When Trading Becomes Social: How Social Trading Platforms Affect the Disposition Effect

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Abstract

Social trading platforms have, over the last decade or so, been gaining a strong foothold in individual investment markets. Users on these platforms can observe ("view") traders' detailed transactions over time. They can also "follow" anyone of those traders, just like with other social media platforms, investing their money in accordance with the strategies of their trader of choice. We study whether and how the disposition effect bias of individual traders is affected by two social features of the platform, "Views" and "Followers." We find a differentiated impact on this bias from those two social features, which is conditional on the level of market turbulence. We attribute this to how traders assess the signal originating from Views and Followers in relation to how committal it is.

Keywords: Social trading, platform, disposition effect, risk

Introduction

Over the last several decades, the financial industry has been witnessing continuous improvements in the way it delivers its services. In turn, new business opportunities and models have been developed, resulting in significant interest from the Information Systems (IS) and related disciplines (Hendershott et al. 2021). At the retail sector level, and starting in the year 2000, these improvements were enabled to a large extent by online platforms, which have widened their user base by lowering the joining barriers and the transaction costs . More recently, these platforms introduced a novel implementation of social trading, which not only enables online real time trading, but also promotes public sharing of information and social networking between traders. More specifically, by allowing users to a) observe ("view") traders' transactions over time along with the losses and gains they make, and to b) "follow" one or multiple traders (just like with other social media platforms), these platforms help them devise their investment strategies. By following them, users can "copy" traders' investment strategies, thus investing their money automatically, simultaneously buying and selling in a way that mirrors the selected traders' investment allocations.[1] Some of the early platforms using this model include eToro (founded in 2006), ZuluTrade (2007), and, more recently, eagleFX (2019). Any user can create an account and explore the traders who currently transact on the site. While it is difficult to quantify the size of this market, eToro, for example, was valued at $US 9.6 billion in 2021.[2]

[1] In a way, copied traders serve a similar role as that of a portfolio manager also receiving monetary compensation.
[2] See the *Business Insider* article on the topic https://markets.businessinsider.com/news/stocks/fintech-acquisition-corp-v-spac-etoro-trading-platform-report-2021-3-1030213279 (Accessed January 8, 2022).

The platform also puts on display several statistics that characterize traders' performance (see Figure 1, left panel) and a detailed listing of all their transactions (see Figure 1, right panel).

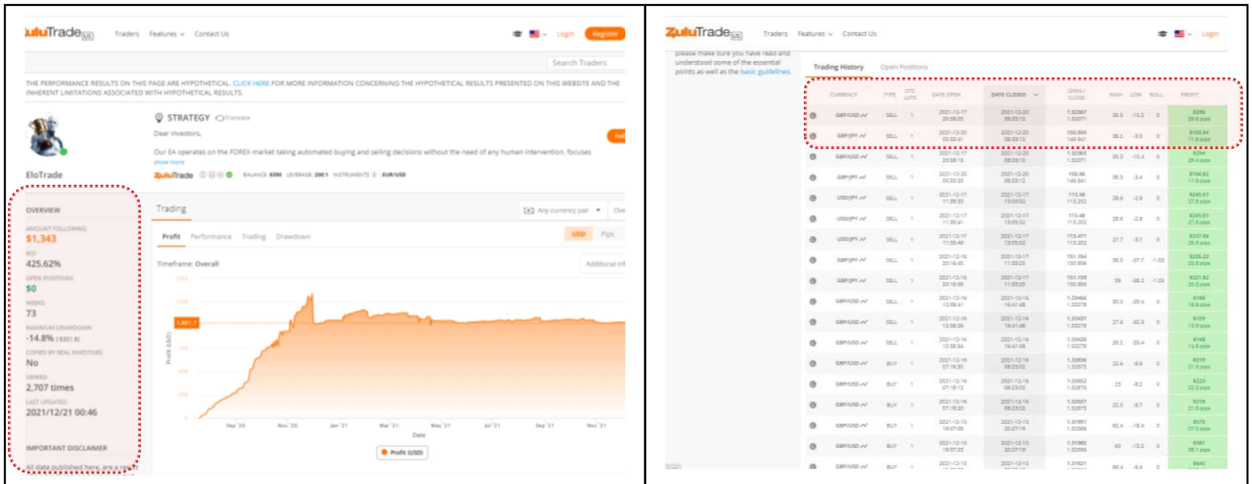

Figure 1. Trader Descriptive Statistics (left) & Detailed Transaction Listing (right)

Notes: The left panel shows the main page for a sample trader on the platform, where the platform provides an overview of the trader's trading history, including performative metrics (e.g., ROI, open positions), some social metrics (e.g., Views and Followers), and their history (e.g., weeks on the platform) – see the listing of this information to the left side of the red overlay. The panel on the right shows trader's trading history, including exchange currencies, lot size, date opened, and date closed, with the red overlay at the top showing sample transactions.

Our research focuses on the well-known bias of the disposition effect that individual traders may experience, selling assets that have appreciated and keeping those that have depreciated, and thus, counter to rational financial behavior, traders act either as risk-averse over gains and risk-seeking over losses. We study this bias in the novel context of online social trading platforms. Distinctive aspects of these social platforms include the abundance of real-time information available at the fingertips of traders on the platform. As such, these social platforms provide very high levels of observability on how users in the social network interact with a trader. In turn, traders' time holding on to their transactions before selling them, and traders' tolerance to risky behavior can be influenced by viewing and copying of investment allocations by fellow users (Gemayel and Preda 2018; Pelster and Breitmayer 2019). Greater and real-time observability of how the social network interacts with a trader can heighten concerns about social perceptions. On the one hand, it can be argued that these platforms create salient investment-relevant information, which can mitigate the disposition effect (Frydman and Rangel 2014). On the other hand, it can be argued that these platforms create an abundance of information, along with tools to navigate them, which can create overconfidence (Havakhor et al. 2020; Rai et al. 1994).

Our research objective is to examine the impact of two platform-based social-trading features on the disposition effect, features that are proxy for platform users' allocation of attention and money to the trader. These features are (i) **views** to the traders' page, which reflect the visible allocation of platform users' *attention* to the trader and (ii) **followers**, who reflect the allocation of *money* to copy the trades of individual traders. We contend that the first feature, Views, is a scrutinizing signal that is indicative of interest from the user base. We label it as scrutinizing because it is not yet committal to the trader. The second feature, Followers, is a signal of commitment to the trader from the user base already investing in line with the trader's strategy and as such may be taken for granted. We therefore delve into the risk-seeking (risk-averse) behavior vis-à-vis losses (gains), and into the transaction holding time in response to the (non) committal signal received.

We note that while there have been studies investigating the disposition effect in a social trading context, there are three important considerations that propel us toward analyzing the role that social factors play in influencing the risk-taking behavior of traders, and how this risk profile changes with market turbulence.

First, the findings from past studies on the disposition effect in a social trading context have been mixed. Second, the roles of specific social trading features, particularly Views and Followers, have not been investigated. Third, whether and how the roles of these social trading features are contingent on market turbulence is also unclear. As such, we focus on, and reveal, that the social features do affect the disposition effect in very different ways and that this effect is influenced by the levels of turbulence in the market.

Our research is situated in the context of *Zulutrade*, one of the leading online financial platforms. We construct a dataset of almost 50,000 financial transactions conducted online by more than 400 traders over a period of one year (January 2019 to December 2019). Using survival analysis to assess traders' transaction holding times, we find that the two social features—Views and Followers, affect the disposition effect, but do so in different directions. Specifically, we find that with increasing Views, we observe a greater marginal increase in holding times for gains relative to losses under both high and low market turbulence levels. We also find that with an increasing number of Followers we observe a smaller marginal increase in holding times for gains relative to losses under both market turbulence levels. We attribute this opposing effect to a differentiation in how the signal originating from Followers and Views is processed under different market conditions. Under low market turbulence, when traders use the signal of Followers as a sure signal of commitment they do not feel the need to adjust their irrational behavior, which accentuates their disposition bias. However, the non-committal signal of Views reflects scrutiny, leading traders to attenuate their non-rational behavior, manifesting as diminished disposition effect. With highly turbulent market conditions, traders' behavior in response to the signal from Views and Followers persists, with traders behaving in an even less (more) rational way with increasing Followers (Views), further accentuating (attenuating) their disposition bias.

