
***Disposition Effect in Social Trading -
The Influence of Feedback and Transparency on Investment Decisions***

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Abstract

This work in progress paper discusses the study of cognitive biases in the new context of social trading platforms. These platforms provide an environment in which investors share information about their portfolio and trading activity with each existing user. The investors receive commission depending on the amount invested by their followers and their own performance. Empiric evidence in the context of financial networks shows that social interaction affects the behaviour of investors. However, very few existing studies show the impact of transparency and feedback on cognitive biases. The present research suggests to expand existing ratio analysis- and logit regression models to include social variables. The goal is to improve our understanding about the importance of social interaction on the behaviour of investors. The present study is in a very early stage and therefore currently only shows some basic summary statistics but nevertheless indicates potential avenues of future analysis.

Introduction

The disposition effect - the propensity of investors to realise small gains sooner than losses – has been extensively studied in the behavioural finance literature. Shefrin & Statman (1985) are the first to develop a conceptual framework to explain the occurrence of this phenomenon. They argue that prospect theory is the basis for the disposition effect illustrating that mental accounting, regret aversion, and self-control can drive the tendency to forego loss realisation. Furthermore in the first large-scale study, Odean (1998) states that the prospect theory by Kahneman and Tversky (1979) implies the disposition effect by “extending prospect theory to investments” (p. 1776). However, there is an ongoing debate whether or not prospect theory is the source of the disposition effect. Besides prospect theory, also realization preference (Barberis and Xiong, 2012, Kaustia, 2010, Ingersoll and Jin, 2013), cognitive dissonance (Chang et al., 2015) and pseudo-rational behaviour (Kaustia, 2010, Odean, 1998) are amongst the theories which try to explain the occurrence of the disposition effect. However, one aspect is rarely considered in this context: social interaction and feedback.

In this paper, we examine the disposition effect from a unique ‘social behaviour’ perspective. Social interaction in financial networks is an emergent area of academic finance literature. Empiric evidence shows that social investors increase their participation in the stock market compared with non-social investors (Harrison et al., 2002, Qin, 2012). Moreover, individuals put more trust in people they know than into financial advisors, weigh word-to-mouth information stronger than professional advice and

use less information to make investment decisions (Garcia, 2012). Therefore it is reasonable to assume that a social environment changes behavioural biases environment. Hence, it is of interest to analyse the presence of cognitive biases within a social context. As a result this research proposes to analyse cognitive dissonance in a social trading platform. Analysing cognitive biases in a transparent environment will help us to understand the impact of social connections on decision making of investors.

The remainder of this working paper is structured as follows: chapter 1 gives an overview of existing research in the context of disposition effect after explaining the functionality of social trading platforms. Moreover, it will discuss the impact of social connections in finance. Chapter two will give an overview of a sample data set. Chapter three introduces two approaches for the methodology and chapter four concludes by providing an outlook for future work.

1. Literature review

Social Trading

Social trading platforms allow its users to observe any user registered on the platform. Currently at least 18 platforms exist; the largest (etoro) has more than 4.5 million users. However, those platforms differ in their investment focus. The majority of those platforms focus on CDFs on foreign exchange currency pairs, commodities and indices.

The process of social trading however is often comparable. Either a user starts trading with his own funds or within a virtual portfolio. The compensation of each portfolio manager is normally based on the assets under management or the number of followers and the performance of the portfolio. However, in some cases, certain quality criteria have to be fulfilled before individuals can invest their real money into a portfolio. After these criteria are satisfied the value of the portfolio or the investment in the fund manager depends on the development of the included stocks. Hence, a 1% increase in the securities within the portfolio roughly translates into a 1% increase of the relevant trader or portfolio.

Prospect Theory as source of disposition effect

Early studies of the disposition effect argue that prospect theory (Tversky and Kahneman, 1992) explains investors behaviour. Referring to prospect theory, Shefrin & Statman (1985) argue that mental accounting, loss aversion, regret aversion and missing self-control lead to the disposition effect.

