An explanation for the emergence of commonly observed stylized facts using data from experimental financial markets*

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May 22, 2007

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*We wish to thank two anonymous referees and the editor for their valuable and very useful comments. Without discussions with and assistance of Michael Hanke, Jörg Moegieler, and Sonja Huber this paper would not have made it to this final version. Financial support by the University of Innsbruck is gratefully acknowledged.

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Abstract

We analyze data from experimental asset markets with pooled linear regression models to explain the emergence of fat tails and volatility clustering in the distribution of returns. Our data suggest that this is mainly caused by the time effects of decreasing uncertainty and increasing homogeneity in traders’ expectations within the experiment and within each period. Traders’ opinions seem to converge towards an endogenously evolving equilibrium in the course of the experiment. Uninformed traders contribute significantly more to fat tails than do informed traders. Fat tails are mainly caused by high returns after the arrival of new information when uncertainty and heterogeneity in opinions is highest.

JEL classification: C91, D53, D8, G1

Keywords: Stylized facts, experimental economics, laboratory markets, fat tails, volatility clustering

1 Introduction and related literature

In this paper we present data from laboratory market experiments which allow us to offer an explanation for the emergence of fat tails in the distribution of returns and of volatility clustering. In a linear regression model we observe a negative influence of trading time on volatility. As we will show, traders’ expectations obviously converge in the course of the experiment which leads to lowered volatility, decreasing use of fundamental information and less frequent trading. Activities by traders with no fundamental information increase
volatility, whereas price fluctuations are uncorrelated with the number of fundamentalists participating in a transaction.

We use laboratory markets to explore these questions because they permit a careful control of some variables of interest that can not be controlled or observed in real-world markets, most notably the information accessible to traders and the timing of arrival of new information. By observing and controlling these variables we derive explanations for the emergence of fat tails and volatility clustering in a near-to-reality market setting.

In the late 60ies and early 70ies of the 20th century several attempts were made to explain and model fat tails and volatility clustering. Mandelbrot suggested that returns in financial markets follow non-Gaussian stable Levy-processes, which was later called ‘Stable Paretian Hypothesis’ (Rachev, 2003, p. ix). Press (1967) suggested compound Poisson processes for the variance parameter of normal distributions as the reason for the emergence of fat tails, and Clark (1973) claims that finite-variance distributions like the lognormal-normal distribution fit the data in financial markets better than any stable regime. He explains this by the different evolution of price series on different days due to varying inflow of information. Trading may be scarce on days when no information is available. When new information arrives on the market, the price process evolves much faster. Campbell et al. (1997) offer an intuitively graspable explanation why fat tails and volatility clustering emerge, when they state "the unconditional distribution is a mixture of normal distributions, some with small variances that concentrate mass around the mean and some with large variances that put mass in the tails of the distribution. Thus the mixed distribution has fatter tails than the normal" (Campbell et al., 1997, p. 481). However, they do not explain when and why variance will be relatively high or low, which would probably be the most interesting information.1

To model volatility clustering Engle (1982) proposed using the class of Au-

toregressive Conditionally Heteroscedastic (ARCH) models, extended to GARCH (Generalized ARCH) by Bollerslev (1986). These approaches provide powerful descriptive models for volatility clustering, but again they do not explain why it emerges.

The 1990ies saw a surge of heterogeneous-agent models (HAM’s) exhibiting the commonly observed stylized facts. In most of these models computerized traders can switch between two trading strategies. Either they use fundamental information (‘fundamentalists’) or they use information inferred from past prices (‘chartists’). The emergence of fat tails and volatility clustering in these models is due to the switching of traders between fundamentalist and chartist strategies. As long as most traders follow a fundamentalist strategy, only small price changes occur. However, sometimes many traders switch to a chartist strategy due to herding behavior, thereby triggering more volatile prices. As time goes by, traders stop riding the bubble and switch back to the fundamentalist strategy that brings prices back to a fundamentally justified value. While these models are consistently able to replicate stylized facts, some of their assumptions seem unrealistic or counterintuitive. E.g., in these models each trader knows the fundamental value of the risky asset, but some buy at much higher prices while they follow a chartist strategy. Our laboratory markets offer a new approach to tackle this difficult and important issue.