We now introduce the concept of the disposition effect and its implications. In subsequent sections we present our theoretical framework, our hypothesis, our empirical context, our estimation approach, and the results. We conclude by presenting the implications of our work.

Background

We start by briefly introducing the recent IS work on social trading platforms, exploring how information technology and its features affect both users and traders. We then review the phenomenon of the disposition effect which has been a focus in behavioral finance for a long period. As our research lies at the intersection of these two streams, our work benefits from these two disciplines. We then briefly summarize the literature on decision making under market turbulence to evaluate the role of different types of signals provided by the social trading features under different levels of market turbulence.

Social Trading Platforms

The nascent literature on social trading platforms has explored the role of platforms, networks and imitation behavior. Regarding platforms, Yang et al. (2022) study the platform and its mechanism of information revelation with a focus on the tension between user-facing transparency and platform-based revenue. They study the impact of delaying the posting of transaction information and the impact on platform revenues. Liu et al. (2022) focus on the challenge arising for all stakeholders from excessive transparency, which leads to copycat behavior and takes away from true investors and from the platform the benefits they would otherwise extract. Danbolt et al. (2021) also study the level of information transparency, based on how much information the trader releases. Regarding networks, Liu et al. (2022) analyze the overall network of user interactions. In Deng et al. (2021), the authors analyze the formation and dissolution of linking investors (copiers) with experts (leaders). Regarding the imitation behavior, Apesteguia et al. (2020) enable investors to directly copy others with a mere click of a button and, indirectly, by providing information on portfolios and the success of traders that users may try to emulate. The authors attempt to elicit subjects' risk preferences and their tendency to follow others, and to identify the determinants of copying behavior. Regarding risk taking, Scheckenbach et al. (2021) study investors' risk taking and the conditions under which they change their risk profile. Overall, these studies suggest that social trading platforms provide features that enable users to copy traders, and traders to both receive information about the actions and choices of users, in addition to sharing information about their trading performance and strategies with users.

Disposition Effect

One of the most common pieces of advice to individual investors is to "cut your losses and let your profits run." The rationale for cutting losses is to avoid the risk of further losses by getting out of losing positions quickly rather than hoping for a rebound, and that for letting the profits run is to have the patience to stay in winning trades so as not to sell them too early (Shefrin and Statman 1985). This is because losing investments usually continue to underperform, while winning ones typically continue to outperform (which is why they were initially purchased). Yet, driven by the belief that the losses will be promptly compensated, traders tend to hold on to their losses. Similarly, driven by the fear of their profits evaporating quickly, traders tend to take their gains off the table early. In their seminal paper, Shefrin and Statman (1985) coined this behavior the *disposition effect*. It is considered a bias as it runs counter to some of the stipulations of modern economics that emphasize the notion that human beings are rational agents who acquire costly information and attempt to maximize wealth while minimizing risk.

The principal explanation for the disposition effect is based on prospect theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), which posits that people evaluate gambles by thinking about gains and losses, rather than final wealth levels. It also posits that people process these gains and losses using a value function that is concave for gains and convex for losses, with this value function steeper for losses than for gains. Barberis and Xiong (2009) provide an intuitive explanation. If an investor is holding a security (say, a stock) that has risen in value since purchase, they may think of that security as trading at a gain. Driven by risk aversion over gains, the investor may then be inclined to sell the security. Similarly, driven by risk seeking over losses, the investor may be inclined to hold on to a security that has gone down in value.

This disposition effect is a well-documented investor behavior bias, found across many asset classes and investor types, even extending to settings in which investors are not typically considered irrational (see Kaustia (2010), for an overview of the related literature). Furthermore, this bias has been systematically observed in lab and in field settings, and identified in a number of countries (Odean 1998; Weber and Camerer 1998). Previous researchers have measured the disposition effect in a number of ways. Odean (1998) compares the proportion of losses to the proportion of gains realized by a large sample of investors at a discount brokerage firm. Over a reasonably long period, the hypothesis is that traders tend to close winning positions and hold on to losing ones (Gemayel and Preda 2018). Hazard models have also been applied in this context (Frydman and Wang 2020).

The question of why traders commit this bias has been the subject of a long stream of studies in finance and behavioral economics, with a recent renewed interest. Danbolt et al. (2021) review a range of explanations proposed in the literature. These include preferences realization (Barberis and Xiong 2012), cognitive dissonance (Chang et al. 2016), emotions (Richards et al. 2018), and belief-based trading (Ben-David and Hirshleifer 2012).

Focusing on how to alleviate this bias, Dhar and Zhu (2006) find that with more trading experience, the disposition effect decreases, and that wealthier individuals and those with professional occupations are on average less vulnerable to it. Other studies have proposed additional mitigating factors, such as, among others, financial sophistication (Dhar and Zhu 2006), delegating investment decisions, and the salience of investment information (Frydman and Rangel 2014). A noteworthy finding is that these studies find the bias to be alleviated but not fully reversed in the presence of these mitigating factors.

Disposition Effect in Social Trading Platforms

Given the long-standing understanding that social interactions shape many aspects of economic activity, researchers have increasingly been moving beyond strictly relying on pure financial indicators, such as price and financial performance. As part of what has been labeled as *social finance* (Hirshleifer 2015; Hirshleifer 2020), researchers now account for the economic impact of how people mutually observe and talk to each other when making financial decisions. They also study mechanisms through which the behavior of other agents affects one's own beliefs and behaviors (see the review by Kuchler and Stroebel (2021)). Recent work has studied the influential role of interactions among neighbors (Haliassos et al. 2020), peers (Kalda 2020), coworkers (Ouimet and Tate 2020; Zhang et al. 2018), family (Cronqvist and Yu 2017) and others (Han and Hirshleifer 2018) in a variety of financial settings, including stock market participation, trading levels, and portfolio allocation.

Social investing in general and on the web has been on the rise. Comparing them to traditional wealth management services, Deng et al. (2021) and Apesteguia et al. (2020) identify a number of unique aspects of social trading platforms. First, such platforms publicly display all traders' transactions (e.g., transaction value, duration, gains or losses) in almost real-time, thereby providing a great degree of transparency. Second, they display trader credentials (e.g., overall performance, volume of transactions, rank, experience level) and they update over time. Third, there are very few barriers to entry and exit, with investors typically allowed to start with a demo account with no risks attached, or with small sums of money to invest. Fourth, they enable platform members to readily and easily allocate (then revoke at any time) their attention and financial resources toward a trader. Fifth, social trading platforms are characterized by traders having high accessibility to information about social networks. As such, social trading platforms are characterized by an abundance of investment-related information. Studies on the disposition effect in other contexts find accessible social networks and socially-inclined traders to amplify the disposition effect (Heimer 2016; Pelster and Hofmann 2018).

The disposition effect has also been identified in social network settings. Studies have found that socially inclined investors become more vulnerable to the disposition effect (Heimer 2016; Pelster and Hofmann 2018). Specifically, Heimer (2016) finds that "access to the social network nearly doubles the magnitude of a trader's disposition effect." Another stream of research has found the opposite impact, arguing that constant observation and scrutiny erodes the disposition effect, as traders become "more self-conscious of their actions and limit their losses to avoid tarnishing their publicly available record" (Gemayel and Preda 2018). A third nuance is provided by Heimer (2016) who argue that financial peer effects asymmetrically relate to gains and losses. Another paper that is closest to our focus is Pelster and Hofmann (2018), who study the role that followers play on the disposition effect but without exploring the role played by risks and risk profiles.