One of the distinct features of mental accounting is that traders no longer consider their overall wealth, or their open positions as a whole, but instead as segregated accounts. For this, a trader creates a reference point for each position. However, there is no clear indication which price should be considered as reference point. Common reference points are the shares purchase price or its highest value during the holding period. The reference points are basis for the evaluation of all subsequent changes in price (Thaler, 1985, Thaler, 2008, Tversky and Kahnemann, 1981). In general, when an

investor sells a share with a loss, he closes a mental account with a loss. Birru (2015) discusses the inattention of investors by showing that they tend to fail to adjust their reference prices after stock splits which can lead to a breakdown of the disposition effect.

The second bias Shefrin and Statman (1985) use to explain the existence of the disposition effect is loss aversion. Tversky and Kahneman (1991) show that the satisfaction of a gain is only half as much as the displeasure of an equal-sized loss. Regret occurs if an agent is aware of the fact that a decision was unbeneficial compared to other available options. Bell (1982) asks how anticipation of regret affects future decisions. The scholarly answer to that question is inconclusive. On the one hand when anticipating a mistake and focusing on the potential regret individuals tend to become more risk averse (Simonson, 1992). Contradicting to that Zeelenberg (1999) finds that individuals who know that they will receive feedback for their actions become risk-seekers. The possibility to get feedback after a decision is enough to change the behaviour of the individual. Especially in a transparent financial market, feedback is easily available. Knowing this, traders might anticipate regret in advance when considering selling a stock with loss and therefore prefer to realize winnings early.

Especially early studies such as Shefrin and Statman (1985) and Odean (1998) base their argumentation on prospect theory. They argue that the convexity of the value function in the loss region results in people's behaviour to avoid realizing losses. Several authors show that the s-shaped value function can result in unprofitable trading behaviours and that this contrarian behavior presents itself in form of the disposition effect (Grinblatt and Keloharju, 2001, Genesove and Mayer, 2001). Yao and Li (2013) use the findings of the disposition effect and develop an elasticity model with prospect theory as basis. They show using this model that the preference components of prospect theory (reference dependence, loss aversion, risk seeking) can explain why individuals act irrational and therefore argue that prospect theory is able to explain disposition effect.

Cognitive Dissonance

Besides prospect theory a very recent discussion introduced cognitive dissonance as possible explanation for the disposition effect. An investor justifies buying a security by evaluating the available information. However, if new information contradicts existing beliefs a mental conflict arises. Festinger (1957) describes the resulting psychological unease as cognitive dissonance. To reduce the psychological unease an individual tries to reduce the existing dissonance. He does so by either adapting one belief (cognition), its importance or by introducing a third cognition which mediates between the existing ones (Chang et al., 2015). Therefore, the individual adapts the own information acquisition process.

Akerlof and Dickens (1982) show that individuals tend to prefer confirming information over disagreeing evidence. They show that workers in a high-risk environment assume their work to be of normal risk. This leads them to reject safety equipment which would imply acknowledging the potential

dangers of their work. Kaustia and Knüpfer (2012) apply this finding to trading and argue that investors assume to be responsible for their successful trades but tend to blame non-alterable external factor for their potential losses. Benabou and Tirole (2002) furthermore show that this self-deception can lead to a selective memory. In their article, they argue that individuals try to sustain self-esteem and confidence in order to sustain motivation and the ability to perform. On the other hand, investors are also able to identify potential threats to their wealth and adjust their behaviour. For example traders can “learn” that they do not have sufficient skills and therefore stop their trading activity (Seru et al., 2010). Therefore, they reduce their cognitive dissonance by adjusting one of the cognitions. Nevertheless, many examples of individuals failing to adjust their beliefs exists which in conclusion let to some catastrophic outcomes. For example Barberis (2011) argues that bankers before and during the financial crisis failed to update their beliefs about the value of their assets because of a mental conflict. Accepting the fact that their holdings were not as valuable as assumed would result in realizing losses.

Considering the concept of mental accounting, it is clear that paper losses result in less unease than realized losses. Therefore, cognitive dissonance is a possible explanation for the disposition effect. While only paper losses occur, the investor can convince himself that his actual belief is right and that the current adverse price movement is part of a temporary mispricing by the market.

