database[1]. The second source is Robert Shiller's database[2] (Shiller, 2000) on historical data on monthly S&P 500 prices and dividends. The last source is the macro history database[3] (Jordà, Schularick, and Taylor, 2017) from which I extract historical data on annual short-term interest rates . Table 1 presents the descriptive statistics of this data.

Table 1: Descriptive statistics data of S&P500 and U.S. interest data.

Moment	**Returns**	**Real Prices**	**Dividends**	**T-bill rate**
Count	2487	1771	1770	146
Mean	0.0	516.59	15.35	4.09
Standard deviation	0.01	556.28	8.67	2.93
Min	-0.09	68.22	5.03	0.09
Max	0.12	2836.53	51.0	16.39

To quantify the disconnect between prices and fundamentals the fundamental value is needed. I calculate it using the fixed equity premium net present value model (Campbell and Shiller, 1988; Shiller, 2014). It states that the fundamental value is the sum of discounted future dividend rates

$$F_t = \sum_{t=1}^{\kappa} \frac{D_t}{(1 + i_t + r)^{t+1}}, \tag{1}$$

where D_t is the dividend and i_t is the short-term interest rate, while r represents the equity price premium, κ represents the horizon which I set to the point at which $\frac{D_t}{(1+i_t+e)^t} < 0.01$. Using this equation, I calculate the expost fundamental value of the S&P500. Because I have annual short-term

[1] https://fred.stlouisfed.org/series/SP500
[2] http://www.econ.yale.edu/s̃hiller/data/ie_data.xls
[3] http://www.macrohistory.net/JST/JSTmoneyR3.xlsx

interest rate data and monthly dividends, I assume the annual interest rate holds for all months in the year.

The unobserved (stable) discount rate needed to determine fundamental value is often calculated as the average discount rate implied by market prices [4]. The implied assumption that arbitrage is effective is, however, contested (Shleifer and Vishny, 1997; Mitchell, Pulvino, and Stafford, 2002; Gromb and Vayanos, 2010). I relax this assumption by assuming the unobserved (stable) discount rate to be constant at 5.2, the level of the equity risk premium estimated by Avdis and Wachter (2017).

I apply the augmented Engel-Granger test (Engle and Granger, 1987) to measure how much the price tends to mean-revert to the fundamental value. The resulting co-integration or 'decoupling moment' reflects the disconnect between the two series.

Then, the stylized facts of stock market returns, are approximated by calculating several of their moments. Calculating the average autocorrelation over 25 lags and over the first and fifth lag measures the (un)predictability of returns. Excess kurtosis proxies excess volatility, or fat tails in the returns, Long memory is measured as the autocorrelation of absolute returns at lag 10, 25, 50 and 100. Volatility clustering is measured as the average autocorrelation of absolute returns over 25 lags.

Table 2 shows the resulting moments and confidence intervals. A bootstrapped time series is the basis for calculating the confidence intervals, see Appendix A.

Since the 95% confidence interval of the decoupling moment is larger than zero, there is a significant disconnect between prices and the fundamental value. The other moments are in line with the widely reported findings of no autocorrelation, volatility clustering, long memory, and fat tails in the returns.

3 The model

In this section the behavioural model is formulated. It extends the agent-based model by Chiarella and Iori (2002) with a stochastic fundamental and a mean-reversion expectations component.

The risky asset, which represents a traded stock market index, has an intrinsic or fundamental value equal to discounted future dividends, F_t. In contrast to Chiarella and Iori (2002), where the fundamental value is constant, it follows a random walk

[4] For example, when calculating ex-post fundamental values for the S&P500 stock index using actual subsequent real dividends and a time-varying interest rate, Shiller (2014) estimates the equity premium such that it is equal to the average observed returns. Similarly, Boswijk, Hommes, and Manzan (2007) estimates the discount rate so that it fits the observed average dividend yield.

Table 2: Moments: empirical values and lower and upper value of the confidence interval (CI).

Moment	Value	CI low	CI high
Decoupling	-3.396	-7.091	0.299
Average autocorrelation	-0.011	-0.015	-0.006
Autocorrelation lag 1	-0.079	-0.129	-0.029
Autocorrelation lag 5	-0.071	-0.124	-0.018
Absolute average autocorrelation	0.323	0.134	0.511
Kurtosis	12.613	2.89	22.337
Absolute autocorrelation lag 10	0.311	0.199	0.424
Absolute autocorrelation lag 25	0.256	0.109	0.404
Absolute autocorrelation lag 50	0.159	0.062	0.257
Absolute autocorrelation lag 100	0.148	0.035	0.261

$$F_{t+1} = F_t + \epsilon_t^F, \tag{2}$$

where $\epsilon_t^F \sim N(0, \sigma^\epsilon)$, and $F_{t+1} \geq 0$. In each period $t \in T$, the price of the risky asset is determined by a limit-order book which matches buy and sell orders submitted by a random set of agents, of size ι drawn from a population of agents of size N.

