When better forecasting abilities can be harmful – results from an experimental financial market[#]

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Abstract

The question of how useful information in a financial market is has been discussed for decades and is still unresolved. In this paper we challenge the widely held belief that success and failure in the stock market can largely be attributed to the information underlying the trading decisions. We present a dynamic multi-period experimental financial market with asymmetrically informed traders whose information is based on future dividends. While the best informed traders can outperform the market, we find that information is not always useful, as average informed traders have significantly lower net returns than the worst informed.

JEL-classification: C91; D82; D83

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1 Introduction

In 1970 Fama published his seminal paper "Efficient Capital Markets," provoking practitioners and many theorists with the thesis that gathering information is useless in efficient markets, as all information is already reflected in prices. However, with the information paradox Grossman (1976) and Grossman/Stiglitz (1980) showed that strong form efficient markets are not possible and that gathering information makes sense up to the point where its marginal cost equals its marginal benefit. In this paper we agree with this statement, but we offer another provocative thesis: our experimental data suggests that apart from its cost, information can be harmful for investors. This experimental result is supported by empirical findings from the past seven decades.

The widespread belief that having more information is always better (or at least never worse) in financial markets is surprising, given that researchers in many different disciplines have shown that more public or private information is not always better for those who use it. Especially game theoretical models teach us that more information may harm some or even all agents. Almost 60 years ago von Neumann and Morgenstern (1947) argued that a player may find it advantageous to forego some information. Savage (1954) lists several cases where information can be disadvantageous due to psychological reasons or because it makes bets impossible. Hirshleifer (1971) shows that public information in markets with risk-averse individuals can make them worse off as it may destroy insurance opportunities that would have been available without the public information. Gersbach (2000a, 2000b) shows that the value of public information in social choice situations may be negative for a majority of voters.

Even in disciplines like supply chain management, models show that information can be harmful: Iyer, Wu, and Preckel (2005) present a model with a decentralized supply chain to

analyze the impact of information sharing on expected costs when a number of independent retailers share production resources. They find that information sharing can increase expected costs in decentralized supply chains and therefore harm all the parties involved. In addition they show that if just one party gets more information, that party may be worse off, while others who did not get additional information may be better off.

For us, the game-theoretical approaches are especially interesting, as we understand the market as a strategic game where investors try to outsmart each other. We think that Gibbons' (1992, 63) conclusion that in game theory "*having more information ... can make a player worse off*" also holds true for financial markets. Schredelseker (1984) shows in a binomial setting that information may be harmful for traders in a market context.[1] However, we are not aware of any widely accepted theory or models arguing that the value of information may be negative in financial markets. In our discipline, the dominant belief is that information is the most important ingredient to achieve above-average returns. This belief persists even though empirical, theoretical and experimental studies suggest that the matter is not that simple.

Cowles raised the first doubts about the usefulness of information processing in financial markets as early as 1933. The abstract of his article "Can Stock Market Forecasters Forecast?" had just three words: "*It is doubtful*." Cowles conducted an extensive study of how well four different groups of stock market forecasters performed relative to the whole market. None did better than could be expected by pure chance, and simple random strategies had outperformed the practitioners – as did the broad market (Cowles 1933). These results were confirmed by a second study covering more than 15 years of forecasts (Cowles 1944).

[1] Schredelseker (2001) shows how traders can switch strategies until equilibrium is reached, where information is just useless but not harmful.

Two decades later Jensen (1965) examined the performance of mutual funds compared to a broadly diversified market portfolio. Only 26 of the 115 funds covered in the study performed better than the market, and on average they fared 15 percent worse than the market over a period of ten years. Jensen, surprised by these results, wrote, "*One must realize that these analysts are extremely well endowed. Moreover, they operate in the securities markets every day and have wide-ranging contacts and associations in both business and financial communities*." If they can't beat the market, how can a small investor taking advice from his bank or some stock market newsletter be expected to?

Malkiel presented similar results in several studies over the years (e.g. Malkiel 1995, 2003a, 2003b). In two more recent papers (Malkiel 2003a, 2003b) he criticized the underperformance of professional investment funds compared to the index: On average, the market outperformed more than 70 percent of actively managed stock market funds over a ten-year period, and the figure for bonds is even worse at 90 percent. It would appear that 30 years after Jensen's studies, most of the highly paid and professionally trained specialists are still not able to beat the market.

Many years ago Cowles stated that "*Market advice for a fee is a paradox. Anyone who really knew [anything about the real value of a stock] just would not share his knowledge. Why should he? In just five years he would be the richest man in the world*." (Bernstein 1992, 35). Yet after seven decades of studies consistently showing that gathering information and trading on it is not necessarily a way to succeed in the stock market, professionally managed funds are still a big industry, and newspapers and media providing stock market information make good money even though evidence suggests that using this information makes investors worse off than a simple random strategy or index investment would.

However, we think Cowles showed great understanding of the human psyche when he wrote, "*Even if I did my negative surveys every five years, or others continued them when I'm gone, it wouldn't matter. People are still going to subscribe to these services. They want to believe that someone really knows. A world in which nobody really knows can be frightening*." (Bernstein 1992, 38).

The impressive growth of index funds since their introduction in the early 1970ies is a rational reaction by market participants if they find that they cannot beat the market by trading on information. In the early 1990ies about one-third of institutional money was already invested in index funds (Bernstein, 1992). Bogle (1999) reports that in 1995 about 40 percent of all funds were invested in index instruments.

With this paper we want to offer an explanation for why average informed traders may perform worse than the least informed in financial markets. Our study suggests that their poor performance is due not to mistakes they make or faulty information; it is inherent to the structure of information and to market dynamics. This will be shown by results from an experimental financial market.

The paper is organized as follows: After the introduction we present our market model and its experimental implementation in section 2. In section 3 we explain the experimental implementation, while section 4 presents experimental results. In section 5 we offer an explanation of the underlying market dynamics which will be supported by a Monte-Carlo-simulation. Section 6 concludes the paper.

2 The Market Model

In the past thirty years several authors (e.g. Grossman/Stiglitz 1980, Hellwig 1982, Figlewski 1982, Kyle 1985, Copeland and Friedman 1992, Ackert et al. 2002) have developed models with asymmetrically informed traders. However, all these models are limited to just two information levels: "uninformed" and "informed". We present a model with more than two information levels. This is not only a quantitative, but also a qualitative change: With just two information levels, it is obvious that the informed will never perform worse than the uninformed. With three or more information levels, though, strategic thinking starts to play a more important role: Now we have a market with several asymmetrically informed agents who try to outsmart each other.

We set up a multi-period model where asymmetrically informed human subjects trade a risky asset. The core of our model and its key innovation is the information system, which provides traders with information about future cash flows (henceforth 'dividends'[2]). This allows us to analyze how heterogeneity in the knowledge of fundamental information influences market variables, as some traders know more about future dividends than others.

We believe that in real-world markets, relevant fundamental information is first known to insiders. A company's managers know about major future developments in their firm well before word begins to spread through the market. This is intuitively obvious. It is also supported by insider trading literature proving that insider information is superior and can generate above-average returns, as for example Lakonishok/Lee (2001), Lin/Howe (1990), Krahnen/Rieck/Theissen (1999), and Jeng/Metrick/Zeckhauser (2003) show. Results of event studies support this reasoning by showing that cumulative abnormal returns start to accumulate long before companies' earnings announcements, this means long before the information becomes publicly available (e.g. Campbell/Lo/MacKinlay 1997). This indicates

[2] For the sake of understandability with participants in the experiment, we chose to use the word 'dividends' for the fundamental information in our model, as 'future cash flows per share' could have confused some.

that better informed traders start trading on the information before it is published. However, few studies distinguish between more information levels than "insiders" and "others."