Decision Making under Market Turbulence

Exchange rates between major currencies are known to display large fluctuations over time, away from their averages, resulting in volatility or turbulence (Frenkel and Mussa 1980). With more turbulence, the rate fluctuations are larger, which translates into higher trading risks but also more opportunities for traders. Such turbulence, and the resulting difficulty in reading the markets, has been shown to affect trader performance. To date, research has focused on the impact of turbulence on capital markets and asset prices, finding that ambiguity about volatility does matter (Baltussen et al. 2018). A number of theoretical papers have explored the implications of noise resulting from turbulence on individual investor trading behavior and on potential nonparticipation (Bossaerts et al. 2010; Kostopoulos et al. 2022). There are also a few studies that have examined the role of market turbulence in affecting the disposition effect—see Fogel and Berry (2010) and Qin (2015). What is unclear from this literature is the role played by the social features of platforms in influencing the risk-taking behavior of traders, and how their risk profile changes with market turbulence. We theorize these nuances in the development of our hypotheses.

Hypotheses

We first theorize as to why two platform social features—Views and Followers—will influence the disposition effect, albeit in opposing directions, and under different levels of market turbulence.

Views vs. Followers: Impact on Disposition Effect

We theorize on the role of two social features of the platform in influencing traders' disposition effect: the *allocation of attention* from platform members to traders (in the form of Views) and the *allocation of money* from platform members to "copy" traders' investment strategies (in the form of Followers). Attention allocation refers to the attention that platform users devote to visiting traders' web pages and viewing their content to learn about their trading strategies, their performance, and so on. This viewing is recorded by the platform and posted on the trader's page as the number of *Views*. By contrast, money allocation manifests in the form of platform members copying traders' trading allocation by investing their own money accordingly, thus replicating traders' financial strategies. This is enabled by the platform with very little friction. This money allocation is also recorded by the platform and posted on the trader's page as the number of F*ollowers*. We theorize that *Views* (allocation of attention by the social network to the trader) and *Followers* (number of investors allocating their money to copy the trader) should both affect the disposition effect, albeit in different ways.

Past work in finance provides some theoretical insights on the role of these two features in affecting the disposition effect. *Allocation of attention* that traders receive suggests that "peers" in their social networks (here, the social platform) look at the trader for information on important financial decisions—see, for example, Bailey et al. (2018). In contrast, the *allocation of money* that traders receive can lead traders to adjust their own utility based on the preferences of others (e.g., Bellet (2019).

To further inform our theorization on how these two social features can affect the disposition effect, we draw on online social contexts outside finance, and on the behavior of individuals in these contexts. In the context of user-generated contributions, audience size or social endorsement have been shown to change the underlying incentives of those endorsed, to contribute more time and effort. Harsanyi (1969) offers two drivers to this change in behavior: "People's behavior can largely be explained in terms of two dominant interests: economic gain and social acceptance." Regarding the first (i.e., economic gain), the economics literature has attributed change in behavior to individuals responding to changes in economic gain (Fehr and Falk 2002). Regarding the second (i.e., social acceptance), social exchange theory (Blau 1964) has attributed change in behavior to individuals responding to changes in social rewards, such as approval, status, or respect. These changes have been made prominent and readily observable by including numerical measures of popularity or reach, such as Followers or friends (Goes et al. 2014). Pu et al. (2020) provide a review of the relevant literature showing that a) an increase in Followers motivates users' pursuit of image and enhances their content volume on Twitter, b) greater audience size motivates users to generate more content, and c) a large number of Followers motivates users to pursue their effort-based image and to invest more effort into their content with the aim of gaining greater social approval. In turn, users' content-generation activities can be altered when their perceived visibility increases (Goes et al. 2014). Huang et al. (2017) find that social-network integration substantially increases users' social presence and further affects the content volume and emotional expression of each content.

However, it remains to be seen how these findings from social media and user-generated content settings transfer to financial settings. In such settings, a nascent stream of work has investigated related issues. Breitmayer et al. (2019) equate the number of investors following traders, and thus the financial commitment of Followers, to the magnitude of traders' social recognition. In doing so, they equate an increase in that magnitude to a confirmation of traders' past investment decisions. They find that recognition increases trading volume, but does not necessarily improve performance. Focusing on performance, researchers have explored how such an endorsement may result in traders adjusting their biases (Gemayel and Preda 2018; Pelster and Breitmayer 2019).

We propose that a greater number of Views is likely to result in a greater marginal increase in holding times for gains relative to losses, thereby attenuating the disposition effect. A greater number of *Views* is an expression of peer interest and scrutiny (allocation of attention) by the social network that can heighten considerations of image arising from how they trade, prompting traders to transact with greater rational deliberation. With such heightened image consideration, we expect that the traders' disposition effect will be attenuated. Specifically, with increases in Views to a trader's page, we expect that the latter will exhibit lower risk aversion for gains and risk seeking for losses with a greater marginal increase in transactions holding times for gains relative to losses.

H1: Under low market turbulence, increases in Views *will attenuate the disposition effect, manifesting as a lower risk aversion to gains than risk seeking to losses (i.e., greater marginal increase in holding times for gains relative to losses).*

By contrast, a greater number of *Followers* is an expression of users' confidence in the trader's decisions and in turn, an expression of the allocation of users' money (see the related work by Appel et al. (2020), in marketing). With an increasing number of individuals indicating their confidence, traders can arguably become overconfident in their abilities, thus becoming more risk-taking. With such overconfidence, we expect that the traders' disposition effect will be accentuated. Specifically, with increases in Followers, we expect them to exhibit greater risk aversion for gains and risk seeking for losses with transactions witnessing a smaller marginal increase in holding times for gains relative to losses.

H2: Under low market turbulence, increases in Followers *will accentuate the disposition effect, manifesting as greater risk aversion to gains than risk seeking to losses (i.e., a smaller marginal increase in holding times for gains relative to losses).*

Views vs. Followers: Impact on the Disposition Effect under Market turbulence

More recent empirical research in finance has shown that risk taking is a function of an investor's risk attitude and the asset's turbulence (see Huber et al. (2022)). Studies have shown that investors overreact to bad news and underreact to good news at times of high market uncertainty, and that investors faced with uncertainty base their decisions on the worst case scenario (Williams 2015).

To assess what drives their behavior, experimental evidence from psychology has shown how people are more likely to rely on heuristics and "rules of thumb" when they face more difficult problems, which are in turn associated with stronger behavioral biases (e.g., Kahneman and Tversky (1979)). Subsequently, theoretical behavioral finance models (Daniel et al. 2001; Hirshleifer 2001) formalized this intuition in the context of investment decisions showing that behavioral biases become stronger under "informationally sparse environments", such as those with turbulence. A number of empirical studies have since verified that the market environment affects the behavior of market participants—see, for example, Necker and Ziegelmeyer (2016). Specifically, markets with turbulence (e.g., high volatility, bear markets, …) increase stockholders' tendency to display the disposition effect—see, for example, work by Muhl and Talpsepp (2018). More specifically, Vasudevan (2019) show that a one standard deviation increase in volatility is associated with an 11% increase in the disposition effect. Using volatility of the market as a control, Chang et al. (2016) and Frydman and Wang (2020), for example, find that the disposition effect increases with volatility and that it affects gains and losses differently. Experimental studies exploring changes in investors' preferences also show that investors are more risk-averse in bust periods (Cohn et al. 2015). Guiso et al. (2018) find that both qualitative and quantitative measures of risk aversion increased substantially following the 2008 crisis. Bernard et al. (2018) show that the disposition effect is more pronounced after busts than in boom markets.