Chang et al. (2015) find that the strength of the effect depends on the degree to which the investor assumes own responsibility. Therefore, they show that the strength of the disposition effect varies across different asset classes. Traders investing in mutual funds show negative disposition effect, whereas an individual trader shows the propensity to forego losses in benefit of small gains. This confirms prior research by Calvet et al. (2009) who show the same tendency of Swedish traders and by Ivković and Weisbenner (2009) who also suggest that individuals show less disposition effect when holding shares in mutual funds. In general, several studies show that investors reward positive performance of funds with additional investments. This effect is often referred to as smart-money or wisdom of the crowd (Chalmers et al., 2013, Christoffersen et al., 2013, Ferreira et al., 2012, Frazzini and Lamont, 2008, Keswani and Stolin, 2008, Spiegel and Zhang, 2013).

Related research by Bailey et al. (2011) analyses behavioural biases of investors in mutual funds. They also show that investors are less biased when investing in these vehicles and argue that this kind of investor shows higher investment sophistication. Chang et al. (2015) argue that basis for this characteristic is that mutual fund investors blame its manager for bad performance. This delegation of failure reduces the negative feeling of realizing a loss and therefore leads to a reversed disposition effect. Moreover, they find that the less active a fund is managed, the stronger the disposition effect becomes. For example, a trader invested in an equity index fund shows no significant disposition effect whereas an investment in an actively managed mutual fund shows a statistically significant reverse disposition effect.

In the context of social trading platforms, investors try to convince follower to invest in their portfolio. Hence, it is sensible to compare the mechanisms of mutual fund holdings to social trading platforms. However, research of mutual fund holdings and their holdings illustrate potential drawbacks regarding the observable time horizons and therefore support the argument above. Table 1 exemplifies that existing studies do have information about the behaviour of mutual funds and money managers. However, it shows that existing research of herding behaviour of fund managers relies on quarterly data. Since it is only possible to observe end-of-quarter holdings, there is no information about inter-period trades. This results in possible observational problems. Existing research about the clientele-effect and “window dressing” demonstrates that mutual funds tend to change their positions just before their quarterly reports in order to include certain stocks (see for example studies by Allen et al. (2000), Graham and Kumar (2006), Sialm and Starks (2012) or Goulart et al. (2015) for a discussion of window dressing and the clientele effect). These studies support my concern that a quarterly frequency is insufficient to discuss herding behaviour.

Insert table 1 around here

Empiric evidence for the impact of social financial networks

There has been much research on the extent to which individual and professional traders act rationally in the marketplace. The efficient market hypothesis characterizes the traditional view and assumes that investors act rationally. Fama (1970, 1991, 2014) argues that the market price of an asset always represents all available information and that returns follow a stochastic distribution. This implies rational and informed choices of traders and furthermore that the quality of decisions is a positive function of information quality. However, it appears that the social environment of individuals can influence their information-processing and motivate them to adapt their behaviour.

Investors tend to observe other informed traders before deciding about an investment decision (Qin, 2012). Additionally social investors increase their participation level, activity and risk level compared with non-social investors (Hong et al., 2004, Kaustia and Knüpfer, 2012). García (2013) suggests that individuals put more trust in people they know than into financial advisors. They use less information to make investment decisions if they trust a certain advisor. Additionally, the author points out that individuals weigh word-to-mouth information stronger than professional advice. Duflo and Saez (2002) as well as Beshears et al. (2015) show that social interaction influences saving decisions of individuals. Social interaction also influences company policies (Shue, 2013, Popadak, 2012) such as governance structures. Companies can even benefit from the social network of their managers as social ties between company managers and bank employees help to reduce interest rates (Hwang and Kim, 2009, Engelberg et al., 2012) and improve IPO performance (Cooney et al., 2015).