The paper is structured as follows: After the introduction, Section 2 covers our market model and its experimental implementation. In Section 3 we explain the emergence of stylized facts by analyzing data from our markets. Section 4 presents some stylized facts of our markets and Section 5 summarizes and concludes the paper.

2 Model and experimental implementation

In each of our experimental markets 20 human traders interact in a continuous double auction for several (20 to 30) periods. They trade dividend-paying stocks of a virtual company for money that earns a known risk-free rate. We present data from four different treatments (called T1 to T4), distinguished by variations in the initial endowment, the incentive structure, and the distribution of fundamental information.

2.1 Trading mechanism

In all four treatments participants trade in a continuous double auction market with open order book. Similar to most stock markets all orders are executed according to price and then time priority. Market orders have priority over limit orders in the order book. This means market orders are always executed instantaneously. Holdings of money and stock are carried over from one period to the next. Participants can submit as many bids and asks as they want, provided they have enough money to buy or enough stocks to sell. However, going short in money or stocks is not allowed in any treatment. Each order and each transaction can be for 1 to 10 stocks in T1 and T2. In T3 and T4 any order size is possible. The trading screen provides participants with current information on their stock and money holdings, and their current total wealth (see screenshots in the Appendix). All transaction prices with the respective time are shown in a chart on the left side of the screen in T2 to T4. In T1 this information is provided in a chronological list. In each treatment participants also get a list of all their sales and purchases. In the center of the screen traders can submit limit orders (specifying price and quantity) or settle transactions immediately through market orders (specifying only the quantity they want to trade).
2.2 Information system

In all markets some or all traders are provided with information on the fundamental value of the stock based on future dividends. The dividend process is a random walk without drift

\[ D_k = D_{k-1} + \epsilon_k, \]  

where \( D_k \) denotes the dividend for the current period and \( \epsilon_k \) is a normally distributed random variable with mean zero and a standard deviation of 15 percent. These dividends are discounted at a known risk-adjusted interest rate, \( r_e \), assuming the last dividend to be a perpetual, to arrive at the conditional present value (\( CPV \)) of the stock:

\[ CPV_{j,k} = \sum_{i=k}^{k+j-1} \frac{D_i}{(1 + r_e)^{i-k}} + \frac{D_{k+j}}{(1 + r_e)^{j-1} \cdot r_e}, \]

where \( CPV_{j,k} \) stands for the conditional present value of the asset in period \( k \) and \( j \) represents the index for the information level of the trader.

In treatment T1 all traders receive the same fundamental information on dividends and the resulting conditional present value of the stock, while treatments T2 to T4 are characterized by an asymmetric information structure. We implement this asymmetric information structure by lagging access to dividend information for different information levels. The best informed (called \( I_5 \) in T2, \( I_4 \) in T3 and T4) always receive current information on the intrinsic value of the stock based on five (in T2) or four (in T3 and T4) future dividends. All other information levels receive the same information one or several periods later, as they know dividends for only one to four (in T2) or one to three future periods (in T3 and T4). Specifically, information level \( I_{x-1} \) receives the same dividend information (and almost the same CPV) as \( I_x \), just one period later. Figure 1 offers a closer look at the resulting conditional present values as a function of time. A main characteristic of this model is that better informed traders receive relevant information earlier than worse informed.
In treatment T2, $I_1$ are the least informed who get information four periods later than the best informed. In T3 and T4 $I_0$ are the least informed who never get any information about dividends. At the start of the experiment participants are randomly assigned to one of the information levels and then keep this level for the whole session. At the start of each period traders are provided with new information. At this time information level $I_x - 1$ receive the information $I_x$ had one period earlier, while the best informed receive new information that nobody knew before.