Accordingly, it gets more challenging to discern signals leading traders to amplify their behavior compared to that under more normal market conditions (i.e., low turbulence). Accordingly, we hypothesize that:

H3: Under high market turbulence, increases in Views *will further attenuate the disposition effect, manifesting as a lower risk aversion to gains than risk seeking to losses (i.e., a greater marginal increase in holding times for gains relative to losses).*

H4: Under high market turbulence, increases in Followers *will further accentuate the disposition effect, manifesting as greater risk aversion to gains than risk seeking to losses (i.e., a smaller marginal increase in holding times for gains relative to losses).*

Empirical Context

We focus on Zulutrade, a global online financial trading platform and multi-asset broker founded in 2007, which, over time, grew to offer retail investors foreign exchange (Forex) trading. Forex trading is the simultaneous buying of one currency, say $US and the selling of another, say Euro. With $US 6.6 trillion exchanged daily in 2019 (compared to $US 33 trillion for the equity market), up from $5.1 trillion three years earlier (Bank for International Settlements 2019), the global Forex market comprises the largest securities market in the world (the U.S. equity markets is 10-fold smaller). The Forex trading market is open 24 hours a day, five days a week across major financial centers across the globe, allowing traders to buy or sell currencies at any time throughout the day. Currencies are always traded in pairs (currency pair), and each currency in a pair is represented by a unique three-letter code (e.g., USD/EUR for the currency pair of US dollars and Euros). These currency pairs are priced in terms of one versus the other, or an exchange rate (e.g., to purchase one Euro, one pays 1.2 US dollars). Other than supply and demand for currencies, exchange rates vary with new interest rates, new country-level economic, and geopolitical tensions, among others. In the Forex market currencies trade in lots, which are blocks of the currency bought. For example, one "standard lot" of USD bought is $US 100,000. The majority of the volume in currency trading is confined to a small set of currency pairs, including the U.S. dollar, the Canadian dollar, the Euro, the British pound, the Swiss franc, the New Zealand dollar, the Australian dollar, and the Japanese yen.

With the trading market open longer than any other market (24 hours a day in different parts of the world, from 5 p.m. EST on Sunday until 4 p.m. EST on Friday), the rapid trade execution, the low barrier to entry due to reduced fees, and the ease of access including user-friendly platforms, the volume of trading is on the increase and the type of traders is now more varied. As such, independent retail traders have increasingly taken part in this trading market and now present a growing fraction ($201 billion) of global daily Forex volume through online brokerage platforms (Bank for International Settlements 2019). In response to the increased interest in this market, several currency exchange indices have been developed, e.g., the Barclay Currency Traders Index, and the Deutsche Bank Currency Harvest G10 Index. Although the Forex market is characterized by a high probability of losing money, individual retail traders have continued to take part in it. This behavior has been attributed to overconfidence, and is even more pronounced with retail traders (Daniel and Hirshleifer 2015). On the other hand, Forex is characterized by its rather limited choice of currency pairs compared to endless choices in other markets.

Zulutrade makes it possible for users to copy (also called 'follow') other traders and thus invest their money using strategies identical to those of traders. The platform is characterized by two main features: a) the availability and observability of transaction data, and b) the display of social information. Regarding the first feature, the platform makes available, almost on a real-time basis, the transaction history of traders (e.g., exchange currency, open date and price, close date and price). It also uses this history to derive aggregate metrics (e.g., return on investment, or number of open trades). It displays it on webpages dedicated to traders and makes it available for anyone to view. Regarding the second feature, the platform allows registered users to view and, if interested, copy investors' trading strategy.[3] In turn, it compiles and displays several social metrics, namely Views (i.e., lifetime number of Views of a trader homepage originating from a registered account) and Followers (i.e., number of users who copy the trading strategy of a trader at a given point in time). The platform also rank-orders traders based on performance metrics. Any such functional account can start with a deposit of as low as $US 300 to conduct spot transactions.[4]

Methodology

Model Formulation

In line with the extant literature (Feng and Seasholes 2005), we use survival analysis to empirically model the disposition effect of individual investors. Such models have a trivariate response (t_o, t, d): t_o is the starting time under observation with $t_o \geq 0$; t is the ending time under observation $t \geq t_o$; and d is an indicator for failure (or termination) with d taking the values of 0 or 1 (Stata manual 2021). It follows that the response variable is the time until an event occurs, which in our context is terminating (selling) the currency exchange transaction, i.e., the time between t_o and t.

Commonly used models to analyze survival data assume homogeneity of individuals in the population, so that individuals with the same value of the observed covariates have the same distribution for survival times. We also note the need to satisfy the additional assumptions of independence and identical distribution of survival data.[5] In many cases, however, the survival of different individuals are different, and the assumption of community homogeneity is not well-founded (which we validate in our data). One of the reasons for this difference can be attributed to the existence of unknown or unobserved risk factors that are not included in the model. In such cases, adding random effects is implemented as a way to account for heterogeneity between different individuals (traders).

More specifically, to model survival, the following accelerated failure time (AFT) model is used to relate the transaction duration to a vector of covariates and a random error term through a linear equation. Let $i = 1, \ldots, n$ panels (here, traders), $j = 1, \ldots, n_i$ observations (here, trader i's transactions), and v_i be unobservable

[3] The platform enables members of the platform to automatically copy the investment strategies of other users, thus allocating their money to reproduce those strategies, and subsequently cancel such allocations almost seamlessly.

[4] Spot transactions are agreements between two parties to buy one currency against selling another currency at an agreed price for instant settlement on the spot date. The exchange rate at which the transaction is done is called the spot exchange rate.

[5] This is the case for both a semi-parametric Cox proportional hazard model, which specifies that the hazard line has no specified distribution, and a parametric approach, which allows multiple distributional assumptions for survival time.

panel-level random effects that are independent and identically distributed $N(0, \sigma_v^2)$. This model takes the general form $T_{i,j}|X_{i,j} = e^{X_{i,j}\beta_{x_{i,j}}}\tau_i$ which can be log-transformed to $ln(T_{i,j}|X_{i,j}) = X_{i,j}\beta_{x_{i,j}} + ln(\tau_i)$ where $T_{i,j}$ is a trader's j observed time to sell transaction i conditional on a set of variables, $X_{i,j}$ is a vector of covariates, $\beta_{x_{i,j}}$ is a vector of coefficients, and τ_j is the random disturbance term.
In our context, a trader i initiates a currency exchange transaction j at t=0 and terminates it at t=T. With both times measured up to the second, the survival time is also measured up to the second. Holding this transaction up to T depends on a number of time-varying covariates.

Two platform social features are focal for this study: Followers and Views, each of which warrants further explanation. The platform displays the number of investors copying the investment strategy of the trader and labels it as Followers. This number reflects the most up to date current tally of investors/copiers. At any given point in time, the platform displays the cumulative tally of the number of unique clicks on a trader's profile originating from registered account, and labels it as Views. We also note that both Followers and Views are a manifestation of the social nature of the platform, as well as featuring of summary information.

As for the control variables, rank is an essential one. The platform provides a setting where traders compete for the "attention" and money of investors. It then compiles a relative ranking of all traders based on three financial performance metrics: maturity (how long a system has been running for), exposure (how many positions might be open at the same time), and drawdown (how many ups and downs the system has experienced). Just like several other online platforms, ranking sorts traders in reverse order of performance, with the best trader ranked as number 1. In line with extant literature, we supplement our focal variables with three sets of control variables, i.e., transaction-centric, trader-centric, and market-centric, which we detail in Table 1. In its developed form, the model can then be written as

$$ln\left(T_{i,j}|G_{i,j}, Z_{i,j}, C_{i,j}\right) = \beta_1 G_{i,j} + \beta_2 FL_{i,j} + \beta_3 VW_{i,j} + \beta_c C_{i,j} + \varepsilon_j \quad \textbf{(1)}$$

The covariates include $G_{i,j}$, a dummy which indicates whether a transaction was a win at the time it was closed (i.e., sold at a higher price than the purchase price)—coded as 1— or coded as 0 if it was a loss. We also include social variables of interest to us, $Z_{i,j}$ that characterize the trader, namely follower count, $FL_{i,j}$ and views, $VW_{i,j}$. We include three sets of control variables $C_{i,j}$ that include transaction-centric variables, trader-centric variables, and market-centric variables. These variables are detailed in Table 1.