To implement an asymmetrical information structure with more information levels, we start with Hellwig`s idea (1982) that insiders have an information advantage because they get relevant information earlier than others. We extend this concept to five information levels *I1* to *I5,* with *x* in *Ix* specifying the number of future dividends known to a trader. As we have a multi-period model, this design implies that information trickles down through the market from the best informed to the broad public over time. Traders *I5* are always the best informed. Information levels *I3* and *I4* represent other major groups of investors, e.g. funds managers and large stake holders who have access to information before the general public does, as it is their job to gather and analyze information and to trade on it before most others in the market can. Finally, information becomes available to the public through newspapers, TV and other media. In our market these groups are represented by *I1* and *I2*. They get the same dividend information as *I5* – just four and three periods later than insiders do. For the sake of simplicity we assume that traders know the exact value of the future dividends and that they never get wrong dividend information. This asymmetric information structure is common knowledge in the experiment.

Traders with information level *I1* know the dividend for this period, traders *I2* know the dividends for this period and the next, and so on until the best informed ("insider") *I5,* who knows the dividends for this and the next four periods. With this construction we get a market with an asymmetric information structure where better informed agents always know future dividends earlier than worse informed ones. The design can easily be adjusted to any desired number of information levels.

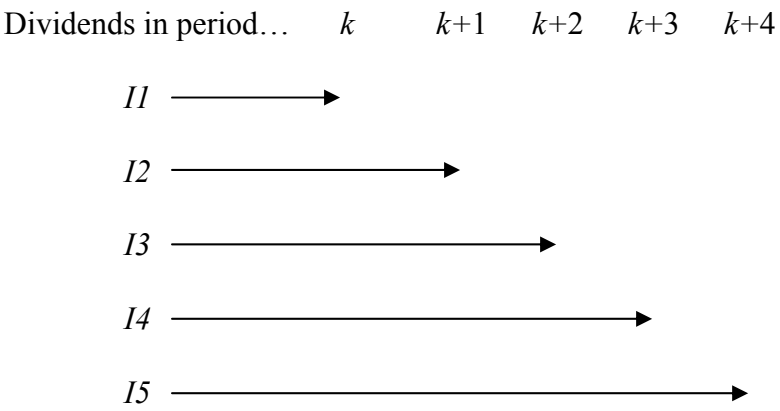

Figure 1: Overview of traders' knowledge about future dividends

At the start of each period, each trader gets information on future dividends. At the end of the period, the actual dividend is paid out and the risk-free rate is paid for cash holdings. At the start of the next period, each trader receives new information previously known only to the next-best-informed trader – or completely unknown, in the case of *I5*. This means that the former dividend for period (k+1) is the dividend for period k one period later. The informational advantage of better informed traders is therefore one of time, as they can buy the risky asset at low prices before dividends rise and sell at high prices if dividends will fall in the future.

The underlying dividend process was designed as a random walk process without drift:

$$D_k = D_{k-1} + \varepsilon \tag{1}$$

D_k represents the dividend in period k and ε is normally distributed with $N(0;\sigma^2)$ with a standard deviation of 15 percent.

3 Experimental implementation

At the start of the experiment, each trader is randomly assigned to an information level and then keeps this level for the whole session. Each trader is given 1,600 talers (experimental currency) in cash and 40 shares of stock in a virtual company whose dividends are derived using the process of equation (1). The total amount of stocks is fixed, while average cash holdings increase slightly at the end of each period due to the payment of interest and dividends. In our experiment information is provided for free, i.e. there are no information costs. The risk-free interest rate r_f is set at 0.5% per period; the risk adjusted interest rate r_e for discounting future cash flows (dividends) and therefore the average dividend yield is 2.0% per period.[3]

In addition to her information we show each trader the conditional present value of the stock ($CPV_{j,k}$) given her information (see screenshot in the Appendix). This is calculated using Gordon's formula, discounting the known dividends and assuming the last one as an infinite stream which is also discounted. $CPV_{j,k}$ stands for the conditional expected value of the asset in period k, j represents the index for the information level of the trader, and r_e is the risk-adjusted interest rate.

$$CPV_{j,k} = \frac{D_{k+j-1}}{(1+r_e)^{j-2} \cdot r_e} + \sum_{i=k}^{k+j-2} \frac{D_i}{(1+r_e)^{i-k}} \tag{2}$$

The resulting paths of the conditional expected values (CPVs) of the asset for five information levels with k=25 periods (here experimental market 2) are shown in Figure 2. Beginning with *I5,* the functions in Figure 2 are shifted to the right for each information level

[3] If we assume that periods represent quarters, the respective risk-free and risk adjusted interest rates are 2.01 and 8.24 percent p.a. We provided traders with these interest rates as we were interested in their trading behavior and their use of information, not in their risk aversion or in their calculating abilities.

Ij by (5-*j*) periods, reflection that better informed participants receive information earlier than less informed traders.

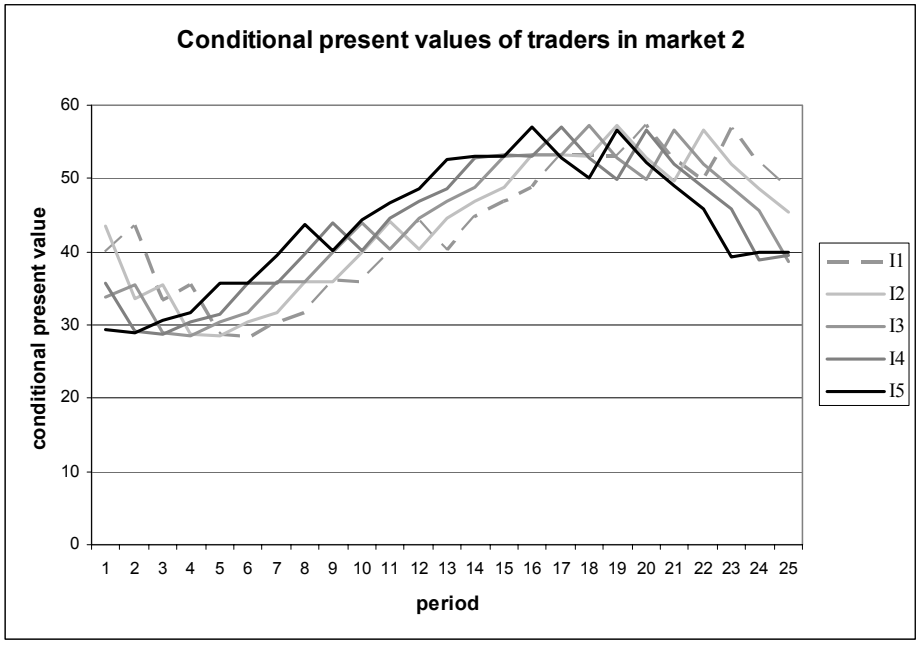

Figure 2: Conditional present values in market 2

Each market was implemented with 20 traders, and four traders were assigned to each information level. The trading mechanism is a continuous double auction with an open order book where traders can freely place limit orders or post market orders for 1 to 10 stocks. Market orders are only allowed under the condition that limit orders are already listed in the order book. Partial execution of limit orders is also possible. There are no transaction costs in the market, and we set practically no limitations on trading, meaning that traders can buy or sell as much as they want at any price within the range [0:200] as long as they have stocks to sell or cash to buy stocks. However, short selling or buying on credit is not allowed. On the screen traders always get information about their cash and stock holdings, their current wealth, their transactions within the current period, a chronological price history of the current period, and the mean price of all previous periods.