In all four treatments the information structure is public knowledge, i.e. traders know how many information levels exist, how many traders are endowed with each information level, and they know their own information level. By comparing results from T1 (homogeneous information) with the other three treatments (heterogeneous information) we can explore whether heterogeneity in information plays a crucial role for the emergence of stylized facts.

### 2.3 Initial endowment

In T1 and T2 all traders have the same initial endowment of 40 stocks and 1,600 units of money each and there are an equal number of traders for each information level (20 traders all with the same information level in T1, four traders for each of five information levels in T2). T3 and T4 feature three important changes compared to T2: i) we introduce a group of traders who do not get any fundamental information at all (named $I_0$), ii) the different information levels have different starting endowments with the better informed also having larger starting endowments, and iii) there are different numbers of traders per information level. The distribution of trader numbers and starting endowment in T3 and T4 was inspired by 'Zipf’s Law' (Zipf, 1949). Specifically, there is only one 'insider' $I_4$, two traders with information level $I_3$, three traders $I_2$, five traders $I_1$ and nine uninformed traders $I_0$. We ensure equal market
power for each information level by providing the well informed with more stocks and money than the worse informed. Specifically $I_4$ has nine times as many stocks and money as each of the nine traders with information level $I_0$. $I_3$ has half, $I_2$ one third, and $I_1$ one fifth of the endowment of $I_4$ (See instructions for T3 and T4 in the Appendix for details). The number of traders and their initial endowment is public information in all treatments.

2.4 Incentive structure

In three of the treatments (T1, T2, and T4) we use a tournament incentive structure, where traders’ real money earnings depend on their performance relative to other traders. We chose this structure as professional fund managers are usually paid in this way (based on their performance relative to a benchmark), and these funds increasingly dominate the market. However, as tournament incentive structures have been criticized by James and Isaac (2000) for their potential to lead to misleading prices, we conducted T3 with another incentive structure. In this treatment the final payment to participants is the final value of their stocks - valued at the closing price of the market - plus their money holdings. This total amount is converted at a known fixed rate.

Insert Table 1 about here

3 Explanation for the occurrence of large price movements and of clustered volatility

We observe very active trading in all markets with a total of 5,573 transactions in all markets of Treatment 1, 4,782 trades in T2, 4,509 trades in T3, and 5,574 trades in T4.

Insert Figure 2 about here

Figure 2 presents a plot of absolute normalized returns of one representative market of each treatment. We see that volatility declines over time as is con-
firmed by the results of our regression model presented in Table 2. We interpret this as declining heterogeneity in expectations of the traders. More remarkably, this finding need not coincide with a decrease in heterogeneity of traders’ fundamental information provided by their CPVs. Apparently expectations are driven not only by fundamental information but also by the prices observed in the market.

We also find a similar pattern of declining volatility within each period. Thus, large outliers of the volatility measure are located in the first 20-30 seconds of each period and occur predominantly in the first half of each experiment. These large returns account for most of the fat tails we observe.

When looking at the literature some other possible causes of large returns can be found. Several authors (Lux and Marchesi, 1999, 2000; Brock and Hommes, 1998) report a positive impact of non-fundamentalists (other terms used are ‘noise-traders’ or ‘chartists’) on price fluctuations. In T3 and T4 we can control for this phenomenon looking at the price fluctuations triggered by the actions of uninformed traders (information level $I_0$).

Similarly, the above cited studies report a negative relationship between trading on the basis of fundamental information and volatility. As these models feature only two types of traders (‘fundamentalists’ and ‘chartists’), a positive influence of one type of strategy automatically implies a negative relationship of the other one. Instead, in our experiments traders can adopt any strategy they want. So, we also test for the influence of fundamentalists on price volatility in T2 to T4.