Before entering the market, each agent determines its expected asset price as a weighted average of fundamental value f, trend-following (momentum) mm, individual noise ns, and a mean-reversion component mr. The weights of these components, represented by $N \times 1$ vectors of weights $w^* := (w^f, w^{mm}, w^{mr}, w^{ns})$, are drawn from random normal distributions: $w^f \sim N(0, \sigma^f)$, $w^{mm} \sim N(0, \sigma^{mm})$, $w^{mr} \sim N(0, \sigma^{mr})$, and $w^{ns} \sim N(0, \sigma^{ns})$. The weights are subsequently normalized.

Each agent x determines expected returns r as

$$\mathrm{E}_{x,t}[r_{t+1}] = w_x^f \frac{p_t^f - p_t}{p_t} + w_x^{mm} \bar{r}_{x,t} - w_x^{mr} \bar{r}_{x,t} + w_x^{ns} \epsilon_{x,t}^{ns}, \tag{3}$$

where p_t^f is the fundamental price. $\epsilon_{x,t}^{ns} \sim N(0, \sigma^{\epsilon^{ns}})$ is an agent-specific noise component drawn from a normal distribution each period. This reflects the heterogeneous expectations of the agents. $\bar{r}_{x,t}$ is the average historical spot return. Because arbitrage opportunities are assumed to be limited, the expectation formation rules for the agents are constant. For every agent the average spot return is calculated over its specific horizon $\phi_x \in \{1, \phi^{max}\}$ as:

$$\bar{r}_{x,t} = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} \frac{p_{t-j} - p_{t-j-1}}{p_{t-j-1}}. \tag{4}$$

Each agent converts its expected return to an expected price by multiplying it by the current price:

$$\mathrm{E}_{x,t}[p_{t+1}] = p_t \exp(\mathrm{E}_{x,t}[r_{t+1}]). \tag{5}$$

If the agent's expected price is larger (smaller) than the current price it will submit a bid b (ask a) order at price:

$$\begin{aligned} & p^b_{x,t} = \mathrm{E}_{x,t}[p_{t+1}](1-\gamma_x) \ and \ \ p^a_{x,t} = \mathrm{E}_{x,t}[p_{t+1}](1+\gamma_x), \\ & where \ p^b_{x,t}, p^a_{x,t} > 0, \end{aligned} \tag{6}$$

where $\gamma_x \sim N(1, \sigma^\gamma)$ is a which reflects heterogeneity in order-book positioning. It is drawn from a normal distribution.

Then, the order volume is drawn from a normal distribution, $v_x \sim N(0, \sigma^v)$ and the order is entered into the limit-order book. The best (highest) bid p^{b*}_t and best (lowest) ask price p^{a*}_t are updated and, the best bid in the order book is matched to the best ask price. If the best bid price is higher than the best ask price $p^{b*}_t > p^{a*}_t$ both orders are matched at the best ask price:

$$p_t = p^{a*}_t, \tag{7}$$

The transaction volume is equal to the lowest of the two orders:

$$v_t = \min(v^{b*}_t, v^{a*}_t). \tag{8}$$

This volume is then subtracted from the two orders. If that results in an order volume reaching zero, it is removed from the order book. The matching procedure is repeated until there are no more remaining orders which can be matched.

To prevent orders from lingering in the order book, the age of the offers in the limit order book increases by one every period. When an order reaches the expiration time ζ, it is removed from the order book.

4 Model dynamics

This section evaluates whether the addition of mean-reversion chartism allows to the model to jointly replicate the decoupling moment as well as the moments which reflect the stylized facts.

The dynamics of the model are explored using Monte Carlo Simulation methods (Hammersley, 2013)[5]. The standard number of Monte Carlo Sim-

[5]The code used for these computational experiments is available on-line at: https://github.com/joerischasfoort/sim-fin-abm.

ulations is $N_r = 15$[6].

First, I calibrate observable parameters using the data and estimate the rest of the parameters using the method of simulated moments (MSM) (Franke, 2009). Then, I test the models ability to match the moments and compare its performance to a version of the model without mean-reversion. Finally, I perform two experiments in which I vary the relative strength of mean-reversion trading versus trend-following and fundamentalism is and explore how this affects the moments.

4.1 Parameter calibration and estimation

I calibrate observable parameters using the data. Simulation time T is set equal to the length the shortest data time series. The initial fundamental value and the standard deviation of its return are obtained from the previously calculated fundamental value. The standard deviation of the spread is set equal to the value reported by Riordan and Storkenmaier (2012).

The values of the unobserved parameters are uncertain and will need to be estimated. Estimating them requires fewer parameters than moments. Therefore, I first reduce the set of uncertain parameters to those which are most important in determining the moments of interest.

Application of the enhanced Morris Method (Morris, 1991) as in Campolongo, Cariboni, and Saltelli (2007), suggest that the two least influential parameters are the number of traders, which are fixed at $N_l = 1000$, and the standard deviation of volume, which is set at $\sigma^v = 7$, see Appendix B for the full results of the Morris Method. The remaining uncertain parameters are now defined to be contained in vector θ.

Table 3 presents an overview of the model parameters. The table shows values for the calibrated parameters and bounds for the uncertain parameters.