In AFT models, the error term is usually parametrized as $\varepsilon_j = ln(\tau_j)$, that has a specific distribution depending on the parametric assumption about the baseline hazard function, and the distribution assumption of τ_j, which implies specific characteristics of the underlying hazard function of the data. We assume τ_j to be distributed as lognormal—note that in the robustness check section we include a number of other distributions, including log logistic, Weibull and gamma (Orbe et al. 2002; Stata manual 2021).

Due to our focus on the disposition effect and in the differentiated impact on transactions terminating with a gain and those terminating with a loss, and in line with the extent literature on the disposition effect, which highlights the differentiated behavior when a transaction ends in gain compared to when it ends in loss, we modify the formulation in (1) to include interaction terms between our variables of interest and the dummy variable $G_{i,j}$. The ensuing model is then expressed as:

$$ln\left(T_{i,j}|G_{i,j},\ FL_{i,j}, VW_{i,j}, C_{i,j}\right) = \beta_1 G_{i,j} + \beta_2 FL_{i,j} + \beta_{2G} FL_{i,j}\cdot G_{i,j} + \beta_3 VW_{i,j} + \beta_{3G} VW_{i,j}\cdot G_{i,j} + \beta_c C_{i,j} + \beta_c C_{i,j}\cdot G_{i,j} + \varepsilon_j \quad \textbf{(2)}$$

where $FL_{i,j}\cdot G_i$, $VW_{i,j}\cdot G_i$, and $C_{i,j}\cdot G_i$ represent the interaction terms between Gain and each of the variables Views and Followers, and representative control variables, respectively.

Variables

Our variables consist of the hazard rate of the transaction as the dependent variable; the transaction outcome, Gain; social variables, Followers and Views; and a number of control variables related to the transaction, trader, and market. Table 1 lists the variables and their definitions (summary statistics are available upon request).

Variable	Definition	Source
Dependent Variable		
$T_{i,j}$	Duration of transaction *i* by trader *j* from open to close	Derived
Transaction Outcome		
Gain	Indicator for whether the transaction was terminated with a gain (value of 1) or loss (a value of 0)	Platform
Social Variables		
Followers	Number of copiers of the trading investment pattern of trader *i* at time *t*	
Views	Cumulative number of views to the focal trader's page from registered accounts at time *t*.	Platform
Control Variables (trader, transaction and market levels)		
Rank	Rank of trader *i* at time *t*	Platform
Profit	Cumulative profit made by trader *j* up to time *t*	Platform
Trades	Cumulative number of transactions by trader *j* at time *t*	Platform
Days	Cumulative number of days *trader j* has been on the platform at time *t*	Platform
Amount Follow	Total amount of money following trader *j* at time *t*	Platform
Total Follower Profit	Total profit of copiers of *trader j* at time *t*	Platform
Lots	Lot size of transaction *i* purchased by trader *j*. A standard lot equals 100,000 units	Platform
Gain days	Cumulative number of days with gain (gain =1) across all transactions of trader *j* at time *t*	Derived
Negative Rate Difference	Difference between the lowest exchange rate observed during the life of transaction *i* and the exchange rate at time of transaction termination (<= 0)	Derived
Conc Transact	Total number of transactions concurrent to transaction *i* purchased by *trader j*	Derived
Conc Currency	Total number of currencies concurrent to transaction *i* purchased by *trader j*	Derived
Last Month Average Rank	Average rank of trader *j* over the month prior to start of transaction *i*	Derived
Rank Change	Difference in rank of trader *j* between time *t* and *t-1*	Derived
Views Change	Difference in number of page views of trader *j* between time *t* and *t-1*	Derived
Average Slippage	Average difference between transaction *i*'s expected price and the actual price at which the transaction is executed (computed by platform)	Platform
Cohort Minimum Rank	Minimum rank amongst ten nearest traders based on to *trader j* at time *t*	Derived
24hr Rateroll Average	Average currency exchange rate over the last 24 hours prior to time *t*	Derived
FX Daily Average	Average exchange rate over the holding time	Derived
Money Flow Index	Money flow index calculated from the typical daily average rate over the last 14 days prior to *t*	Derived
Bollinger Band	Three-day average of the envelopes based on at a standard deviation level above and below a simple moving average of the currency exchange rate	Derived
Market Index	Forex market index measuring overall exchange rates volatility based on the Generalized Autoregressive Conditional Heteroskedasticity model	Derived

Table 1. Model Variables, Definitions and Data Sources

Notes: Variables classified as: a) Dependent Variable, b) Transaction Outcome (which we also use for the interaction terms), c) Social Variables (i.e., the variables we analyze), and d) Control Variables (which characterize the trader, transaction, platform and/or market). These variables correspond to trader *j* at time *t* when transaction *i* starts. The source of the variables is listed as either Platform, i.e., as displayed on the platform, or Derived, i.e., which we compute.

Data Collection

We develop a crawler that visited Zulutrade between January 2019 and December 2019.[6] The crawler visited the front page of Zulutrade, where it identified the first 500 traders as of January 2019 by extracting their trader IDs. It then recurrently (twice every week) and visited the page of each of those traders. The crawler visited the overview page and recorded, for each trader, of all their summary statistics (see Figure 1, left panel). The crawlers also visited each of the traders' history page and collected the individual transactions as they arrived (see Figure 1, right panel). We also collect data external to the platform related to the volume and exchange rate of all the exchange currencies in our dataset. After eliminating the traders who remained inactive during the collection period, our dataset consisted of more than 400 traders who completed close to 50,000 transactions in one year.

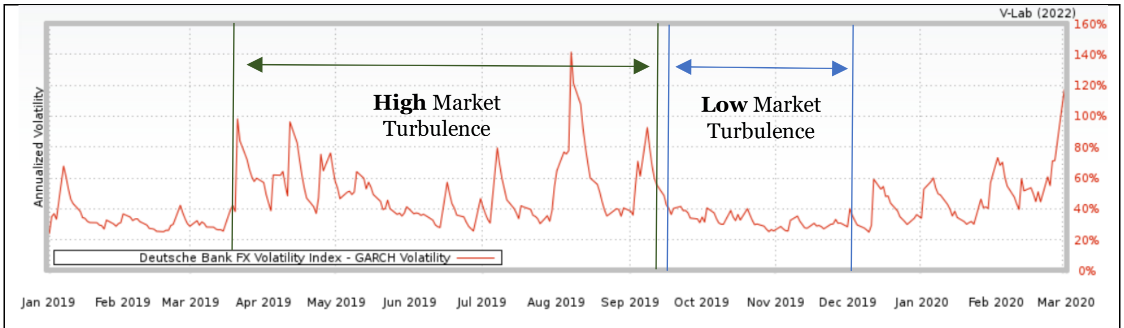

Figure 2. Plot of Deutsche Bank Forex Volatility Index during 2019

Notes: The graph depicts the Deutsche Bank FX Index with data from NY University Volatility Lab.

Data slicing: We slice the data into two different slices based on their market turbulence. In line with other work in finance that uses an aggregate market index to assess market volatility (see, for example, Kumar (2009)), we use a market index to guide us in the slicing. Figure 2 displays the Forex Market Index during 2019 and identifies the time span of each of the two slices (Low Market Turbulence and High Market Turbulence). For instance, in their study of the disposition effect, Birru (2015) do so over different data slices, making use of a stock splitting event.

Model Estimation and Analysis

We fit a random-effects parametric survival-time model. For estimation purposes, we assume the conditional distribution of the response given the random effects to be lognormal[7]. We use a robust standard error estimation while clustering the estimators based on the panel variable (trader), thus allowing for intragroup correlation. This requires the Huber/White/sandwich variance-covariance estimator to be calculated for the regression coefficients (Arellano 2003; Wooldridge 2010).