In an earlier paper we find a positive relationship between the heterogeneity of fundamental information and volatility (Kirchler and Huber, 2007). In this paper we reexamine this finding only in T2. In T1 all traders receive the same fundamental information. In the regression model of T3 and T4 we observe a high collinearity between the number of uninformed per trade and the difference in CPVs of the two trading partners. We eliminate the latter and focus on the impact of uninformed traders on volatility.
Finally, Scalas et al. (2006) find an impact of the time span between consecutive trades on price developments. We test whether we find a relationship in the experimental data as well.

To measure the importance of the different possible causes for high volatility we run pooled linear regressions. As dependent variable we use absolute normalized returns for each tick at time \( t \) according to equation 4:

\[
R_t = \log P_t - \log P_{t-1},
\]

\[
|y_{\text{norm},i,t}| = \frac{|R_{i,t} - \overline{R}_i|}{\sigma_i},
\]

where \( i \) represents the index for a single market within each treatment, \( t \) indicates tick and \( \overline{R}_i \) is the average return in the market. This normalization allows pooling data of different markets within one treatment.\(^3\) The first two independent variables of our regression model

\[
|y_{\text{norm},i,t}| = \alpha + \beta_1 I_0 i + \beta_2 \text{FUND}_i + \beta_3 \text{PER}_i + \beta_4 T_i + \beta_5 \text{CPV}_i + + \beta_6 \text{WT T}_{\text{norm},i} + \sum_{i=1}^{5} \gamma_i M_i + \sum_{i=1}^{5} \sum_{k=1}^{K} \delta_{i,k} (y_{i,t-k} \cdot M_i) + u_{i,t},
\]

are the number of uninformed traders, \( I0 \) (with the possible values ranging from zero to two uninformed traders per transaction), and the percentage of fundamental strategy in each trade, \( \text{FUND} \). A trader uses a fundamental strategy if he buys when the price is lower than his fundamental information and vice versa. Possible values: 0, 0.5 (if one of the two traders in a transaction uses fundamental information - of course, uninformed traders are excluded from this analysis) and 1 (both traders in a transaction use their fundamental information). The third and fourth factors are period, \( \text{PER} \), and trading time within each period, \( T \), to control for time-dependent effects. The difference in the con-

\(^3\)See Plerou et al. (1999) for the application of normalized returns on real data.
ditional expected values, $CPV$, of the two trading partners at each transaction and the normalized waiting times between trades, $WTT_{\text{norm}}$, complete our regression model. We normalized the waiting times between trades according to equation 6:

$$WTT_{\text{norm},i,t} = \frac{WTT_{i,t} - \overline{WTT}_i}{\sigma_i},$$ (6)

where $i$ represents the index for a single market within each treatment, $t$ indicates tick and $\overline{WTT}_i$ is the average waiting time in the market.

To account for specific characteristics of each market, we absorb those into market dummies. Additionally, we include AR-terms which interact with the market dummies. We account for potential heteroscedasticity and non-gaussianity in the residuals by using Newey-West statistics (Newey and West, 1987).

Insert Table 2 about here

One of the clearest results is that the coefficient of the variable period, $PER$, has a significant negative effect on volatility in all treatments. In addition, volatility declines significantly within each single period in all four treatments (Variable $T$). The time between consecutive trades, $WTT_{\text{norm}}$, is positively related to the volatility measure. The more time has passed since the previous transaction, the larger the price change. This holds true in T1 with homogeneous information as well as in the three treatments with heterogeneous information. This suggests that the occurrence of new information, rather than heterogeneity in fundamental information available, is the main source of high volatility in our markets.

While in the above cited literature on heterogeneous agent models (HAM's), activities by fundamentalists decrease volatility, we don’t find a clear tendency between the percentage of fundamentalists and volatility in our markets. Only in T3 a significantly negative coefficient of $FUND$ exists. However, activities by uninformed traders, $I0$, increase volatility significantly, which is in line with these models.
From this analysis we conclude that the uncertainty and heterogeneity in traders expectations decline in the course of the experiment and within each period. Due to this learning and adaption of strategies the market seems to converge to some kind of endogenously evolving equilibrium.