With the number of uncertain parameters less than the number of moments to be explained, we are now ready to estimate the parameters in vector θ. To do so, I follow the MSM procedure as set out in detail by Franke and Westerhoff (2012). This yields parameter values of the model which minimize the function:

$$J(m^{sim}, m^{emp}) = (m^{sim} - m^{emp})' W (m^{sim} - m^{emp}), \tag{9}$$

where m^{emp} is a vector containing the empirical moments described in Table 2, m^{sim} the model-generated moments vector, and W the weighting matrix. The purpose of the weighting matrix is that moments with low variance and those which correlate with each other have lower weights. Therefore,

[6]This number limits the influence of randomness without demanding too much computational resources.

Table 3: Model parameters. Important uncertain parameters are italic. Their values are bounds which are shown as lower, upper.

Symbol	Description	Values
N_r	number of runs	15
T	total periods of simulation time	1235
F_0	initial fundamental value	166
σ^F	standard deviation ΔF	0.053
σ^γ	standard deviation maximum spread	0.004
N_l	number of traders	1000
σ^v	standard deviation volume	7
ι	*trader sample size*	1, 100
σ^{ϵ^n}	*standard deviation noise component*	0.05, 0.30
σ^f	*standard deviation fundamental weight*	0, 100
σ^{mm}	*standard deviation momentum weight*	0, 100
σ^e	*standard deviation noise weight*	0, 100
σ^{mr}	*standard deviation mean-reversion weight*	0, 100
ϕ^{max}	*maximum horizon length*	5, 30
ζ	*order expiration days*	5, 100

following Franke and Westerhoff (2016), I set the weighting matrix equal to the inverse of the variance-covariance matrix of the bootstrapped moments.

Given that the model moments vector m^{sim} is a function of the parameters θ, it can be rewritten as $m(\theta, S)$ and the minimization problem can be formalized as:

$$\arg\min_{\theta} J\left(m(\theta, S), m^{emp}\right), \tag{10}$$

where S is the simulation time horizon used for the estimation procedure. To increase the robustness of the estimation, it is common practice to set the simulation time to be ten times the empirical time series length $S = 10T$ (Franke, 2009; Franke and Westerhoff, 2012).

To solve the minimization problem of Equation 10, I employ an evolutionary algorithm (Thiele, Kurth, and Grimm, 2014) which I describe in detail in Appendix C. Table 4 shows the resulting estimated parameters.

4.2 Empirical performance

I primarily use Equation 9 to measure how well the model is able to match the moments. Since it is a cost function, I will refer to its outcome as its J-cost. The model with mean-reversion (MR) will be compared to an estimated version of the model without the mean-reversion component which

Table 4: Estimated parameters.

Symbol	Description	Values
ι	trader sample size	19
σ^{ϵ^n}	standard deviation noise component	0.11
σ^v	standard deviation volume	7
σ^f	standard deviation fundamental weight	8.49
σ^{mm}	standard deviation momentum weight	43.06
σ^e	standard deviation noise weight	73.28
σ^{mr}	standard deviation mean-reversion weight	93.64
ϕ^{max}	maximum horizon length	10

I refer to as the 'no mean-reversion model' (NMR). To control for the effects of randomness, I simulate both models 5000 times. As its empirical counterparts, I use the 5000 bootstrapped time-series used in the estimation procedure.

Following (Franke and Westerhoff, 2012), I compare the distribution of J-costs of the MR and NMR models to the distribution of J-costs of the bootstrapped data and its 95% confidence interval. I calculate the p-value of both models as the quantile of the simulated J-costs at which the empirical J-95% interval lies. As a robustness check, I also perform a pairwise comparison of both individual and pooled simulations. For the pairwise comparison, I compare the J-cost of MR and NMR for each individual Monte-Carlo run. During each comparison, the model with the lowest cost is awarded a point. This yields a ratio of model wins which I shall refer to as the pairwise score. For the pool wise comparison I divide the J-costs of both models into non-overlapping pools of size 10 and calculate the average J-cost for each pool. Counting how often one model wins a pool compared to the other yields the pool wise score.

To gain a deeper insight into the generation of individual moments, I calculate their Moment Coverage Ratios (MCR) (Franke and Westerhoff, 2012) for every moment. The MCR measures the percentage of times the simulated moment is within the confidence bounds of its empirical counterpart. As a yardstick, I also calculate the MCRs for the bootstrapped empirical data series.

Table 5 provides an overview of J-cost performance and MCRs of both models and the bootstrapped data, bold values highlight a superior model performance. Regarding the overall J-scores, the models do not perform as well as the models reviewed in Franke and Westerhoff (2012). The models perform especially poorly with regards to the long memory moments. This is not surprising since there is no herding or switching component.

That being said, the MR model outperforms the NMR model on the

P-value, pairwise, and pool wise scores. Furthermore, the decoupling MCR shows that the MR model is able to produce a superior decoupling from fundamentals while still being able to produce the main stylized facts of financial markets which are also produced by the Chiarella and Iori (2002) model.