We run our estimation of equation (2) with a data slice characterized by turbulence (April till September 2019, see Table 2 column (2), and a data slice characterized by no turbulence (October till December 2019), see Table 2 column (1).

[6] It is worth noting that this range covers a period of severe market turbulence caused by the spread of Covid-19 starting in March 2020. In future extensions, we intend to replicate our analyses for the post-Covid period.
[7] Our estimation is robust to other conditional distributions of the response including exponential and lognormal.

	Model (1) **High Market Turbulence**	**Model (2)** **Low Market Turbulence**
Gain	-0.5336	0.7155
	(0.4245)	(0.7719)
Views	6.7e-07	-8.1e-06*
	(8.6e-06)	(3.7e-06)
Gain#Views	1.9e-06**	2.3e-06***
	(7.8e-07)	(3.4e-07)
Followers	-0.0014	0.0068**
	(0.0026)	(0.0022)
Gain#Followers	-0.0046**	-0.0057**
	(0.0018)	(0.0019)
Rank	3.5e-05*	4.8e-05*
	(1.8e-05)	(1.9e-05)
Gain#Rank	-1.3e-05	-1.5e-05
	(1.3e-05)	(2.2e-05)
Days	-0.0064	-6.7e-04
	(0.0064)	(3.8e-04)
Days Square	2.7e-06	2.7e-07*
	(2.0e-06)	(1.1e-07)
Gain#Days	-1.4e-04	-8.8e-06
	(8.5e-05)	(8.5e-05)
Trader-level Controls	✓	✓
Transaction-level Controls	✓	✓
Platform-level Controls	✓	✓
Market-level Controls	✓	✓
Sum of logs of the panel-level likelihood	0.4215***	0.3752***
	(0.0286)	(0.0504)
N	11,477	8,981

Table 2. Regression Results from the Survival Analysis (Eq 2)

Notes: The first column lists the independent variables used. Interactions between any two variables is indicated by the symbol # separating these two variables. The second and third columns display the estimation results of Equation 2 for the high market turbulence data slice, and the low market turbulence data slice, respectively. For each variable, regression estimates are listed first followed by the robust standard error in parentheses. Significance at p<0.1 is shown as *, p<0.05 shown as **, and p<0.01 shown as ***. The two rows before last show model-level statistics. The last row shows the number of observations.

Controls

Rank is significant and positive for both models ($\beta^{(1)}$=3.5*10^{-5}, p<0.1, and $\beta^{(2)}$=4.8*10^{-5}, p<0.1). As a higher rank means lower performance, this suggests that lower ranked traders exhibit shorter holding times. Days is significant and positive in its square form, for model (2) only ($\beta^{(2)}$=2.7*10^{-7}, p<0.1), indicating that traders who have been longer on the platform have a U-shaped relationship with transaction holding time. None of the Days-related variables are significant for model (1). Though not reported here for ease of exposition, Concur_Transact (the total number of concurrent transactions held) and Concur_Currency (the total number of concurrent currencies held) are both significant and negative for both models (1) and (2), indicating that a diverse portfolio in transactions and currencies exhibit shorter holding times.

Views

The variable Views is significant and positive in its interaction with Gains for both models from Table 2 ($\beta_{3G}^{(1)}$=1.9*10-6, p<0.05 in Model (1), and $\beta_{3G}^{(2)}$=2.3*10-6, p<0.01 in Model (2)), thus affecting transaction holding times differently for losses than for gains at each level of market turbulence (i.e., High or Low). This finding provides support that, at higher Views to the trader's page, reflecting greater user attention, the trader witnesses a greater marginal increase in holding times for gains relative to losses. This finding is persistent across models (1) under high market turbulence, and model (2) under low market turbulence. It suggests an increase in risk aversion over gains and risk seeking over loss, providing evidence for an attenuated disposition effect. These findings support H1 and H3.

Followers

Next we discuss the findings for Followers. This variable is significant and negative in its interaction term, with Gains for each of the models in Table 2, with $\beta_{2G}^{(1)}$=-0.0046, p<0.05 in Model (1), and $\beta_{2G}^{(2)}$=-0.0057, p<0.05 in Model (2), thus affecting transaction holding times differently for losses than for gains. This finding means that, with a higher number of Followers to the trader's portfolio, reflecting greater commitment from users on the social trading platform, the trader witnesses a smaller marginal increase in holding times for gains relative to losses. This finding is persistent across models both under high market turbulence and low market turbulence. The slower transaction holding times for gains compared to losses suggest an increase in risk aversion to gains and risk seeking to losses, providing evidence for an accentuated disposition effect. These findings support H2 and H4.

A comparison between Model (1) and Model (2) allows us to assess whether there is a significant difference between the impact of a) the interaction terms for Gain and Views, and b) the interaction term between Gain and Followers across these two models. This comparison is implemented by running the following one-tailed Z-test: $\frac{\beta_1-\beta_2}{\sqrt{SE(\beta_1)^2+SE(\beta_2)^2}}$ where β_1 and β_2 are the coefficients of interest in Model (1) and Model (2) respectively, and $SE(\beta_1)$ and $SE(\beta_1)$ are the standard errors of the coefficients of interest in Model (1) and Model (2), respectively. The Z-test comparing the coefficients for the interaction between Gain and Views in Model 1 with that in Model 2 (i.e., $\frac{\beta_{3G}^{(1)}-\beta_{3G}^{(2)}}{\sqrt{SE\left(\beta_{3G}^{(1)}\right)^2+SE\left(\beta_{3G}^{(2)}\right)^2}}$) is not significant. However, the Z-test comparing the coefficients of the interaction term between Gains and Followers in Model 1 with that in Model 2 (i.e., $\frac{\beta_{2G}^{(1)}-\beta_{2G}^{(2)}}{\sqrt{SE\left(\beta_{2G}^{(1)}\right)^2+SE\left(\beta_{2G}^{(2)}\right)^2}}$) is significant (p < . 1), suggesting a stronger effect under high market turbulence.

We attribute this differentiation in impact from Views and Followers under Low Market Turbulence and High Market Turbulence to the difference in the signal originating from Followers and Views, and how this signal is processed under different levels of market turbulence. Under normal market conditions (low market turbulence), traders use the signal of Followers as a commitment signal, indicating to them that they have little to worry about, but then behave in a less responsible and accountable manner. This leads traders to behave less rationally, which further accentuates their disposition bias, whereby they increase their risk aversion to gains and their risk seeking to losses, resulting in a slower transaction time of gains relative to losses. By contrast, the signal of views is non-committal, exposing traders to scrutiny, dissuading them from changing their behavior. Under high turbulence conditions, traders process the committal signal from Followers by becoming even more risk seeking to losses, thus behaving in a less rational way, which accentuates their disposition effect. The disposition effect from the non-committal signal of Views observed under Low Market Turbulence has no varying effect under High Market Turbulence because of persistent scrutiny.

Implications and Conclusion

Our research contributes to a burgeoning body of research on social trading platforms (e.g., Apesteguia et al. (2020), with significant implications for research at the intersection of digital platforms and behavioral decision-making, and the emerging interdisciplinary literature on FinTech. We summarize our findings and implications in Table 3.

H1: <u>Views</u> x Gains under <u>Low</u> Market Turbulence	• Evidence of an attenuated disposition effect. • Manifests as a decrease in risk aversion over gains compared to losses. • Greater marginal increase in holding times for gains relative to losses.
H2: <u>Followers</u> x Gains under <u>Low</u> Market Turbulence	• Evidence of an accentuated disposition effect. • Manifests as an increase in risk aversion over gains compared to losses. • Smaller marginal increase in holding times for gains relative to losses.
H3: <u>Views</u> x Gains under <u>High</u> Market Turbulence	• Evidence of an attenuated disposition effect. • Manifests as a decrease in risk aversion over gains compared to losses. • Greater marginal increase in holding times for gains relative to losses.
H4: <u>Followers</u> x Gains under <u>High</u> Market Turbulence	• Evidence of an accentuated disposition effect. • Manifests as an increase in risk aversion over gains compared to losses. • Smaller marginal increase in holding times for gains relative to losses.
Comparing Views x Gains at <u>Low</u> vs <u>High</u> Market Turbulence	• Evidence of no differentiation in the role that Views play as the level of turbulence increases.
Comparing Followers x Gains at <u>Low</u> vs <u>High</u> Market Turbulence	• Evidence of an amplification of the role that Followers play as the level of market turbulence increases.