With respect to volatility clustering we think the time-dependent effects we report are the main origin for this stylized fact. The market as a whole switches from a heterogeneous expectations regime to a relatively homogeneous one in the course of the experiment and within each period.

In a next step we analyze what strategies yield the pattern of lowered volatility as a function of trading time. We define the percentage of fundamental strategy in each trade (only for those traders that are endowed with a CPV) as dependent variable. As independent variables we use the time-dependent variables 'period' and 'time' that has passed since the beginning of the current period. The difference in CPV’s of the two trading partners completes the model.

Again, we add market dummies to control for idiosyncratic effects due to specific market dynamics. To control for autocorrelation in the residuals, we add AR-terms that interact with the market dummies. With the Newey-West correction we account for heteroscedasticity and non-gaussianity

\[
FUND_{i,t} = \alpha + \beta_3PER_i + \beta_4T_i + \beta_5CPV_i + \gamma_iM_i + \sum_{k=1}^{K} \delta_{i,k}(FUND_{i,t-k} \times M_i) + u_{i,t}. \tag{7}
\]

The coefficient of the variable period, PER, is significantly negative, which indicates that the percentage of use of fundamental information declines in all treatments as a function of time, while prices stabilize over time. This finding is remarkable as in the above cited studies on HAM’s, fundamentalists stabilize the market. Instead, in our markets the stabilization of prices is not due to
increased use of the fundamental strategy. The difference in \( CPV \) is positively related to the percentage of fundamental strategy, whereas we find no clear tendency for the variable \( T \).

We observe a lower frequency of trading towards the end of the experiment. In our linear regression model we define the normalized waiting time between trades, \( WTT_{\text{norm}} \), as dependent variable. As independent variables we focus on the number of uninformed, \( I0 \) and the variable \( PER \). Again we add market dummies, AR-terms that interact with market dummies, and the Newey-West test statistics to the model

\[
WTT_{i,t} = \alpha + \beta_1 I0_i + \beta_2 PER_i + \sum_{i=1}^{5} \gamma_i M_i + \sum_{i=1}^{5} \sum_{k=1}^{K} \delta_{i,k} (WTT_{i,t-k} M_i) + u_{i,t}.
\]

(8)

The variable period, \( PER \), is positively correlated with the normalized waiting times between trades in treatments T1, T3 and T4 and uncorrelated in T2. This means that waiting times increase in the course of the experiment, indicating less frequent trading over time.

4 Stylized facts

The normalization of returns according to equation 4 allows pooling the different markets of each treatment. The Kolmogorov-Smirnov test on gaussianity rejects the null hypothesis in all four treatments. Figure 5 shows the cumulative distribution function (CDF) of absolute normalized returns of the different treatments. We find that the probability of large absolute price fluctuations is much higher than expected by a normal distribution with same mean and variance, represented by the solid line.

Insert Table 4 about here

Insert Figure 3 about here
To look at the scaling properties in more detail we compute the excess kurtosis and the Hill Estimator for the 10%, 5% and 2.5% tail of the distribution (Hill, 1975). Table 5 indicates large values of excess kurtosis and Hill Estimators ranging from 1.83 to 3.63. Voit (2003) reports values within the range of 2 to 6 for tick data on real financial markets. The treatments also show the typical pattern of increasing Hill estimators with decreasing tail size.

Another important stylized fact is the volatility clustering property, which manifests as periods of tranquillity interrupted by periods of turbulence. The change between these two regimes is a slow process so that large returns slowly decline until a tranquil state is reached. This is measured by the autocorrelation function (ACF) of absolute returns, which slowly decays to zero in real financial markets. The autocorrelation of returns, though, rapidly decays to zero with no significant autocorrelation for lags larger than 1 (Campbell et al., 1997). As we have time series data for this analysis we cannot pool normalized returns for this analysis and thus have to look at each market separately. Figure 5 shows the ACF of absolute normalized returns (solid line with asterisks) and normalized returns (solid line) of one representative market for each treatment. We notice the long memory of absolute normalized returns with a long range of significant values ($p < 0.05$), whereas normalized returns quickly converge towards zero showing hardly any significant values. Again, price data of our experimental markets is similar to real market data.