At the start of each session traders were briefed with identical written instructions[4], which took about 15 minutes to go through. After this introduction we implemented four trial periods to allow participants to become familiar with the trading screen. At the end of each session traders were paid in real cash according to their relative performance in the market. Trading was randomly terminated between periods 20 and 30 (each period 100 seconds long) with equal probability for each period.[5]

We conducted five sessions with a total of 100 business students from the University of Innsbruck in January and February 2005. Each session lasted about 80 minutes, and students were paid an average of 16 euros. The experiment was programmed and conducted with z-Tree (Fischbacher 1999).

4 Results

4.1 General remarks and basic statistics on the markets

We observed very active trading in all our markets, with an average of almost 900 transactions in each session, or one transaction every three seconds.

Table 1: Overview data

Market	Average mean prices (basis *T*)	Std. dev. mean prices (basis *T*)	Number of periods *K*	Number of transactions *T*
Market 1	40.84	3.69	25	354
Market 2	45.41	8.16	25	652
Market 3	37.18	2.58	24	1067
Market 4	37.85	4.02	26	1224
Market 5	38.77	6.80	27	1168

[4] See experimental instructions in the Appendix.

[5] One market ended after 24 periods, two after 25, one after 26, and one after 27.

While levels of trading activity varied widely, none of the traders was completely inactive.[6] We saw no decrease in trading activity over time nor a breakdown of the market as several no-trade theorems suggest for markets with asymmetric information (e.g. Lucas 1978, Judd/Kubler/Schmedders 2003). While we did expect insiders to trade more actively than less informed investors, there was no significant difference between trading activity across information levels.[7] If the no-trade argument were valid in our markets, we should see at least a significant decrease in trading activity over time. However, trading activity did not significantly change over time, even the worst informed participated actively until the end of the session.

4.2 Information and return

To compare the performance and traders and information levels across markets, we computed the average final wealth in each market and compared each trader's wealth with the average of his market. A net return of zero is therefore the benchmark or market return. Figure 3 shows the results for each individual trader (diamonds) and the average for each information level (solid line).

We clearly see that information does matter, as we find significant differences between the information levels. However, there is obviously no linear relationship, as traders *I1* with a net return of almost zero trade more successfully than the better informed traders *I2* and *I3,* who have average net losses of -6.7 and -6.6 percent, respectively (both are significantly different from zero on the 1 percent level, Mann-Whitney-U-Test, N=5). As expected, the best informed *I4* and *I5* are able to beat the market with average net returns 5.3 and 9.6 percent above the market return (both are significantly different from zero on the 10 percent level,

[6] The number of transactions ranged from 8 to 323 for individual traders, with an average of 89.

[7] The averages for information levels were between 72 and 105.

Mann-Whitney-U-Test, N=5)[8]. We also see that individual skill and probably luck play a role, as the variability of returns is very large and we find net winners and net losers in each information level.

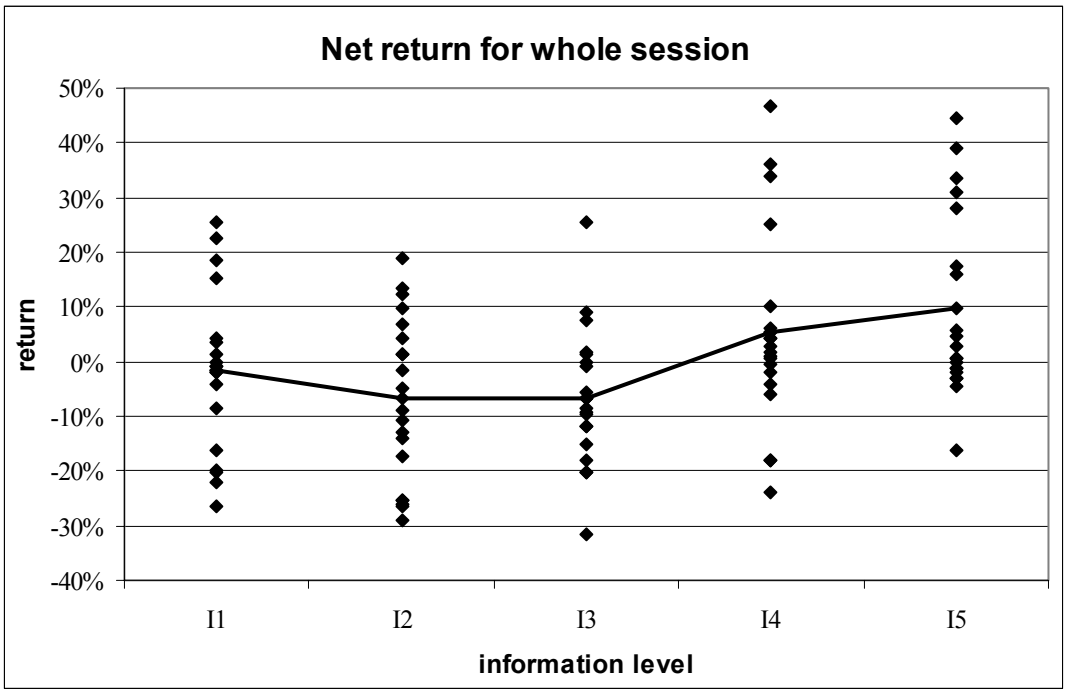

Figure 3: Relationship between information level and net return

The statistical comparison of net return on the different information levels confirms the findings from Figure 3: *I5* performs significantly better than I1 (on the 10 percent level) and than *I2* and *I3* (on the 5 percent level, Mann-Whitney-U-Test, N=5). For the second best informed *I4,* we find similar significances. This confirms that the best informed are able to outperform the market, as many earlier studies have already shown. While there is no difference between *I2* and *I3,* it is remarkable that the worst informed *I1* is significantly better than *I2* (on the 5 percent level) and *I3* (on the 10 percent level).

[8] If we test for individual traders instead of aggregated data for information levels, the results for I5 are significant on the 1 percent level (p=0.000, Mann-Whitney-U-Test, N=20).

Table 2: p-values of Mann-Whitney-U-Test on differences between information levels (N=5)

	I1	I2	I3	I4	I5
I1					
I2	0.047**				
I3	0.076*	0.754			
I4	0.076*	0.047**	0.076*		
I5	0.076*	0.047**	0.028**	0.917	

* significant on the 10 percent level
** significant on the 5 percent level

We do not claim that this is inevitably the situation in real markets, as the average informed should learn that they will be better off, if they forego some information. Consequently they should stop gathering information and e.g. invest in the index. The spectacular growth of index products in the past years is probably evidence of this learning process. However, the empirical evidence Cowles (1933, 1944), Jensen (1965, 1969), Malkiel (2003a, 2000b), and many others have gathered with data for the past 100 years shows that a clear majority of actively managed funds and professional stock market forecasters perform significantly worse than the market return. These people undoubtedly process huge amounts of information, but they are not insiders.