For all these interactions, communication is of utmost importance. For example, research by Shiller and Pound (1989) shows that word-of-mouth communication strongly affects individual investors. In

their study, one third of the subjects argue that persons other than their stock broker convinced them of their investment decisions. In addition, the neighbourhood of individuals strongly influences investment decisions. For example, Kaustia and Knüpfer (2012) analyse the stock market entry decisions of individuals and the influence of their social environment on that decision in Finland. They find that a successful neighbourhood convinces other individuals to enter the stock market in the following month. This implies that the communication with peers can lead to higher activity in the stock market. An increase in communication activity between investors may increase the trading activity in social trading platforms compared to traditional brokerage accounts. This involves both, active communication by commenting on certain activities but also passive communication since all activities are transparent.

Besides the participation, also the position in a social network influences the investment performance. Ozsoylev et al. (2014) show that central agents are able to trade earlier and are more profitable than their “neighbours”. According to the authors, this proves the gradual incorporation of new information into asset prices, which results in “gradual decentralized diffusion” (p. 1327). This suggests that better informed central agents are able to outperform others. Applying this finding to social trading suggests that investors with a high number of social connections trade better compared to “unsocial” traders. Hence, it is possible to conclude that social interaction can result in very similar behaviour of individuals.

2. Data and research question

A European based social trading platform agreed (myportfolio¹) to provide their full data set including trading- and holding data of about 15,000 portfolio managers. Currently 1,432 equity traders at this platform manage around 100 million EUR. We have access to their daily trading data, demographic data and amount of assets under management. The demographic includes zip codes, age, trading experience and traded risk classes. However, not all of those portfolio managers currently have investable portfolios. **Error! Reference source not found.** summarises assets under management data of all users trading equities and ETFs.

Our sub-sample represents roughly 10% of the final dataset. In the first step we exclude data from traders who trade ETFs, options, futures, and other derivatives to make our results comparable to the existing literature. We also exclude portfolios which executed less than 10 trades. This leaves us with 798 portfolios. Currently 144 of them manage assets with an overall value of 5,515,265 EUR.

Insert table 2 around here

In the analysed sample we have 106,849 trading observations, 61,439 buy- and 43,288 sell orders. The most active trader has made 6204 trades and the average trader executed 69 buy- and 60 sell orders

¹ We anonymise the name of the trading platform while the paper is work in progress

with a median of 20 buy- and 14 sell orders. On average the portfolios after the correction exist since 550 days. The oldest is 3.6 years, the youngest one day.

Error! Reference source not found. summarises some of the main indicators of the current sub-sample. The average return of the 798 portfolios is 13% since their creation when considering all portfolios. It is apparent that as the amount of assets under management increases, the return of the portfolio increases as well. The mean return of all portfolios which have at least 1 EUR invested is 42%. For those with more than 100,000 EUR the return is 138%. However, in our dataset only five portfolios manage more than 100,000 EUR of assets. In the larger sample of future analysis this number is expected to be about 10 times higher.

Analysing the trading activity shows some interesting results. The five most traded stocks shown in **Error! Reference source not found.** account for 7.5% of all trading activity. Especially U.S. and German stocks are very popular among the investors accounting for more than 50% of all traded stocks. Moreover, the investors appear to follow on average very active trading strategies with the average trader executing more than 1,000 trades. One possible explanation for this could be that no additional transaction fees occur except the buy-sell spread.

Research Question and Methodology

Based on the data quality this study will have a very solid basis to analyse the impact of transparency and feedback on the behaviour of portfolio managers. This will help to address one central research question: What is the impact of social feedback and transparency on investment behaviour? When answering this we hope to also address questions such as: How do social peer effects influence the decision making of retail investors and fund managers? What is the impact of transparency on cognitive biases of retail investors and fund managers? How does market-level herding affect the investment decisions of individual investors and professional managers?