This provides an answer to the primary question of this paper: the decoupling scenario is consistent with the stylized facts of stock market returns.

Table 5: Performance of the benchmark model without mean-reversion (NMR), the model with a mean-reversion component (MR) and bootstrapped empirical data. The best score is bold.

Indicator	**NMR**	**MR**	**Empirical**
P-value	0.0003	**0.0007**	-
Pairwise score	0.33	**0.67**	-
Pool wise score	0.50	0.50	-
Moment Coverage Ratios			
Average autocorrelation	**98.0**	94.0	95.06
Autocorrelation lag 1	**94.0**	41.0	95.08
Autocorrelation lag 5	74.0	**78.0**	95.78
Average autocorrelation abs	0.0	0.0	94.64
Kurtosis	**94.0**	92.0	91.76
Autocorrelation abs lag 10	0.0	0.0	91.52
Autocorrelation abs lag 25	**1.0**	0.0	90.22
Autocorrelation abs lag 50	1.0	**4.0**	86.60
Autocorrelation abs lag 100	**1.0**	0.0	72.80
Decoupling	0.0	**54.0**	98.02

4.3 Experiments: the relative popularity of mean-reversion trading

Even though we established mean-reversion trading improves the models ability to match the moments, the mechanisms through which this happens are unknown. Therefore, in this section, I explore how the impact of increased popularity of mean-reversion trading versus the other two trading strategies; trend-following and fundamentalism[7] affects the moments.

I perform two experiments. In the first experiment, I increase the weight of the mean-reversion component at the expense of the fundamentalist com-

[7]I exclude the noise trading component because, rather than a strategy, it reflects heterogeneity of expectations.

ponent with parameter w^{mrf}. In the second experiment, I increase the mean-reversion weight versus the trend-following weight with parameter w^{mr-mm}. In both cases, I keep the rest of the expectations constant at their estimated level.

Table 6 shows the parameter values and bounds that will be used for the experiments. To make this set-up work, I keep the other expectation components constant at their estimated levels. The rest of the uncertain parameters of Table 3 remain uncertain.

Table 6: Experiment parameters.

Symbol	**Description**	**Values**
Experiment 1		
w^{mrf}	mean-reversion versus fundamentalism	(0, 100)
$\sigma^{mr} + \sigma^{f}$	total mean-reversion and fundamentalism	102.13
Experiment 2		
w^{mr-mm}	mean-reversion versus chartism	(0, 100)
$\sigma^{mr} + \sigma^{mm}$	total of mean-reversion and chartism	136.7

To account for this uncertainty, I sample the parameter space containing the parameter of interest for the experiment and the uncertain parameters for both experiments using Latin Hypercube Sampling (McKay, Beckman, and Conover, 1979; Saltelli et al., 2008). Then, I simulate the model with $N_r = 5$ on the sampled sets of parameters.

To measure the strength of the impact as a consequence of changes of the parameter, Marino et al. (2008) and Thiele, Kurth, and Grimm (2014) recommend performing a partial correlation analysis if the relationship is expected to be linear, a partial ranked correlation analysis if the relationship is expected to be non-linear but monotonic, and a variance decomposition technique if the relationship is expected to be non-monotonic.

4.3.1 Experiment 1: mean-reversion expectations replace fundamentalist expectations

For the first experiment, Figure 1 shows scatter plots of the relation between the the J-score, every MCR and the parameter w^{mrf}. It reveals that all three types of relationships exist.

The impacts of changes in w^{mrf} on the J-cost seems linear and monotonic. The Pearson's correlation coefficient between these two variables reveals a negative correlation of -0.43 implying that increasing the fraction of mean-reversion trading to fundamentalism decrease (improves) the J-cost.