Scalas et al. (2006) and Kaizoji and Kaizoji (2004) find that the survival function of waiting times between trades is non-exponential, but exhibits fat tails. In real financial markets the probability of large waiting times is much higher than can be expected by an exponential function with the same parameters. Figure 5 takes a closer look at this fact. The survival function of normalized
waiting times does not coincide with the exponential fit, but shows large outliers in the tail of the distribution. Again, regarding this fact, the treatments show very similar properties to real-world financial markets.

5 Conclusion

We present data from experimental asset markets for the explanation of fat tails in the distribution of returns and for the volatility clustering property. The latter is mainly caused by the time effects of decreasing uncertainty and increasing homogeneity in traders’ expectations within the experiment and within each period. Thus, the probability of large price deviations is highest at the beginning of the experiment and at the beginning of each period due to traders’ heterogeneity in expectations. When we relate this finding to the suggestion of Campbell et al. (1997) that fat tails are caused by variations in volatility our results show that volatility is highest after the occurrence of new information, and decreases as information is reflected in prices. Traders’ opinions seem to converge towards an endogenously evolving equilibrium in the course of the experiment. Besides these time effects, the actions of uninformed traders contribute significantly more to fat tails than do informed traders.
References


Figures and Tables

Figure 1: Conditional present values (CPV) as a function of period of market 1 in treatment 4. The dots represent the resulting prices.
<table>
<thead>
<tr>
<th>Description</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dividend in $t_0$</td>
<td>0.80</td>
<td>0.80</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>S.d. dividend</td>
<td>0.08</td>
<td>0.12</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td># of information</td>
<td>1</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>levels</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of traders per</td>
<td>20</td>
<td>4</td>
<td>varying</td>
<td>varying</td>
</tr>
<tr>
<td>information level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stocks in $t_0$</td>
<td>40</td>
<td>40</td>
<td>varying</td>
<td>varying</td>
</tr>
<tr>
<td>Cash in $t_0$</td>
<td>1600</td>
<td>1600</td>
<td>varying</td>
<td>varying</td>
</tr>
<tr>
<td>Incentive structure</td>
<td>tournament</td>
<td>tournament</td>
<td>abs. wealth</td>
<td>tournament</td>
</tr>
<tr>
<td>$r_c$</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>$r_f$</td>
<td>0.5%</td>
<td>0.5%</td>
<td>0.5%</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

Table 1: Overview over properties of the four treatments
Figure 2: Normalized returns as a function of time of Market 2 of T1 (top left), Market 3 of T2 (top right), Market 2 of T3 (bottom left) and of Market 5 of T4.
<table>
<thead>
<tr>
<th>Variable</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.4612***</td>
<td>0.5723***</td>
<td>0.4437***</td>
<td>0.5962***</td>
</tr>
<tr>
<td></td>
<td>(0.0460)</td>
<td>(0.0700)</td>
<td>(0.0605)</td>
<td>(0.0739)</td>
</tr>
<tr>
<td>$I_0$</td>
<td>-</td>
<td>-</td>
<td>0.0443**</td>
<td>0.0481*</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.0214)</td>
<td>(0.0264)</td>
</tr>
<tr>
<td>$FUND$</td>
<td>-</td>
<td>0.0438</td>
<td>-0.0813**</td>
<td>-0.0301</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.0550)</td>
<td>(0.0321)</td>
<td>(0.0287)</td>
</tr>
<tr>
<td>$PER$</td>
<td>-0.0137***</td>
<td>-0.0200***</td>
<td>-0.0031*</td>
<td>-0.0131***</td>
</tr>
<tr>
<td></td>
<td>(0.0017)</td>
<td>(0.0020)</td>
<td>(0.0017)</td>
<td>(0.0019)</td>
</tr>
<tr>
<td>$T$</td>
<td>-0.0015***</td>
<td>-0.0027***</td>
<td>-0.0030***</td>
<td>-0.0023***</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0005)</td>
<td>(0.0006)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>$CPV$</td>
<td>-</td>
<td>0.0016</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.0039)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$WTT_{norm}$</td>
<td>0.0253*</td>
<td>0.0656***</td>
<td>0.0495***</td>
<td>0.0244*</td>
</tr>
<tr>
<td></td>
<td>(0.0137)</td>
<td>(0.0165)</td>
<td>(0.0155)</td>
<td>(0.0148)</td>
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<tr>
<td>#AR-terms</td>
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<td>5</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>$R^2$</td>
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<td>0.252</td>
<td>0.280</td>
<td>0.250</td>
</tr>
<tr>
<td>$n$</td>
<td>5,547</td>
<td>4,756</td>
<td>4,129</td>
<td>4,478</td>
</tr>
</tbody>
</table>