Table 3. Summary of Findings and Implications

Our study shows that the disposition effect—a well-documented problem in traditional financial trading contexts—manifests itself in a social trading context. The context is arguably characterized by an abundance of real-time information, along with high observability of traders' actions to their peers and the actions of peers to traders. These characteristics are likely to create overconfidence in traders, who perceive a boost in their image, which leads them to act rather quickly to realize their gains (and the accompanying social acclaim) while holding on to losses, with the expectation that the latter will reduce or revert to a gain.

More specifically, our study investigates how two social-trading features, Views and Followers, affect the disposition effect. By differentiating between two types of peer influence in these platforms our study reconciles the conflicting evidence regarding the disposition effect arising from peer influence that has been reported in the social trading literature. Some work finds that traders increase their disposition effect when trading under the increased scrutiny of their peers (Pelster and Hofmann 2018), while others find a decrease in disposition effect under similar circumstances (Gemayel and Preda 2018). In differentiating between the two social trading features, we distinguish between allocation of attention in the form of Views, which is an expression of interest by peers, and allocation of money in the form of Followers, which is an expression of confidence in trading strategies by peers. With increased interest from users, traders are likely to focus more on quickly building their image, leading them to behave rationally (in an economic sense). By contrast, with increases in Followers, the commitment signal results in overconfidence, increasing the bias in traders. In sum, we find that, while Views attenuate the disposition effect, Followers accentuate the effect.

Interestingly, we find that under conditions of high market turbulence, Views play no stronger role, while Followers further accentuate the disposition effect. Our findings reveal that non-committal scrutinizing signals of Views remain difficult to further process under turbulent market conditions. As such, they do not "move the needle", and therefore have no further effect on the disposition effect. We also find that the signal from Followers are given more importance relative to low turbulence times, leading to an accentuation of the disposition effect.

Our work contributes to the broader interdisciplinary literature on FinTech and its aim to study "technology tools, platforms, and ecosystems that make financial services or products more accessible, efficient, and affordable" (Hendershott et al. 2017). It also contributes to the literature on the design of trading platforms (Kannan et al. 2022). Our study suggests that designers of these platforms need to consider the impact of social features on traders' risk seeking and risk aversion. Future research could investigate how platforms can be designed to sensitize traders to changes in their risk taking with respect to gains and losses resulting from changes in different types of social interactions. Such designs, which can help traders become more aware of how their risk taking, sways with social information and can therefore help mitigate the disposition effect in these contexts.

References

Apesteguia, J., Oechssler, J., and Weidenholzer, S. 2020. "Copy Trading," *Management Science* (66:12), pp. 5608-5622.

Appel, G., Grewal, L., Hadi, R., and Stephen, A. T. 2020. "The Future of Social Media in Marketing.," *Journal of the Academy of Marketing Science* (48:1), pp. 79-95.

Arellano, M. 2003. *Panel Data Econometrics*. Oxford: Oxford University Press.

Bailey, M., Cao, R., Kuchler, T., and Stroebel, J. 2018. "The Economic Effects of Social Networks: Evidence from the Housing Market.," *Journal of Political Economy* (126), pp. 2224–2276.

Baltussen, G., Van Bekkum, S., and Van Der Grient, B. 2018. "Unknown Unknowns: Uncertainty About Risk and Stock Returns," *Journal of Financial and Quantitative Analysis* (53:4), pp. 1615-1651.

Bank for International Settlements. 2019. "Foreign Exchange Turnover in April 2019: Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity.," Basel, Switzerland.

Barberis, N., and Xiong, W. 2009. "What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation," *Journal of Finance* (64:2), pp. 751-784.

Barberis, N., and Xiong, W. 2012. "Realization Utility," *Journal of Financial Economics* (104), pp. 251-271.

Bellet, C. 2019. "The Mcmansion Effect: Top House Size and Positional Externalities in Us Suburbs."

Ben-David, I., and Hirshleifer, D. 2012. "Are Investors Really Reluctant to Realize Their Losses? Trading Responses to Past Returns and the Disposition Effect," *Review of Financial Studies* (25:8), pp. 2485–2532.

Bernard, S., Loos, B., and Weber, M. 2018. "The Disposition Effect in Boom and Bust Markets." SSRN.

Birru, J. 2015. "Confusion of Confusions: A Test of the Disposition Effect and Momentum," *The Review of Financial Studies* (28:7), pp. 1849-1873.

Blau, P. 1964. *Exchange and Power in Social Life*. New Brunswick, NJ: Transaction Publishers.

Bossaerts, P., Ghirardato, P., Guarnaschelli, S., and Zame, W. R. 2010. "Ambiguity in Asset Markets: Theory and Experiment," *The Review of Financial Studies* (23:4), pp. 1325-1359.

Breitmayer, B., Mensmann, M., and Pelster, M. 2019. "Social Recognition and Investor Overconfidence."

Chang, T. Y., Solomon, D. H., and Westerfield, M. M. 2016. "Looking for Someone to Blame: Delegation, Cognitivedissonance, and the Disposition Effect," *Journal of Finance* (71), pp. 267–302.

Cohn, A., Engelmann, J., Fehr, E., and Maréchal, M. A. 2015. "Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals," *American Economic Review* (105:2), pp. 860-885.

Cronqvist, H., and Yu, F. 2017. "Shaped by Their Daughters: Executives, Female Socialization, and Corporate Social Responsibility," *Journal of Financial Economics* (126:3), pp. 543-562.

Danbolt, J., Eshraghi, A., and Lukas, M. 2021. "Investment Transparency and the Disposition Effect," *European Financial Management* (Article in Advance).

Daniel, K., and Hirshleifer, D. 2015. "Overconfident Investors, Predictable Returns, and Excessive Trading," *Journal of Economic Perspectives* (29:4), pp. 61-88.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. 2001. "Overconfidence, Arbitrage, and Equilibrium Asset Pricing," *The Journal of Finance* (56:3), pp. 921-965.

Deng, J., Yang, M., Pelster, M., and Tan, Y. 2021. "A Boon or a Bane? An Examination of Social Communication in Social Trading. An Examination of Social Communication in Social Trading." SSRN.

Dhar, R., and Zhu, N. 2006. "Up Close and Personal: Investor Sophistication and the Disposition Effect," *Management Science* (52:5), pp. 726-740.

Fehr, E., and Falk, A. 2002. "Psychological Foundations of Incentives.," *European Economic Review* (46:4), pp. 687–724.

Feng, L., and Seasholes, M. 2005. "Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Finance Markets?," *Review of Finance 9* (9), pp. 305–351.

Fogel, S. O. C., and Berry, T. 2010. "The Disposition Effect and Individual Investor Decisions: The Roles of Regret and Counterfactual Alternatives," in *Handbook of Behavioral Finance*. Edward Elgar Publishing.