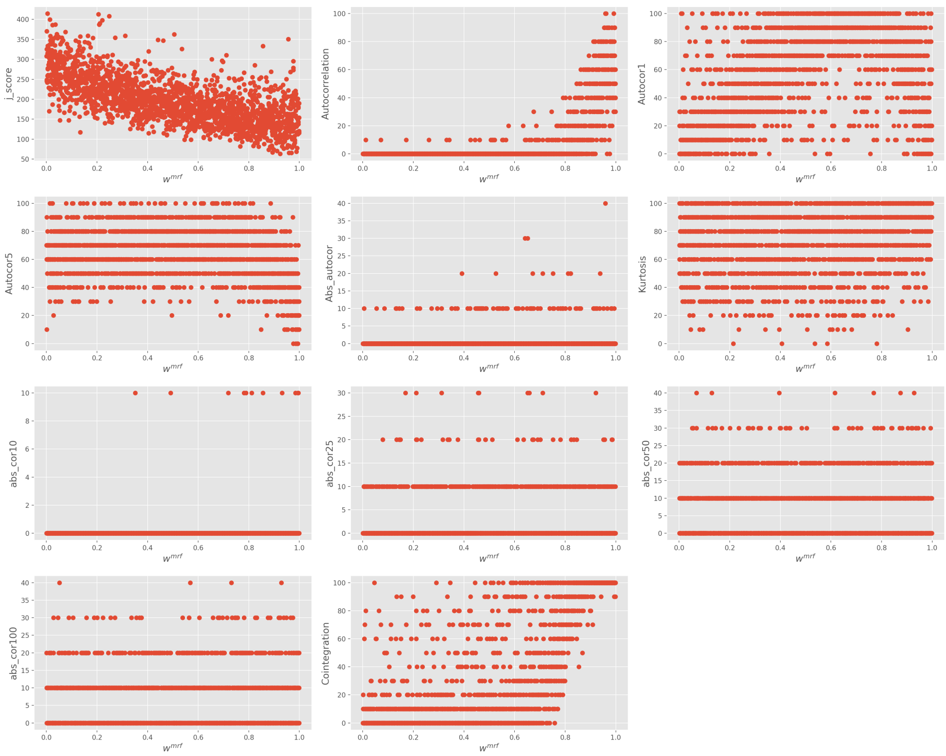

Figure 1: Scatter plots comparing the weight of the mean-reversion component over fundamentlist w^{mrf} to the J-score and moment coverage ratio's of the simulated model moments.

Second, increasing w^{mrf} seems to have a positive but non-linear effect on the MCR of the autocorrelation and decoupling moments. To deal with the non-linearity of the relationship, I calculate Spearman's correlation coefficient which transforms the data to ranks first. The resulting correlation coefficients imply that increasing w^{mrf} is associated with a 0.41 higher autocorrelation MCR and 0.49 higher decoupling MCR across the parameter space.

Because the relationship between w^{mrf} and the other MCRs seems either non-monotonic or non-existent, I apply a variance decomposition technique to asses their sensitivity to a change in w^{mrf}. To this end, I apply the Extended Fourier amplitude sensitivity test (eFast) (Cukier et al., 1973; Saltelli, Tarantola, and Chan, 1999) which uses Fourier series expansion to measure the strength of the influence of inputs on the model output. According to Thiele, Kurth, and Grimm (2014), it delivers all information needed for a comprehensive global sensitivity analysis while being more robust than the somewhat more extensive Sobol's method (Sobol, 2001; Saltelli et al., 2010) at low sample sizes.

The eFast analysis yields two measures of parameter sensitivity: first-order sensitivity $S1$ and a total sensitivity index ST. The latter takes into account the interaction effects with changes in the other uncertain parameters. Figure 2 shows the effects. In line with the findings of the estimation procedure, the model is not likely to replicate the average and lag 10 absolute autocorrelation which results in a low impact on the variance. The first-order effects on the J-cost, autocorrelation and co integration moments are most pronounced. For the rest of the moments there seem to be strong overall sensitivity to changes in the uncertain parameters but low first order sensitivity to w^{mrf}, in line with what can be seen in Figure 1.

4.3.2 Experiment 2: mean-reversion expectations replace chartist expectations

Figure 3 provides the initial scatter plot overview of the relationships between w^{mr-mm} the J-cost and the MCRs.

Because for this experiment the relationship between w^{mr-mm} and the model output seems either non-monotonic or non-existent, I directly perform the eFast sensitivity analysis.

Figure 4 show the outcome of the sensitivity analysis. The blue bars indicate that there is some variability in the model's ability to capture the moments. This is largely the result of the other uncertain parameters because the absence of orange bars shows that the first order effects of w^{mr-mm} on model output are mostly non-existent.

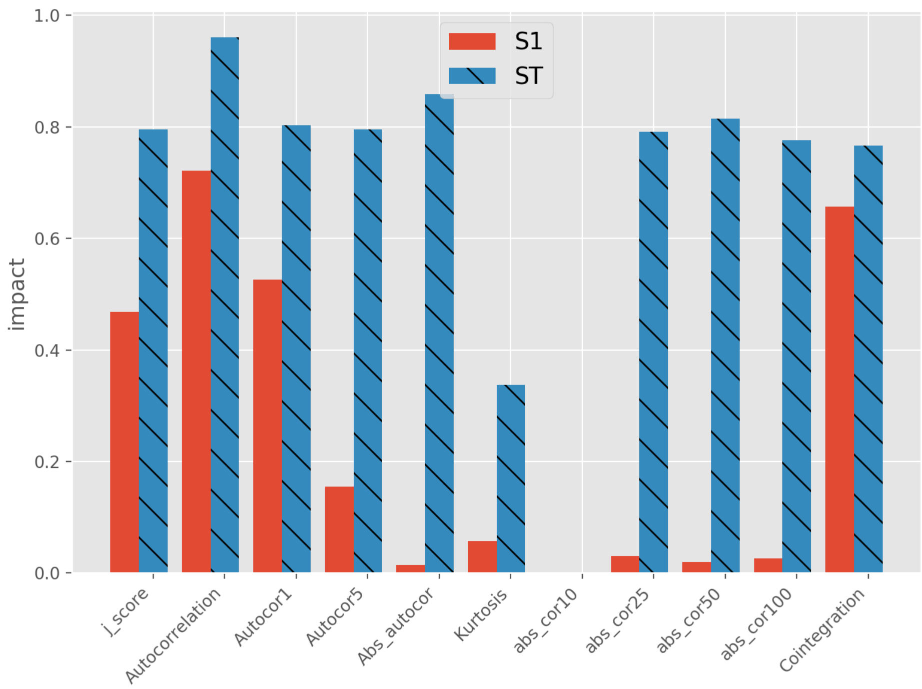

Figure 2: Results of eFAST sensitivity analysis. Contribution of changes in the weight of the mean-reversion component over fundamental component w^{mrf} to variance in output for the J-score and several moment coverage ratio's for model moments. S1 measures the first degree sensitivity whereas ST measures the total sensitivity to changes in all uncertain parameters.