*, ** and *** represent the 10%, 5% and the 1% significance levels.

Table 2: Explanatory variables for the dependent variable normalized absolute returns, $|\hat{R}_{norm,t,i}|$: $I_0$ indicates the number of uninformed, $FUND$ stands for the percentage of fundamentalists, $PER$ represents trading period, $T$ measures trading time within each period, $CPV$ stands for the difference in conditional present values of the trading partners and $WTT_{norm}$ describes the normalized waiting time between trades. The standard errors are given in parentheses. Note, that with the normalization of returns all markets within one treatment can be pooled.
<table>
<thead>
<tr>
<th>Variable</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>-</td>
<td>-0.2834***</td>
<td>0.4492***</td>
<td>0.4479***</td>
</tr>
<tr>
<td></td>
<td>(0.0392)</td>
<td>(0.0341)</td>
<td>(0.0417)</td>
<td></td>
</tr>
<tr>
<td>PER</td>
<td>-0.0010**</td>
<td>-0.0033***</td>
<td>-0.0037***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0008)</td>
<td>(0.0012)</td>
<td></td>
</tr>
<tr>
<td>$T$</td>
<td>-0.0002*</td>
<td>-0.0001</td>
<td>-0.0005*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0002)</td>
<td>(0.0003)</td>
<td></td>
</tr>
<tr>
<td>CPV</td>
<td>0.0116***</td>
<td>0.0099***</td>
<td>0.0193***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
<td>(0.0017)</td>
<td>(0.0023)</td>
<td></td>
</tr>
<tr>
<td>#AR-terms</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.137</td>
<td>0.156</td>
<td>0.250</td>
<td></td>
</tr>
<tr>
<td>$n$</td>
<td>4,766</td>
<td>1,791</td>
<td>1,336</td>
<td></td>
</tr>
</tbody>
</table>

*, ** and *** represent the 10%, 5% and the 1% significance levels.

Table 3: Explanatory variables for the dependent variable $FUND$ (percentage of fundamental strategy). $PER$ indicates trading period, $T$ measures trading time within each period and $CPV$ is the difference in conditional present values of the trading partners. The standard errors are given in parentheses. Note, that after the normalization of returns all markets within one treatment are pooled.
<table>
<thead>
<tr>
<th>Variable</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.6649***</td>
<td>0.7000***</td>
<td>0.6602***</td>
<td>0.6339***</td>
</tr>
<tr>
<td></td>
<td>(0.0335)</td>
<td>(0.0360)</td>
<td>(0.0407)</td>
<td>(0.0298)</td>
</tr>
<tr>
<td>$I0$</td>
<td>-</td>
<td>-</td>
<td>0.0498***</td>
<td>0.0326**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0169)</td>
<td>(0.0149)</td>
</tr>
<tr>
<td>$PER$</td>
<td>0.0031**</td>
<td>-0.0006</td>
<td>0.0029*</td>
<td>0.0033***</td>
</tr>
<tr>
<td></td>
<td>(0.0014)</td>
<td>(0.0014)</td>
<td>(0.0017)</td>
<td>(0.0016)</td>
</tr>
<tr>
<td>#AR-terms</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.003</td>
<td>0.003</td>
<td>0.009</td>
<td>0.003</td>
</tr>
<tr>
<td>$n$</td>
<td>5,567</td>
<td>4,771</td>
<td>4,503</td>
<td>5,373</td>
</tr>
</tbody>
</table>