In the present paper which is the first in this research project the focus is on the disposition effect. Many different studies show the existence of the disposition effect. In the literature three main approaches exist to show the effect in trader's behaviour. Odean (1998) applies a ratio analysis comparing realized gains and losses to their respective paper gains and losses. Grinblatt and Keloharju (2001) establish a second approach by applying a logit regression model which allows them for the first time to consider different trader characteristics

3. Methodology

Ratio analysis

Odean (1998) conducts the first large-scale empiric analysis of the disposition effect. For this, he analyses 10,000 discount brokerage accounts of individual traders. To measure the disposition effect

Odean (1998) records the number of sold stock positions which show either a gain or a loss compared to the average purchasing price which he collects from the CRSP database. However, this counting only occurs if both, daily high and daily low, are above or below the average purchasing price. If it lies in between these two barriers, the trade is not counted. The same is true for days without trading activity in the portfolio. Afterwards, collecting the number of realized gains and losses, he compares this amount with the number of paper gains or losses. Using these figures, he calculates the following ratios:

$$\text{Proportion of Gains Realized (PGR)} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}}$$

$$\text{Proportion of Losses Realized (PLR)} = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}}$$

A significant larger PGR indicates the tendency of investors to hold winning stocks shorter than their losing counterparts. Therefore, the H_0 is that the differences in the ratios are equal to zero. However, this approach shows a potential weakness. It only considers absolute values for the number of realized (paper) gains and losses - it does not consider the magnitude of gains and losses. Other authors such as Liu et al. (2014) also apply a ratio analysis but not only consider the number of trades but also the magnitude of winnings and losses.

Odean furthermore suggests to cluster the data into different months. He finds that the disposition effect is present from January to November. Nevertheless, he does not find evidence for it in December. This shows that at least some of the present investors are aware of potential tax advantages when realizing losses. He shows that the realized losses in December are 1.8 higher compared to the other months. Additionally testing for the impact of trading frequency he finds that high frequency traders show smaller differences of the ratio. Overall, the results show that investors are 1.5 more likely to realize a gain than a loss. However, another drawback of that analysis is that it does not consider the overall market development. A bullish market might result in several winning positions in the portfolio of the trader. Therefore, this can result in a high number of realized and paper gains. This might bias the result of Odean.

The goal of the present research is to replicate the analysis by Odean in a social trading environment in order to compare the magnitude of the disposition effect to its occurrence in other markets.

Logit Regression Models

To adjust for the mentioned drawback and in order to be able to consider traders characteristics Grinblatt and Keloharju (2001) develop a logit regression model. Grinblatt and Han (2005) expand their work and show the disposition effect as representation within the demand function of investors.

$$D_t^{DE} = 1 + b_t[(F_t - P_t) + \lambda(R_t - P_t)]$$

Lambda “measures the relative importance of the capital gain component of demand” (p.1854) hence it shows how the disposition effect influences the demand. If investors assume their old reference price (R_t) and if $P_t < R_t$ they will view their position as loss and therefore sell their position less frequently.

A very recent study by Birru (2015) expands this model and utilizes the same dataset as Barber and Odean (2000) and existing work by Grinblatt et al. (2012), Kaustia (2010) and Linnainmaa (2010). The model is established as:

$$Sale_{i,t} = \beta_0 + \beta_1 Gain_{i,t} + \beta_2 Max_{i,t} + \beta_3 Min_{i,t} + \beta_4 December_{i,t} + \beta_5 December_{i,t} \times Gain_{i,t} + \beta_6 X_{i,t} + \varepsilon_{i,t}$$

In this case, gain takes a value of one if stock appreciated since purchase and zero otherwise. Hence, a positive and significant value for gain indicates the presence of disposition effect. The purchase price is the share-weighted average using closing prices from CRSP database. This price calculation also includes commissions. The variable Min takes a value of one if stock is trading at its lowest price relative to the past month; Max does the same with highest price. Birru assumes that both, min and max, to have positive coefficients. The December dummy variable included for tax-loss selling in December. Following Grinblatt and Keloharju (2001), Birru includes control variables for past returns using market-adjusted returns and index returns with different time horizons. Testing for the interaction between Gain and the other variables he controls for potentially different behaviour for winning and losing shares. Moreover, the model controls for volatility, calendar month-effects and industry fixed effects. As it is common practice, the present research applies maximum likelihood regression coefficients and standard errors for logit regressions when testing for the disposition effect.