Our experimental finding is in no way due to wrong information or the costs of information: All the information in our experiment is provided for free and is always correct. If information costs were included, the returns for average and high information level would decrease most, stressing even more the better performance of the worst informed.

Equilibrium models usually assume that traders who systematically underperform will quit the market. However, this is only true if they have better alternatives. Figure 4 shows the returns per period of each trader (diamonds) and each information level (solid line). Here we have not net returns, but the average change in wealth from one period to the next. Due to interest payments and dividends, only two of our 100 traders actually lost money, and only 15 traders earned less than the risk-free rate of 0.5 percent per period (broken grey line). For 85

of 100 traders, quitting the market and investing at the risk-free rate would not be a good choice, as it would mean earning less. Note that the average return for every single information level is far above the risk-free rate of 0.5 percent per period.

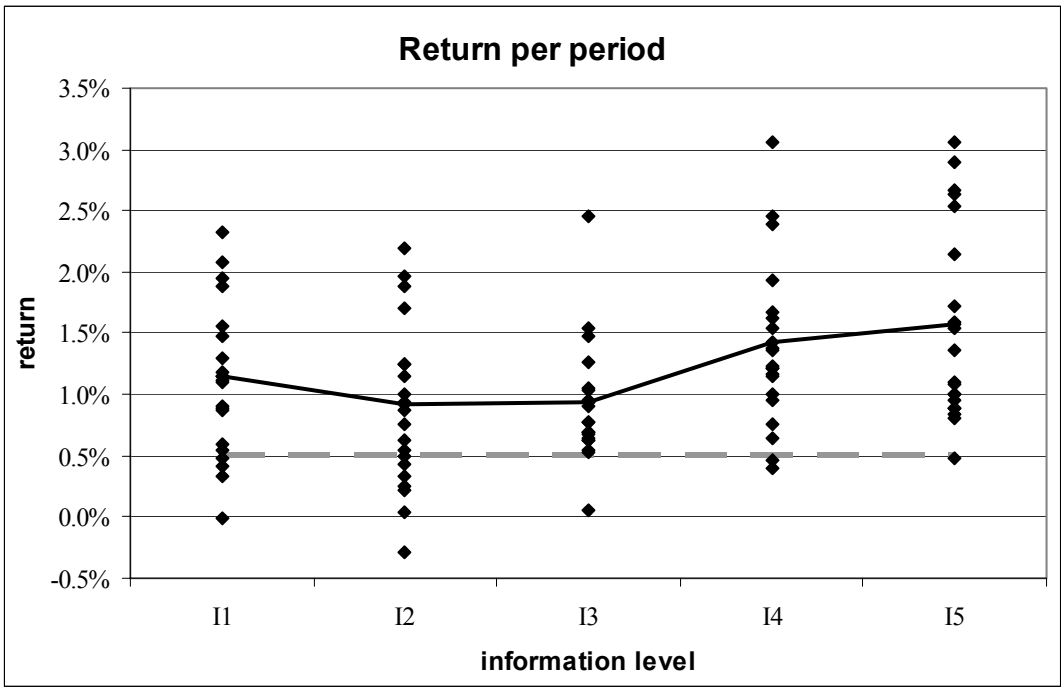

Figure 4: Relationship between information level and return per period

4.3 Processing of information

To understand the results presented above we have to know whether or not traders in our markets process the fundamental information provided. We will therefore present three analyses examining (i) whether traders used the information provided, (ii) whether trading behavior was driven by differences in information, and (iii) whether relative differences in expected values played a role.

Our model presents us with a clear benchmark for how and to what extent our participants used information: In each period, each trader has some fundamental information about future dividends and the conditional present value ($CPV_{j,k}$) that is calculated based on

these dividends. We provided this information to determine the degree to which it is used by traders. If traders use their information, we talk about "active information processing" or a "fundamentalist strategy". To operationalize this terminus we use the definition of Lux (1998, 151), who states that *"the fundamentalist strategy ... implies buying (selling) when prices are below (above) the fundamental value."* For each transaction, we computed whether each trader acted according to this definition. In the case of buying the following condition must be satisfied to subsume the transaction under active information processing:

$$CPV_{j,k} > P_t \tag{3}$$

i.e. the conditional expected value of trader j in period k ($CPV_{j,k}$) must be higher than the price P_t, whereas in the case of selling the following statement must be true:

$$CPV_{j,k} < P_t \tag{4}$$

In Table 3 we see that on average almost two-thirds of all transactions were driven by this strategy, reflecting a high degree of information processing in the markets.

Table 3: Percentage of fundamental trading in the five markets

	I1	*I2*	*I3*	*I4*	*I5*	**Total***	% of transactions where at least one party processed information
Market 1	69.1	50.4	50.0	55.2	67.8	**57.9**	98.0
Market 2	64.8	67.8	75.5	64.3	80.7	**71.6**	93.9
Market 3	69.0	59.9	68.2	64.9	63.2	**64.8**	95.4
Market 4	61.4	63.4	75.3	44.8	65.5	**60.3**	94.7
Market 5	64.8	57.0	55.0	51.2	68.6	**65.6**	96.0
Average*	**66.5**	**59.8**	**63.9**	**56.8**	**72.7**	**63.9**	**95.3**

* The total and average may deviate from the mean due to the different number of transactions in different markets and across information levels.

In most cases, traders buy the risky asset if their CPV is higher than the current market price and vice versa. In more than 95 percent of all transactions at least one party used her fundamental information. This shows that in less than 5 percent of all transactions we have pure noise trading, meaning trading for reasons other than information (Black 1986).

If traders use their information, we can expect to see neighboring information levels to buy and sell stocks at similar times as they have similar information. *I1* and *I5,* on the other hand, have very different information, and their trading behavior should therefore be negatively correlated. To measure the trading behavior of traders of different information levels, we took the number of stocks they owned in each period and compared the changes in the stock holdings from period to period. The Pearson correlation coefficients for the different information levels with all other levels were z-transformed according to Fisher, to allow us to calculate aggregate numbers for all five markets. The averages presented in the table below show a clear picture as the correlation between neighboring information levels is usually much higher than for other pairs of information levels.

Table 4: Correlations between the stock holdings of different information levels

	I1	I2	I3	I4	I5
I1	1.00				
I2	0.71	1.00			
I3	0.04	0.15	1.00		
I4	-0.53	-0.54	-0.42	1.00	
I5	-0.74	-0.80	-0.46	0.27	1.00

We have now established that information is actively processed by traders in our markets. This is confirmed by the correlation of the stock holdings of traders and their CPVs relative to other traders. If traders use their fundamental information when trading in a market (instead of e.g. using technical rules or trend chasing) we can expect those with above average expectations to buy assets while those with lower than average CPVs are most likely to sell. Prices should therefore reflect the median expectation, while those with higher expectations buy and those with lower expectations sell. To analyze this conjecture, we calculated the relative CPV ($rCPV_{j,k}$) of each trader in each period according to the formula

$$rCPV_{j,k} = \frac{CPV_{j,k}}{\overline{CPV_k}} \tag{5}$$

Numbers larger than 1 indicate that the trader has a relatively high estimate and is likely to buy in this period, and vice versa. Next, we calculated the Pearson correlation between the rCPVs and the stock holdings in each period and Fisher z-transformed the results to allow us to compute averages.