*, ** and *** represent the 10%, 5% and the 1% significance levels.

Table 4: Explanatory variables for the dependent variable $WTT_{norm}$ (normalized waiting times between trades). $I0$ indicates the number of uninformed and $PER$ represents trading period. The standard errors are given in parentheses. Again, all markets within one treatment are pooled.
Figure 3: Cumulative distribution function of absolute normalized returns of T1 (top left), T2 (top right), T3 (bottom left) and T4. The probability of large absolute returns in the experiments is higher than can be expected by a normal distribution with same mean and variance.
<table>
<thead>
<tr>
<th>Tail size</th>
<th>T1</th>
<th>T2</th>
<th>T3</th>
<th>T4</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>1.828</td>
<td>1.873</td>
<td>1.865</td>
<td>1.907</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.086)</td>
<td>(0.088)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>5%</td>
<td>2.400</td>
<td>2.838</td>
<td>2.166</td>
<td>2.417</td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.185)</td>
<td>(0.146)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>2.5%</td>
<td>3.075</td>
<td>3.634</td>
<td>2.774</td>
<td>2.972</td>
</tr>
<tr>
<td></td>
<td>(0.265)</td>
<td>(0.339)</td>
<td>(0.267)</td>
<td>(0.261)</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>21.545</td>
<td>18.096</td>
<td>37.838</td>
<td>53.252</td>
</tr>
<tr>
<td></td>
<td>(1.055)</td>
<td>(1.152)</td>
<td>(0.796)</td>
<td>(0.671)</td>
</tr>
</tbody>
</table>

Table 5: Excess kurtosis and Hill estimator of the the 10, 5 and 2.5% tail. The corresponding standard errors are given in parentheses. With large values of excess kurtosis and Hill estimators ranging from from 1.83 to 3.63, the experimental markets yield very similar properties compared to real market data.
Figure 4: Autocorrelation function of absolute normalized returns (solid line with asterisks) and normalized returns (solid line) of Market 2 of T1 (top left), Market 3 of T2 (top right), Market 2 of T3 (bottom left) and of Market 5 of T4. The dashed lines represent the 95 percent confidence intervals. The autocorrelation function of absolute returns slowly decays to zero which is evidence of an existing volatility clustering property in our experimental markets.
Figure 5: Waiting time survival function of trades in normalized seconds of T1 (top left), T2 (top right), T3 (bottom left) and T4. The solid line represents the standard exponential survival function. Similar to real market data the empirically observed data does not fit the exponential function.
Figure A1: M1_T1: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A2: M2_T1: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A3: M3_T1: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A4: M4\_T1: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A5: M5_T1: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A6: M1_T2: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A7: M2_T2: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A8: M3_T2: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A9: M4_T2: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A10: M5_T2: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A11: M1_T3: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A12: M2_T3: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A13: M3_T3: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A14: M4_T3: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A15: M5,T3: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A16: M1_T4: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A17: M2_T4: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A18: M3_T4: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A19: M4_T4: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.
Figure A20: M5,T4: Prices, conditional expected values and normalized returns as a function of time - (top). Autocorrelation function of absolute normalized returns (solid line with asterisks) and of normalized returns (solid line) - (bottom). The dashed lines represent the 95% confidence bounds.