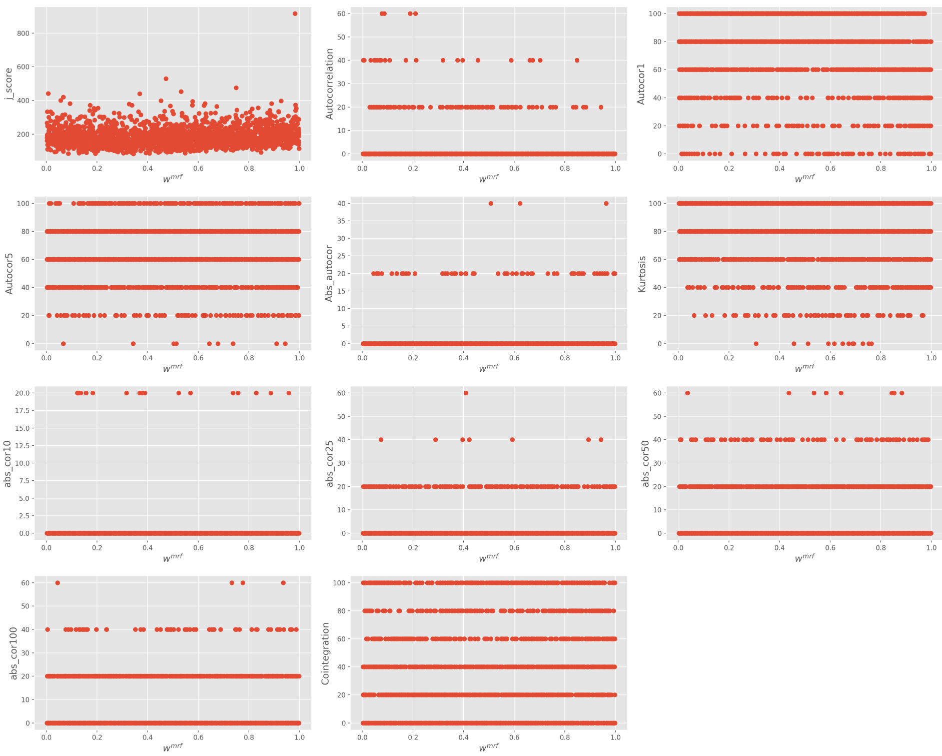

Figure 3: Scatter plots comparing the weight of the mean-reversion component over chartists w^{mr-mm} to the J-score and moment coverage ratio's of the simulated model moments.

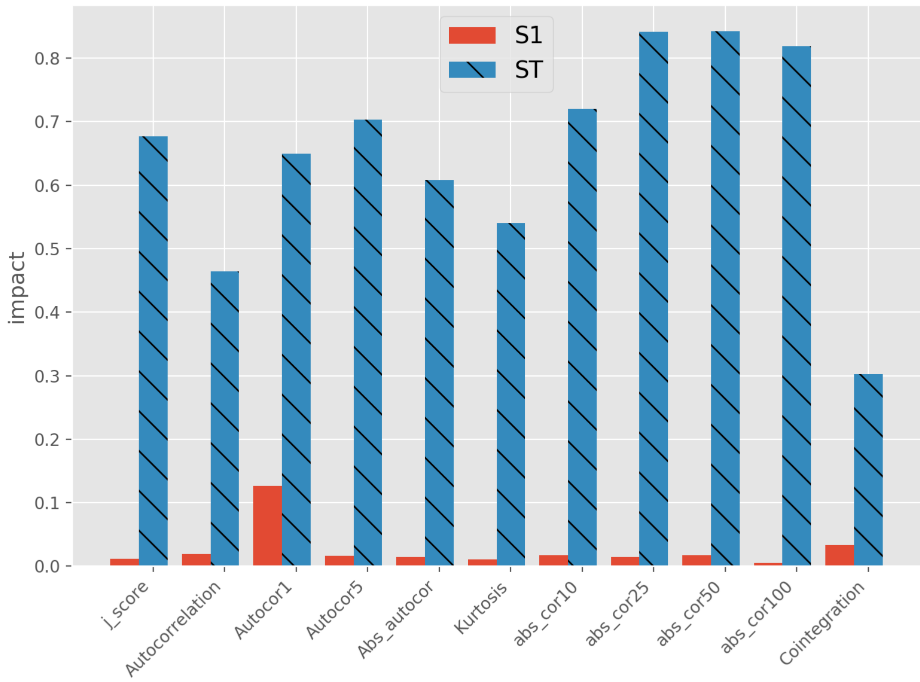

Figure 4: Results of eFAST sensitivity analysis for the second experiment. Contribution of changes in the weight of the mean-reversion component over chartist component w^{mr-mm} to variance in output for the J-score and several moment coverage ratio's for model moments. S1 measures the first degree sensitivity whereas ST measures the total sensitivity to changes in all uncertain parameters.