Frenkel, J., and Mussa, M. L. 1980. "Efficiency of Foreign Exchange Markets and Measures of Turbulence," *The American Economic Review* (70:2), pp. 374-381.
Frydman, C., and Rangel, A. 2014. "Debiasing the Disposition Effect by Reducing the Saliency of Information About a Stock's Purchase Price," *Journal of economic behavior & organization* (107), pp. 541-552.
Frydman, C., and Wang, B. 2020. "The Impact of Salience on Investor Behavior: Evidence from a Natural Experiment.," *Journal of Finance* (75:1), pp. 229-276.
Gemayel, R., and Preda, A. 2018. "Does a Scopic Regime Erode the Disposition Effect? Evidence from a Social Trading Platform," *Journal of Economic Behavior & Organization* (154), pp. 175-190.
Goes, P. B., Lin, M., and Yeung, C. A. 2014. "“Popularity Effect” in User Generated Content: Evidence from Online Product Reviews.," *Information Systems Research* (25:2), pp. 222–238.
Guiso, L., Sapienza, P., and Zingales, L. 2018. "Time Varying Risk Aversion," *Journal of Financial Economics* (128:3), pp. 403-421.
Haliassos, M., Jansson, T., and Karabulut, Y. 2020. "Financial Literacy Externalities," *The Review of Financial Studies* (33:2), pp. 950-989.
Han, B., and Hirshleifer, D. 2018. "Social Transmission Bias and Investor Behavior." National Bureau of Economic Research.
Harsanyi, J. C. 1969. "Rational-Choice Models of Political Behavior Vs. Functionalist and Conformist Theories," *World Politics* (21:4), pp. 513–538.
Havakhor, T., Rahman, M. S., Zhang, T., and Zhu, C. 2020. "Tech-Enabled Financial Data Access, Retail Investors, and Gambling-Like Behavior in the Stock Market: Evidence from a Natural Experiment."
Heimer, R. 2016. "Peer Pressure: Social Interaction and the Disposition Effect," *The Review of Financial Studies* (29:11), pp. 3177–3209.
Hendershott, T., Zhang, M. X., Zhao, J. L., and Zheng, E. 2017. "Call for Papers—Special Issue of Information Systems Research Fintech–Innovating the Financial Industry through Emerging Information Technologies.," *Information Systems Research* (28:4), pp. 885-886.
Hendershott, T., Zhang, X., Zhao, J. L., and Zheng, Z. 2021. "Fintech as a Game Changer: Overview of Research Frontiers," *Information Systems Research* (32:1), pp. 1-17.
Hirshleifer, D. 2001. "Investor Psychology and Asset Pricing," *The Journal of Finance* (56:4), pp. 1533-1597.
Hirshleifer, D. 2015. "Behavioral Finance," *Annual Review of Financial Economics* (7), pp. 133–159.
Hirshleifer, D. 2020. "Presidential Address: Social Transmission Bias in Economics and Finance," *Journal of Finance* (75:4), pp. 1779–1831.
Huang, P., Tafti, A. R., and Mithas, S. 2017. "Platform Sponsor's Investments and User Contributions in Knowledge Communities: The Role of Knowledge Seeding," *MIS Quarterly* (42:1), pp. 213-240.
Huber, C., Huber, J., and Kirchler, M. 2022. "Volatility Shocks and Investment Behavior," *Journal of Economic Behavior & Organization* (194), pp. 56-70.
Kahneman, D., and Tversky, A. 1979. "Prospect Theory: An Analysis of Decision under Risk," *Econometrica* (47:2), pp. 263-292.
Kalda, A. 2020. "Peer Financial Distress and Individual Leverage," *The Review of Financial Studies* (33:7), pp. 3348-3390.
Kannan, K., Saha, R. L., and Khern-am-nuai, W. 2022. "Identifying Perverse Incentives in Buyer Profiling on Online Trading Platforms.," *Information Systems Research*. (Articles in Advance.).
Kaustia, M. 2010. "Disposition Effect," in *Behavioral Finance: Investors, Corporations, and Markets,* H.K. Baker and J.R. Nofsinger (eds.). John Wiley and Sons, Inc, pp. 169–189.
Kostopoulos, D., Meyer, S., and Uhr, C. 2022. "Ambiguity About Volatility and Investor Behavior," *Journal of Financial Economics* (Articles in Advance).
Kuchler, T., and Stroebel, J. 2021. "Social Finance," *Annual Review of Financial Economics* (13), pp. 37-55.
Kumar, A. 2009. "Hard-to-Value Stocks, Behavioral Biases, and Informed Trading," *Journal of Financial and Quantitative Analysis* (44:6), pp. 1375-1401.
Liu, Y., Yang, M., and Tan, Y. 2022. "Someone Is Mimicking You: Investigating Copycats in Social Trading." SSRN.
Muhl, S., and Talpsepp, T. 2018. "Faster Learning in Troubled Times: How Market Conditions Affect the Disposition Effect," *The Quarterly Review of Economics and Finance* (68), pp. 226-236.
Necker, S., and Ziegelmeyer, M. 2016. "Household Risk Taking after the Financial Crisis," *The Quarterly Review of Economics and Finance* (59:141-160).

Odean, T. 1998. "Volume, Volatility, Price, and Profit When All Traders Are above Average.," *Journal of finance* (53:6), pp. 1887-1934.
Orbe, J., Ferreira, E., and Núñez-Antón, V. 2002. "Comparing Proportional Hazards and Accelerated Failure Time Models for Survival Analysis," *Statistics in Medicine* (21:22), pp. 3493-3510.
Ouimet, P., and Tate, G. 2020. "Learning from Coworkers: Peer Effects on Individual Investment Decisions," *Journal of Finance* (75:1), pp. 133-172.
Pelster, M., and Breitmayer, B. 2019. "Attracting Attention from Peers: Excitement in Social Trading," *Journal of Economic Behavior & Organization* (161), pp. 158-179.
Pelster, M., and Hofmann, A. 2018. "About the Fear of Reputational Loss: Social Trading and the Disposition Effect," *Journal of Banking & Finance* (94), pp. 76-88.
Pu, J., Chen, Y. C., Qiu, L., and Cheng, H. K. 2020. "Does Identity Disclosure Help or Hurt User Content Generation? Social Presence, Inhibition, and Displacement Effects.," *Information Systems Research* (31:2), pp. 297-322.
Qin, J. 2015. "A Model of Regret, Investor Behavior, and Market Turbulence," *Journal of Economic Theory*:150–174).
Rai, A., Stubbart, C., and Paper, D. 1994. "Can Executive Information Systems Reinforce Biases?," *Accounting, Management and Information Technologies* (4:2), pp. 87-106.
Richards, D. W., Fenton-O'Creevy, M., Rutterford, J., and Kodwani, D. G. 2018. "Is the Disposition Effect Related Toinvestors'reliance on System 1 and System 2 Processes or Their Strategy of Emotion Regulation?," *Journal ofEconomic Psychology* (66), pp. 79–92.
Scheckenbach, I., Wimmer, M., and Dorfleitner, G. 2021. "The Higher You Fly, the Harder You Try Not to Fall: An Analysis of the Risk Taking Behavior in Social Trading," *The Quarterly Review of Economics and Finance* (82), pp. 239-259.
Shefrin, H., and Statman, M. 1985. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence," *Journal of Finance* (40:3), pp. 777-790.
Stata manual. 2021. "Stata: Release 17 - Survival Analysis Reference Manual," S. LLC. (ed.). College Station, TX: StataCorp LLC.
Tversky, A., and Kahneman, D. 1992. "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *Journal of Risk and uncertainty* (5:4), pp. 297-323.
Vasudevan, E. V. 2019. "Some Gains Are Riskier Than Others: Volatility Changes, Belief Revisions, and the Disposition Effect.." SSRN.
Weber, M., and Camerer, C. F. 1998. "The Disposition Effect in Securities Trading: An Experimental Analysis," *Journal of Economic Behavior & Organization* (33:2), pp. 167-184.
Williams, C. D. 2015. "Asymmetric Responses to Earnings News: A Case for Ambiguity," *The Accounting Review* (90:2), pp. 785-817.
Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT.
Yang, M., Zheng, Z., and Mookerjee, V. 2022. "How Much Is Financial Advice Worth? The Transparency-Revenue Tension in Social Trading," *Management Science* (Articles in Advance).
Zhang, A. C., Fang, J., Jacobsen, B., and Marshall, B. R. 2018. "Peer Effects, Personal Characteristics and Asset Allocation," *Journal of Banking & Finance* (90), pp. 76-95.