Table 5: Correlation between the relative conditional present values of traders and their share holdings (Fisher z-transformed values)

	I1	I2	I3	I4	I5	
Market 1	0.52	0.07	0.43	0.27	0.16	
Market 2	1.13	0.92	0.73	0.35	1.32	
Market 3	0.96	0.86	0.68	0.69	0.94	
Market 4	1.19	0.60	0.67	0.38	0.85	
Market 5	0.68	0.81	0.25	0.65	0.84	
Average	0.90	0.65	0.55	0.47	0.82	
Correlation	0.71	0.57	0.50	0.44	0.68	**0.58**

Our conjecture is confirmed as the correlation is positive for each information level in each of the five markets and we find an average correlation of 0.58. This is significantly different from zero (p=0.000, Mann-Whitney U Test, N=25). The deviation from a correlation of 1 can in part be attributed to cash and short selling constraints, as traders who had sold all their shares could not sell more even if their CPV relative to those of other information levels fell to lower levels than in earlier periods.

4.4 Forecasting abilities and price formation

As our traders have forecasting abilities in the sense that they know future dividends, we can expect prices to lead the development of dividends by several periods. To test this conjecture, we computed the Pearson correlation between the development of prices and the development of the CPVs of the five information levels.

Table 6: Pearson correlation between average prices per period and CPVs

	I1	I2	I3	I4	I5
Market 1	0.82	0.94	**0.96**	0.89	0.78
Market 2	0.85	0.93	**0.97**	0.94	0.87
Market 3	0.70	**0.86**	0.82	0.61	0.28
Market 4	0.65	0.81	**0.85**	0.75	0.53
Market 5	0.90	0.96	**0.98**	0.97	0.93

The results show that prices lead dividends by three periods in four markets and by two periods in Market 3. Our market is therefore not strong-form efficient in the sense that "*all available information is reflected in prices*" (Fama 1970), as "insider information" known only to *I4* and *I5* is not. Traders using this information are therefore able to outperform the market, as we saw in Figure 3.

We think this can be explained by how price formation works in markets. As the number of shares is fixed, the number of shares bought always equals the number of shares sold. Traders with the highest estimate about the value of an asset will usually buy, while those with the lowest CPV will sell. Table 5 confirmed that this conjecture holds true for our markets. 'Active information processors' (as defined above) buy if prices are below their expectations and sell if prices are higher than their expectations. For the trader with the highest CPV in a certain period, the only possible option is to buy: Since she is the one with the highest estimate, no one is willing to buy at the prices she is asking. The reverse is also true: The trader with the lowest CPV can only sell. Consequently the price must be between these boundaries, and it seems intuitively obvious to assume that the price should reflect the median trader's expectation if all traders buy if prices are below their CPV and sell otherwise. At the median CPV, the supply and demand curves intersect, and prices should therefore reflect this value. In his seminal paper, Smith (1982) has shown that prices in a double auction market quickly reflect the intersection of supply and demand curves. However, his analysis was in a static environment where equilibration is easier to achieve than in our dynamic

setting. The relation only holds perfectly if all traders use the information they get and if they all trade the same number of shares. If they do not, we will see deviations from this price.

To test whether this line of argument holds true for our markets, we computed the Pearson correlation between average prices per period and the median CPV of the five traders. This means that we took the median CPV for every period and correlated the development of this series with the development of average prices. The correlations range from 0.89 to 0.99 in the five markets and are higher than any correlation for any individual information level (see Table 6). The respective R^2 are 0.80 and higher, confirming that at least four-fifths of all price movements are explained by changes in fundamental information as reflected by changes in the median CPV. Although participants in our markets clearly traded different numbers of shares,[9] the median CPV serves quite well as a proxy for the price.

Table 7: Pearson correlations and R^2 between the median CPV of each period and the respective average market price

	Pearson-correlation	R^2
Market 1	0.965	0.932
Market 2	0.991	0.983
Market 3	0.894	0.800
Market 4	0.940	0.883
Market 5	0.988	0.977

In most periods (more than 86 percent of all periods across all markets) average prices increased when the median present value rose and decreased when the median CPV was lower than before. In the few periods when prices and the median moved in different directions (in total 17 out of 122 periods) the absolute change in the median was relatively small (on average only 0.24, compared to an average of 1.50 in all other periods). This shows

[9] The number of transactions ranged from 8 to 323 for different traders.

that deviations from the behavior described occurred only when the new information signal was not very strong in any direction.

As our traders know future dividends and therefore have forecasting abilities, it is not surprising that market prices move ahead of fundamentals. As the correlations above show, the median CPV is a good proxy for changes in prices. Prices do not reflect all the available (i.e. also insider) information, but only about half of the future dividends known to the insider. This indicates that our markets are not strong-form efficient (cf. Fama 1970). Kyle (1989) found a similar result in a different market setting.

5 How price dynamics influence returns of asymmetrically informed traders

We showed above that in our markets, traders with above average expectations usually buy from those whose expectations are below average. In addition, we saw that price changes reflect changes in the median expectation: The correlations between average prices per period and the respective median expected present values in our markets range from 0.89 to 0.99. While the average market price quite accurately reflected changes in expectations, individual trader behavior gives a more mixed picture. As we saw in Table 5, most participants bought shares when their conditional present value was higher than the median, and vice versa.

Our traders used the information provided at least to some degree, and prices reflected this information quite well. But we still have no answer to the question of why better informed traders, who know more future dividends than others, may fare worse in the market. We think this counterintuitive result can be explained if we look at what happens in two distinct phases of a price path. Basically, there are only two ways for a price path to develop from one period to the next: either the sign of the price change is the same as in the last period or periods (a ‘trend’), or the sign of the price change is different than in the last period or

periods (typical of a 'trend reversal'). This simple distinction is crucial for our analysis, as the value of information is different in the two situations.

When a trend, i.e. a sustained series of subsequent upward (or downward) movements, begins, it is undoubtedly advantageous to know about it as early as possible. In the case of an upward trend, a well informed trader can buy while prices are still low, while worse informed buy later at higher prices, and vice versa for a negative trend. Figure 5 shows this development for a market with five traders. While prices are rising over time reflecting approximately the CPV of trader I3, who is the median trader, the insiders are buying at still-low prices from worse informed traders who have lower CPVs. In situations like this, being better informed is never a disadvantage.