4.3.3 Evaluation of the experiments

The results of the experiments show that the improvement of the models ability to capture the moments is largely a result of mean-reversion expectations replacing fundamentalist expectations. Particularly, replacing fundamentalist expectations with mean-reversion expectations increases the models ability to reproduce the observed autocorrelation and decoupling with the fundamental value.

5 Conclusion

In this paper, I set out to explore whether the 'decoupling scenario' is plausible. Concretely, I wanted to find out if a behavioural model which generates longer price fluctuations around the fundamental value is consistent with the main stylized facts of financial markets.

The answer to that question is a resounding yes. The estimated mean-reversion trading model presented in this paper generates a decoupling between prices and fundamentals. This does not hurt its ability to replicate the stylized facts of no autocorrelation, volatility clustering, fat tails, and long memory in returns.

It does so by introducing a mean-reversion chartism component alongside the standard trend-following chartist component. In the chartist fundamentalist framework the chartist component is mainly responsible for fat tails and volatility clustering in the returns while the fundamentalist component prevents them from being excessively large. In my model, the mean-reversion component also counteracts the chartist forces. However, because it is not tied to the fundamental value, the model price and fundamental values become decoupled.

I conclude that the Shiller (2014) suggestion that in financial markets prices and the unobserved fundamental value can be structurally decoupled for extended periods of time is plausible. This could have important policy implications because it implies the current market with its high share of algorithmic and index trading might no longer be effectively channeling funds to the most productive investments. The scenario therefore warrants further exploration.

A Appendix Block bootstrap procedure

To calculate the confidence intervals for model parameters, I perform a block bootstrap on the data from which I extract the confidence intervals of the moments. To do so reliably, I make a distinction between moments which are recorded over different time lengths and perform three separate bootstrap procedures.

I follow the approach set out by Franke and Westerhoff (2012). That means that I divide the original data into blocks of size b. Then, randomly sampling from these blocks without replacement, I create 5000 unique new time series.

To ensure the diversity of these time series, ideally, there are plenty of blocks. Therefore, for returns, I calculate the moments related to the predictability, volatility clustering and fat tails using block size $b = 250$. Because of the longer fundamental data series length, I create time series of the returns of the historical price and fundamental value for the decoupling moment with block size $b = 205$. However, to capture some of the longer term moments related to related to long memory, I needed to use a bigger block size of $b = 625$ on the nominal returns series.

B Appendix Sensitivity to parameters

To assess parameter importance, I subject the uncertain parameters to a screening analysis which delivers measures of the relative importance of every parameter for every moment (Ginot et al., 2006). A screening method cannot quantify the strength of the effects. Instead, it will rank parameters by their importance (Thiele, Kurth, and Grimm, 2014).

The screening method I apply here is the enhanced Morris method (Morris, 1991) of Campolongo, Cariboni, and Saltelli (2007). According to Thiele, Kurth, and Grimm (2014), this is the most suitable method for ABMs because it does not require knowledge of the signs of the relationships between parameters and output in advance.

Given a set of model outputs simulated over a sample of the full parameter space, the enhanced Morris method will yield three measures for every output, parameter pair: the mean effect μ, the enhanced mean effect μ^*, and the standard deviation σ. μ gives an indication of the average effect of varying the parameter on the output. The enhanced μ^* does the same while taking into account the effects of opposite signs which occur if the relationship is non-monotonic. Finally, σ measures the variance in the output which occurs when varying the input parameter.

Combining these measures can yield the following insights about the relationship between the parameter and model output of interest. High μ and high μ^* means that the parameter is of importance. Low μ and high μ^* indicates that the parameter is of importance and that this relationship is non-monotonic. The combination of μ^* and σ provides information about non-linear and or interaction effects. Low μ^* and high σ indicates that a parameters effect on output is non-linear and/or dependent on other parameter values. If both indicators are low (high) both the first-order and interaction effects are weak (strong). Finally, high μ^* and low σ indicates that the effect is strong and this is mainly a first-order effect.

Using the Campolongo, Cariboni, and Saltelli (2007) sampling tool, I sample 5000 different combinations of the uncertain parameters within the bounds declared in Table 3. Then, I simulate 2 runs of the model for every parameter set in the sample. Table 7 presents an overview of the ranked importance of parameters.

Table 7: Results of the Morris Method. Impact ranks of the parameters: ι trader sample size, σ^{ϵ^n} standard deviation of noise, σ^v standard deviation of volume, σ^f weight fundamentalists, σ^{mm} weight momentum, σ^e weight random, σ^{mr} weight mean-reversion, ϕ^{max} maximum horizon, N_l number of traders, ζ maximum order expiration ticks on different simulated model moments, where μ measures the average parameter impact, μ^* measures the average adjusted impact and σ measures the variance in impact.