Following Grinblatt and Keloharju (2001) and Birru (2015) this work will include control variables for different past return patterns. These include market adjusted stock returns over different horizons, index returns and interaction terms between gain and the control variables. Moreover, this study will control for market volatility and consider the effect of stock splits and other capital measures.

However, the main contribution will be to show the impact of additional variables which were excluded up to now since they are not observable in a traditional market environment. We therefore introduce social variables. Firstly, we will analyse the follower effect, namely if the number of followers, or in our case, the amount invested in the portfolio changes the behaviour of the fund manager. Hence we will include additional interaction term between gain and assets under management. Further ideas include to analyse the communication behaviour of fund managers. For this it will be possible to analyse the amount of comments and find if behavioural biases are related to communication frequency. Hence we include another interaction term between gain and number of comments.

4. Outlook and Contribution

A recent trend in the discussion about cognitive biases focuses on how transparency and saliency influence the behaviour of individuals. The more salient a potential negative decision is, the stronger are the associated behavioural biases (Frydman and Rangel, 2014). Additionally, an individual acts more carefully when he or she is being observed. A study by Godager et al. (2015) shows that disclosing physicians performance positively influences their behaviour. Applying this to the findings of mutual fund manager suggests that an increase in transparency can positively influence their behaviour and eventually their performance. Our research improves the understanding of decision-making processes and biases of retail and professional investors through utilising an unexplored dataset in a novel trading environment. It also illustrates the impact of market transparency on the behaviour of financial agents since a social trading platform enables everyone to observe each other. Moreover our paper will contribute to the growing literature on financial disintermediation by discussing herding and influence processes in a novel environment.

Tables

Table 1 Overview of herding studies of mutual funds, it shows the number and types of funds analysed, the observed time period and frequency of the data

Authors	Number and type of funds	Time horizon	Data frequency
Lakonishok et al. (1992)	769 tax exempt pension funds	1985-1989	quarterly
Grinblatt et al. (1995)	274 mutual funds	1974-1984	quarterly
Wermers (1999)	2,400 mutual funds	1974-1994	quarterly
Pool et al. (2015)	2,558 mutual funds and 4,622 money managers	1996-2010	quarterly

Table 2 Assets under management at myportfolio

Number AuM > 0	1,432
Lowest AuM	7.29
Sum of AuM	100,235,558 EUR
highest AuM	11,156,931 EUR
Average	69,996 EUR
Median	5,660 EUR

Table 3 top traded stocks

Most traded stocks	Number of Trades	Countries of origin of traded stocks	Number of different stocks traded per country
APPLE	2223	United States	692
VOLKSWAGEN	1711	Germany	492
DAIMLER	1383	United Kingdom	97
NORDEX	1356	Canada	94
DEUTSCHE BANK	1205	France	90

Table 4 shows the summary statistics of our sub-sample. We report the mean, standard deviation minimum and maximum value as well as the 10th, 25th, 50th and 75th percentile for the return of the portfolios, the number of dividend payments, number of transaction

Panel (all assets in '000s EUR)		Mean	St. Dev.	Min	Max	P10	P25	P50	P75	N
A: > 0 AUM	Assets	31.66	113.36	0.01	807.98	0.18	0.75	3.71	17.87	109
	Return	0.42	1.21	-0.67	11.36	-0.04	0.02	0.13	0.36	109
B: > 20 AUM	Assets	125.11	214.35	20.10	807.98	20.45	22.98	46.81	89.21	25
	Return	0.72	0.99	-0.12	3.97	-0.04	0.03	0.36	0.92	25
C: > 100 AUM	Assets	451.45	325.77	120.55	807.98	120.55	144.38	427.86	756.51	5
	Return	1.39	0.88	0.11	2.35	0.11	0.92	1.71	1.84	5
D: > 200 AUM	Assets	664.11	206.21	427.86	807.98	427.86	427.86	756.51	807.98	3
	Return	1.66	0.72	0.92	2.35	0.92	0.92	1.71	2.35	3

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