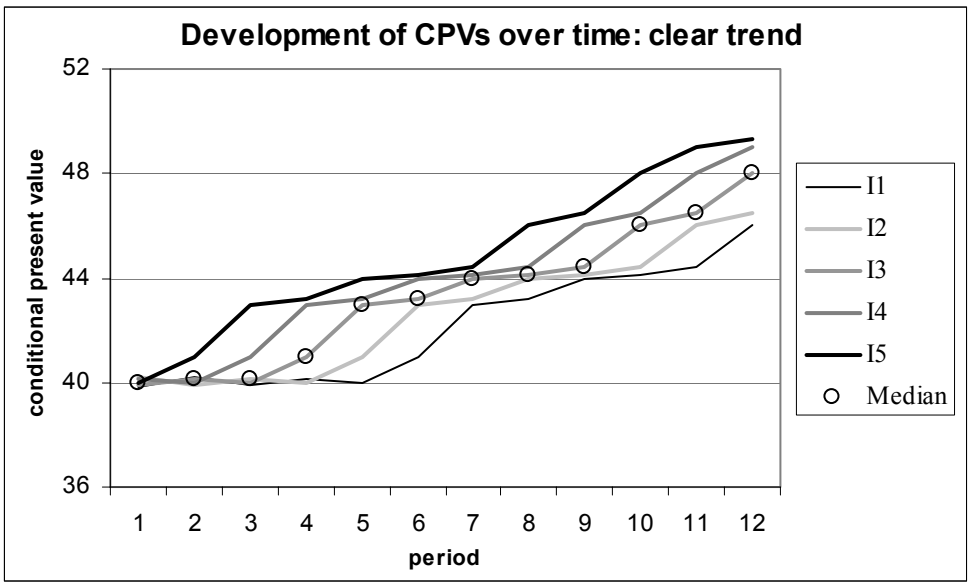

Figure 5: Development of CPVs over time during an upward trend

The second possibility in a market is the lack of clear trends. Figure 6 presents a market situation where expected dividends and therefore CPVs first increase, then decrease, then rise and fall again. This situation is more complicated to analyze, as it is much more dynamic: In Figure 5, *I5* always had the highest expectation, *I4* the second highest, and so on, making the

average informed *I3* the median trader. Now the roles and relative positions in the market change every few periods.

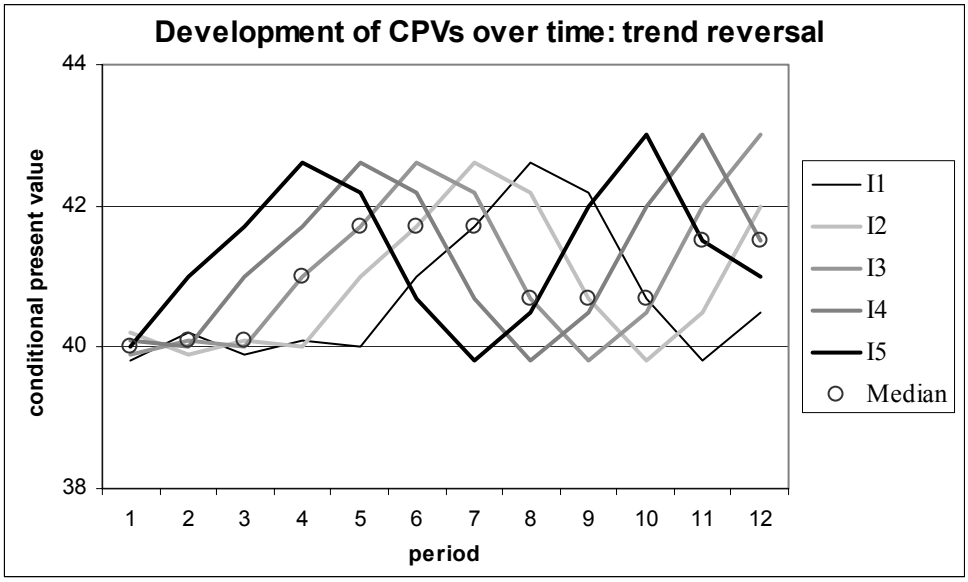

Figure 6: Development of CPVs over time in a market without a clear trend

Periods 1 to 5 resemble the situation in Figure 5, as we see a clear upward trend. In the next period the situation changes dramatically: *I5* is the first to see falling dividends and is on the seller side in period 6, as her CPV is the lowest. While *I3* and *I4* are buying (they have estimates higher than the median) the worst informed *I1* is also selling. However, he is doing so not because he knows about a future fall in dividends, but because he is not aware of the rising dividends ahead. In periods 5 to 7, prices (proxied by the median) are highest, and in these periods the insider and the worst informed sell. They see different dynamics – *I5* sees falling dividends, while *I1* sees dividends rising soon – but they take similar action as they are on the same side of the market. Prices will subsequently fall as the median CPV decreases, and *I1* will buy shares at relatively cheap prices in periods 8 and 9, when he has the highest expectations. *I5* also buys in periods 9 and 10 – this time *I1* is even one period ahead of the insider – again not because he knows so much, but because he knows so little. The same is true in periods 11 and 12, when *I1* is ahead of *I5* in selling shares to the average informed at

high prices. This example shows that any time trends are not clear, being worse informed is not necessarily a disadvantage. The worst informed traders and insiders buy low and sell higher, while the average informed traders are the net losers in this situation. The high correlation between prices and the median CPV that we found in our markets and the net returns of traders, with *I2* and *I3* performing worst, support this line of argument.

Knowing which price dynamics dominate is a crucial factor in estimating the value of information in markets: If clear trends are more common than trend reversals, then the expected value of additional information will never be negative, but if trend reversals are more likely, more information may be disadvantageous for some traders.

To find out which pattern dominates, we conducted a simple Monte Carlo simulation with a setting similar to that in the experiment. The same random-walk dividend process as in the experiment served as the basis for calculating the CPVs of several traders distinguished by their knowledge about future dividends. Again, *I1* knows only the first dividend, *I2* the first and the second, etc. As it is well established that the best informed (insiders) are able to outperform other traders (see our results in section 4, and e.g. Lakonishok/Lee 2001, Lin/Howe 1990, Krahnen/Rieck/Theissen. 1999, and Jeng/Metrick/Zeckhauser 2003 for other studies), we chose a simple analysis: We conducted one million simulation runs and for each run determined which trader was the median trader. If the best informed was the median trader, we discarded that run. Otherwise we checked to see which side of market the insider was on ('buy' if his CPV was higher than the median and vice versa='sell' if it was lower) and which other traders were on the same side.

The results for five information levels are presented in Table 8: We see that *I1* is on the same side as the insider more often than either *I2* or *I3*. This is in part due to the fact that

especially *I3* has the median CPV most of the time, but it still supports our findings from the experimental study; namely that in a market a trader with only minimal information may be significantly more successful than a better informed trader.

Table 8: Results of Monte-Carlo simulation with five information levels

	I1	I2	I3	I4
same side as insider I5	18.1%	11.4%	16.9%	53.5%

To gain some additional insights we conducted the same Monte Carlo simulation with different numbers of traders – namely 9, 19, and 101 different information levels.[10] Table 9 presents the results, whereby the second column shows how often the worst informed *I1* is on the same side as the insider. We see that this number increases with the number of traders. This is mostly due to the fact that each trader has a lower probability of being the median trader when the total number of market participants increases.

Table 9: Results of Monte-Carlo simulations with different numbers of information levels

Number of traders	I1 on same side as the insider	Least often on the insider's market side	First trader on insider's side more often than I1
5	18.1%	I2 (11.4%)	I4
9	27.3%	I4 (21.1%)	I6
19	32.2.%	I7 (26.7%)	I10
101	35.6%	I30 (30.6%)	I48

In the third column we see which trader is most infrequently on the same market side as the insider and how often he is on the same side. This trader is never *I1*, but usually a trader who has approximately one-third of all the information known to the insider. Finally, the last column shows which trader is the first to be on the insider's market side more often than *I1*.

[10] We arbitrarily chose uneven numbers close to 10, 20, and 100. Simulations with other numbers ranging from 7 to 1000 delivered similar results.

Usually the only traders who are on the same side as the insider more often than the worst informed are those who have half or more the insider's knowledge about dividends. For example with 101 different information levels, trader *I30* fares worst, while only traders who know 48 or more future dividends will be on the insider's side of the market more often than a trader who knows only one dividend. All results are for one million simulation runs and are therefore very robust.