Moment		ι	σ^{ϵ^n}	σ^v	σ^f	σ^{mm}	σ^e	σ^{mr}	ϕ^{max}	N_l	ζ
Autocorrelation	μ	1	8	4	9	2	10	7	6	5	3
	μ^*	3	5	9	2	6	1	4	8	10	7
	σ	4	5	9	2	6	1	3	8	10	7
Autocor1	μ	7	6	3	10	1	8	2	3	5	9
	μ^*	3	4	8	1	6	2	6	9	10	5
	σ	4	3	8	2	5	1	5	9	10	7
Autocor5	μ	1	8	4	9	3	10	7	5	6	2
	μ^*	3	4	10	2	7	1	5	8	9	6
	σ	3	4	9	2	7	1	5	8	10	6
Abs autocor	μ	2	9	7	3	4	10	5	8	6	1
	μ^*	4	3	10	5	6	1	6	8	9	1
	σ	4	3	10	5	6	1	7	8	9	2
Kurtosis	μ	9	8	7	3	6	10	2	5	4	1
	μ^*	2	4	7	6	3	1	8	9	10	5
	σ	3	4	5	7	2	1	9	8	10	6
Abs autocor 10	μ	2	9	6	3	4	10	5	8	7	1
	μ^*	4	3	10	5	7	1	7	6	9	2
	σ	4	2	10	5	7	1	7	6	9	2
Abs autocor 25	μ	2	9	4	4	2	10	7	4	8	1
	μ^*	3	4	10	4	7	1	9	6	7	2
	σ	3	2	10	3	7	1	9	6	7	5
Abs autocor 50	μ	2	9	6	10	4	6	3	6	5	1
	μ^*	1	7	10	5	8	1	5	4	3	8
	σ	2	5	10	7	8	1	5	4	3	9
Abs autocor 100	μ	1	6	2	7	7	2	9	10	2	5
	μ^*	1	8	10	5	9	2	5	4	2	5
	σ	1	8	10	5	9	1	5	4	3	5
Decoupling	μ	8	7	4	10	1	9	3	6	5	2
	μ^*	2	5	10	1	7	3	6	9	8	4
	σ	2	5	10	1	6	3	7	8	9	4

To find the most influential parameters overall, I sum the ranks for μ^* for each parameter over all moments. This yields the following ranking of overall importance:

1. σ^e weight random,
2. ι trader sample size,
3. σ^f weight fundamentalists,
4. ζ maximum order expiration ticks,
5. σ^{ϵ^n} standard deviation of noise ,
6. σ^{mr} weight mean-reversion,
7. σ^{mm} weight momentum,
8. ϕ^{max} maximum horizon,
9. N_l number of traders,
10. σ^v standard deviation of volume.

Besides total importance, the Morris Method also provides information about the importance of parameter uncertainty for individual moments. The autocorrelation moments are mostly influenced by changes in the trader sample size, weight of the random component and the weight of the fundamentalist component. While surprising at first, this last component makes sense since the fundamental follows an AR(1) process. Regarding the volatility clustering moment, absolute autocorrelation is mostly influenced by the trader sample size, random weight and expiration time of orders. The heavy tails moment, kurtosis, is primarily influence by changes in the random weight, trader sample size and standard deviation of noise. For the long memory moments the overall biggest influencers are sample size, weight of the random component, and the random component. There is some heterogeneity between the different lag sizes. Notably, the chartist component and horizon components are important for absolute autocorrelation at longer lags. Finally, for our moment of primary interest: the decoupling between prices and fundamentals, the fundamentalist component is the most important determinant.

The primary goal of the sensitivity analysis was to determine which uncertain parameters could be safely discarded for the model estimation. To make the decision, I follow the set of criteria: the parameter must not be one of the expectation components; the parameter must not be a top three determinant for the groups of moments; the parameter should be near the bottom of the list for overall impact. After applying these criteria, I determine the number of traders N_l and the standard deviation of volume σ^v are the least important parameters.

C Appendix Evolutionary algorithm

The evolutionary optimization algorithm starts out with an initial set (population) of 500 parameters which was sampled from within the bounds of κ using Latin Hypercube Sampling (LHS) methods (McKay, Beckman, and Conover, 1979). LHS has become the sampling method of choice for ABMs because of its ability to sample the parameter space efficiently (Thiele, Kurth, and Grimm, 2014). Then, I simulate the model using Monte Carlo methods varying the seed of the random number generator N_r times for all parameter sets in the population and calculate its J-value using Equation (9). A lower J-function is better and stands for a higher fitness of the simulation. 30% of the fittest simulations and a 20% of random simulation become parents which are combined to create a set of children. Then, 10% of parameters mutate at random in 10% of the parents. The resulting set of parameters is the next generation which will be simulated. I repeat this procedure until the average population costs reaches a steady state.

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