Finally we show the overall picture these Monte Carlo simulations present. Figure 7 illustrates how often each of the 101 information levels is on the same side of the market as the insider (*I101*). We see that the function has a negative slope until *I30* and then slowly ascends. *I48* is the first to do better than *I1,* and *I59* the first to be on the same side as the insider more than half of the time.

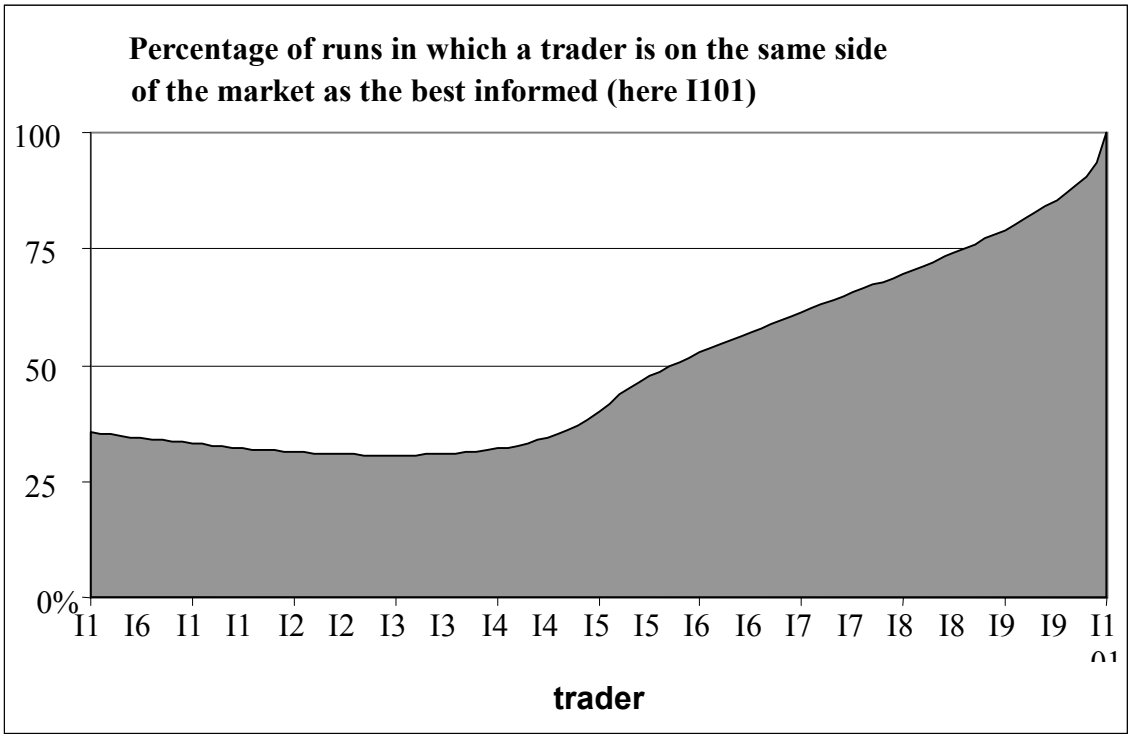

Figure 7: Percentage of runs in which a trader is on the same side as the best informed

The results presented above are clearly not a final answer, as we set simplifying assumptions and equated being on the same side as the insider with being successful. However, they may still contribute to an understanding of what happens in markets and how this influences the value of information.

6 Conclusion

In this paper we presented results from an experimental financial market with asymmetrically informed traders. Our goal was to examine how information is processed in a market and how valuable it is for traders. Fama once wrote, "*fundamental analysis is a fairly useless procedure both for the average analyst and the average investor*" (in Bernstein 1992, 161). The trading results of different information levels in our experiment confirm that statement: While the best informed (*I4* and *I5*) can outperform the market, all the others cannot. More information does not help these underperforming traders, as *I2* and *I3* fare significantly worse than *I1*.

It may well be that investment funds and private investors spend money to acquire information about the future outlook for a specific company or branch, but this information is never perfect. As a result, situations may arise where not acquiring the information and simply investing in the index would have made the investor better off – not just because of the money he saves on the information, but also because this information may harm his return in the market. William Fouse, who initiated the emission of the first index fund in 1970, warned about the "*quicksand premise that increasing knowledge about a company guarantees greater forecasting success*" (in Bernstein 1992, 245). With this study we support this notion, as we show that more information and better forecasting abilities do not necessarily improve a trader's performance in the stock market. While we confirm that insiders will always be

among the most successful traders, we show that traders with average forecasting abilities may have worse returns than traders with only minimal forecasting abilities.

We see strong empirical evidence to support this. For decades, many influential people have been saying that gathering and analyzing fundamental information is not a fruitful method for most investors, yet active information gathering is still widespread. This may be due in part to overconfidence, and the self-interest of fee-earning advisors and funds managers may be another factor. However, the extraordinary growth of index funds and other investment policies mimicking index performance show that as investors become more experienced, they probably also become more moderate and more willing to accept the market return that they actually receive instead of a promise – often unfulfilled – of earning more.

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Appendix

Dear Participant! We welcome you to this experimental session and kindly ask you to refrain from talking to each other for the duration of the experiment.

Background of the experiment

This experiment is concerned with replicating an asset market where traders can trade the stocks of a fictitious company for *k* consecutive periods (quarters of a year).

Characteristics of the market

Each trader is initially given 1600 talers (experimental currency) and 40 stocks. The only fundamental information you receive is the dividend of the stock (quarterly dividend equals quarterly profit of the company) which follows a random walk process without drift:

$$D_k = D_{k-1} + \varepsilon$$

D_k denotes the dividend of period *k* and ε represents a normally distributed random variable with an expected value of zero and a standard deviation of 15 percent. This period's dividend is therefore the best estimate for next period's dividend. The market is characterized by asymmetric information. The worst informed trader knows only the dividend of the current period, while better informed traders can estimate the dividends of the companies a few months into the future. At the end of each period (after 100 seconds), you will receive the current dividend for each stock you own. A risk-free interest rate of 0.5% is paid for the cash holdings in each period. The risk-adjusted interest rate for valuation of the stock equals to 2.0% per period.

Calculation of the conditional expected value (present value, PV)

Generally it is up to you to decide what kind of information you trade and how you evaluate the stock. If you want to use your fundamental information (expected future dividends) you can see the present value (PV) of all future dividends (of course only those you can estimate on the basis of your information level) on the bottom left side of the trading screen. Your PV

is derived using Gordon's well-known formula, discounting the dividends you know with the risk adjusted interest rate of 2.0% and assuming the last one as a continuous, infinite stream which is also discounted. If you follow this information, it makes sense to buy at a price that is lower than your PV and sell at a price that is higher than your PV.

$$BW_k = \sum_{k=0}^{n-1} \frac{D_k}{1.02^k} + \frac{\frac{D_n}{0.02}}{1.02^{n-1}}$$

n indicates the 'last' dividend you know

Example: The dividends of this (*k*=0) and the next 2 periods are 0.791; 0.814; 0.802. The PV on the basis of this information level is calculated as follows: $0.791 + 0.814/1.02 + 0.802/0.02/1.02^2 = 40.23$. This PV on the basis of your information level is shown on the bottom left side of the trading screen.

Trading

The trading mechanism is implemented as a double auction. This means that each trader can buy or sell stocks. You can enter as many bids and asks within the price range of 0 and 200 (with a precision of one decimal place) as you wish. Additionally, you have to insert the quantity you want to trade (1 to 10 shares). A new offer to buy is only accepted if the sum of this and all your outstanding offers to buy (price multiplied by the corresponding quantity) is not higher than your current cash holding. Otherwise a message box appears to inform you that the offer is not valid. This check is made to prevent your cash holdings from dropping below zero. A new offer to sell will be accepted if the sum of that offer and all your outstanding offers to sell is lower than your current stock holding. Otherwise a message box appears. This check is made to prevent your stock holdings from dropping below zero.

Example: Your current cash holdings equal 600 talers. Your outstanding offers to buy equal 532.5 talers, containing one offer of 10 stocks at a price of 35 talers and another offer of 5 stocks at a price of 36.5 talers. In this case, the product (price times number of shares) of your new offer to buy (price multiplied by number of stocks) should not exceed 67.5 talers.

Wealth

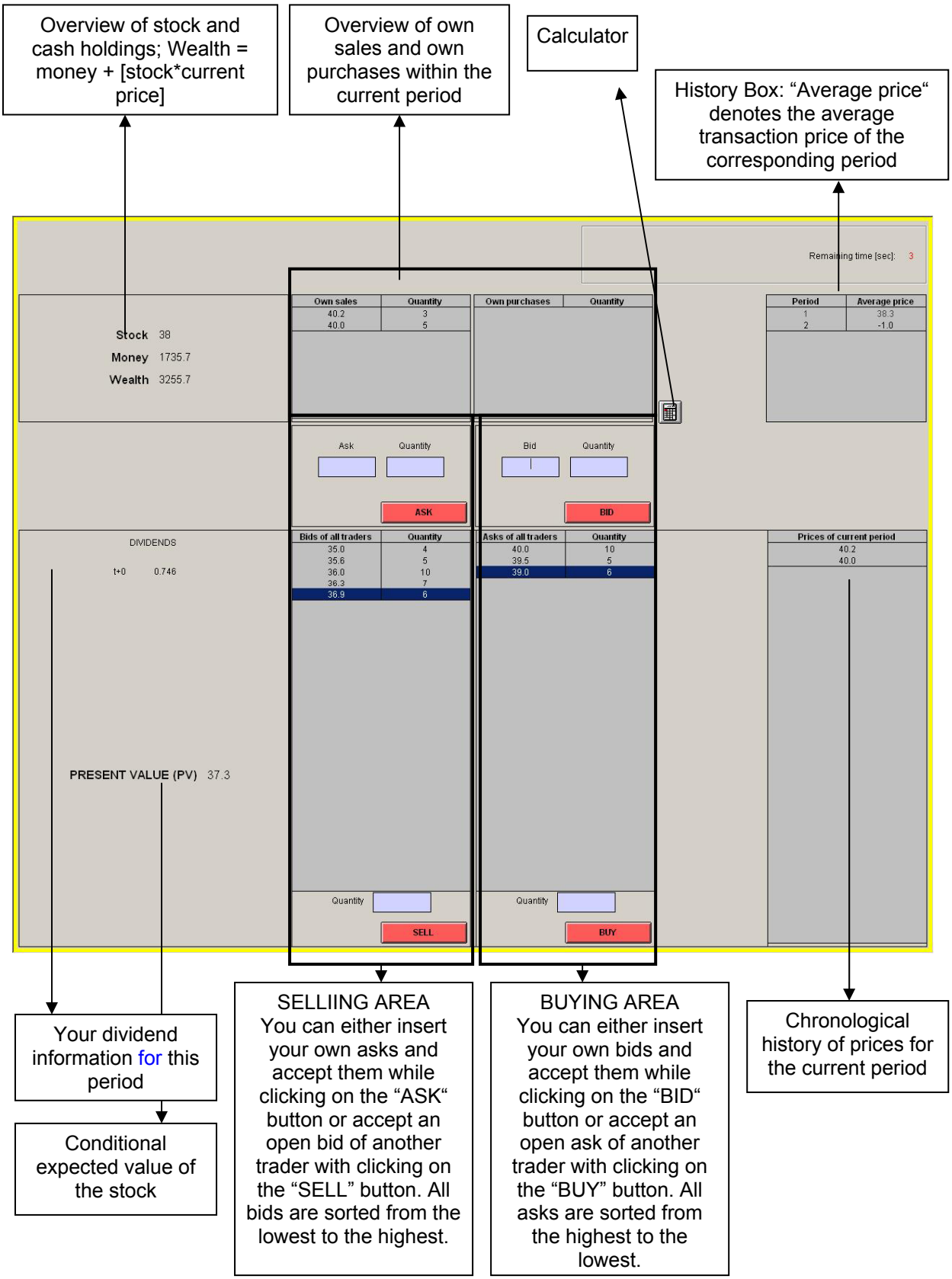
Your wealth is the sum of your cash holding and the total number of the stocks you hold multiplied by the current price. If you buy a stock, your cash holdings decrease, and at the

same time your stock position increases by the quantity you traded. Generally, the current price on the market (marking-to-market) is used to evaluate your wealth, so your wealth will change even if you have not participated in the last transaction. After each trading period (quarter) has ended, you receive an interest rate of 0.5% per quarter on your current cash holdings, and the dividends for your stocks are added to your cash.

Example: If you own 1600 in cash and 35 stocks with a price of 50 that pays a dividend of 0.815 at the end of a period, your wealth increases from 3350 to 3386.53 (+8.0 interest earnings (1600x0.005), +28.53 dividend earnings (35x0.815)).

Important details

- The experiment will be randomly terminated between period 20 and 30, with equal probability for each period.
- Your pay-off at the end of the experiment depends on your relative performance in the market. This means that your wealth at the end of each period will be compared with the average wealth in the market at the same time. This relation is summed up across all periods. Generally, your pay-off will be above average if you can manage to 'outperform' the market. Note that your pay-off will be calibrated according to your information level.


Overview of stock and cash holdings; Wealth = money + [stock*current price]
Overview of own sales and own purchases within the current period
Calculator
History Box: “Average price“ denotes the average transaction price of the corresponding period
Remaining time [sec]: 3
Stock 38
Money 1735.7
Wealth 3255.7
Own sales
Quantity
40.2
3
40.0
5
Own purchases
Quantity
Period
Average price
1
38.3
2
-1.0
Ask
Quantity
ASK
Bid
Quantity
BID
DIVIDENDS
t+0 0.746
Bids of all traders
Quantity
35.0
4
35.6
5
36.0
10
36.3
7
36.9
6
Asks of all traders
Quantity
40.0
10
39.5
5
39.0
6
Prices of current period
40.2
40.0
PRESENT VALUE (PV) 37.3
Quantity
SELL
Quantity
BUY
Your dividend information for this period
Conditional expected value of the stock
SELLIING AREA
You can either insert your own asks and accept them while clicking on the “ASK“ button or accept an open bid of another trader with clicking on the “SELL” button. All bids are sorted from the lowest to the highest.
BUYING AREA
You can either insert your own bids and accept them while clicking on the “BID“ button or accept an open ask of another trader with clicking on the “BUY” button. All asks are sorted from the highest to the lowest.
Chronological history of prices for the current period