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Social interaction contributes to some traders' disposition effect. New data from an investment-specific social network linked to individual-level trading records builds evidence of this connection. To credibly estimate causal peer effects, I exploit the staggered entry of retail brokerages into partnerships with the social trading web platform and compare trader activity before and after exposure to these new social conditions. Access to the social network nearly doubles the magnitude of a trader's disposition effect. Traders connected in the network develop correlated levels of the disposition effect, a finding that can be replicated using workhorse data from a large discount brokerage.

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[T]he time has come to move beyond behavioral finance to "social finance". –
David Hirshleifer (2015)

The disposition effect – the tendency to sell winning assets, while holding onto losers – is considered an investment mistake according to the traditional assumptions underlying models of decision making under uncertainty. With notable asset pricing and welfare implications, the disposition effect is found across many asset classes and investor types, even extending to settings in which investors are not typically considered irrational.[1] Theoretical explanations often rely on modifications to standard preferences and beliefs. However, these explanations – most notably Cumulative Prospect Theory (Tversky and Kahneman 1992) – sometimes struggle to motivate individuals to trade at all (Barberis and Xiong 2009).

Motivated by studies linking social interaction to increased market participation and turnover, including recent efforts highlighting asymmetries in financial peer effects, this paper proposes social interaction as a unified explanation for why those who trade also have the disposition effect.[2,3] Simultaneous with these network effects, self-image or reputation concerns crucially contribute to the disposition effect, because the appearance of success enables more socially persuasive interaction with others. As a result, traders value the option to recount victories and "seek to report positively about themselves, as constrained by the need to ... satisfy presentational norms" (Han and Hirshleifer 2013). Likewise, losing positions are subject to scrutiny from peers: "...The traders who get wiped out hope against hope...They refuse to take losses... When you're breaking in a new trader, the hardest thing to learn is to admit that you're wrong. It's a hard pill to swallow. You have to be man enough to admit to your ***peers*** that you're wrong and get out. Then you're alive and playing the game the next day." (Shefrin and Statman 1985, pg. 783) Thus, financial peer effects – like the disposition effect – asymmetrically relate to gains and losses.

To study social interaction's relation to the disposition effect, I employ a new sample of retail traders who participate in an investment-specific online social network, called myForexBook.[4] The setting is ideal for conducting rigorous tests of peer effects and to better understand peer effects' underlying mechanisms. The myForexBook data includes over two million time-stamped trades and over one hundred thousand time-stamped messages and friendships made by over five thousand traders. The myForexBook Web platform directly extracts trading records from partnering brokerages, including trades executed before

[1]Because of the high volume of potential citations, I refer readers to Kaustia (2010a)'s excellent overview of the literature.

[2]In no particular order, empirical evidence includes Ozsoylev et al. (2014), Hong, Kubik, and Stein (2004), Brown et al. (2008), Heimer (2014), Nofsinger and Sias (1999), Hwang, Huang, and Lou (2015), and Georgarakos and Pasini (2011). Theoretical mechanisms include reduced participation costs (Hong, Kubik, and Stein 2001), protection against adverse selection concerns (Davies 2014), social utility (Becker 1991), and herding (Shiller 2000). Notably, a desire for social status causes excessive trading, both theoretically and empirically (Hong et al. 2014).

[3]Evidence of asymmetries in financial peer effects include Shiller and Pound (1989), Kaustia and Knüpfer (2012), and Heimer and Simon (2013), or East, Hammond, and Wright (2007) with respect to consumer products.

[4]Per the data-provider's request of anonymity, myForexBook is a pseudonym.

joining the network. Hence, in contrast to recent studies using data from internet message boards, these trades are not self-reported.[5]

The myForexBook data are a good representation of the changing landscape of retail trading, while retaining a lineage to widely studied data on individual investors from a discount brokerage during the early 1990s (Barber and Odean 2000b). Conventional investment clubs were common around the time of this early research (Barber and Odean 2000a), but they have largely been replaced by Web-based social media. For example, Seeking Alpha, an online message board primarily used by retail traders, averages over three million distinct visitors per day. Leading retail brokerages, such as TD Ameritrade, have even integrated social networking features into their Web interface.

Among these potential data sources, myForexBook is uniquely suited to overcome well-known challenges to empirically identify peer effects (Manski 1993). The development of myForexBook – which is among the first attempts to directly link brokerage accounts to a social network – can be considered a technological innovation that makes it easier for retail traders to communicate. Drawing from this insight, while exploiting the gradual entrance of new traders into myForexBook over the course of the sample period, I conduct a panel analysis that compares a trader's disposition effect before and after exposure to the network. Difference-in-differences estimates from this analysis can be interpreted causally, because a trader is unable to access the network until a brokerage has reached legal and technological agreements with myForexBook. The staggered incorporation of new brokerages is like an instrumental variable that predicts trader entry, but is uncorrelated with trader characteristics and behavior according to empirical tests. Therefore, traders who enter the network are in the treatment group, while those contemporaneously constrained from joining myForexBook constitute the control group.

This paper's key finding is that exposure to myForexBook nearly doubles the susceptibility to the disposition effect on traders' market orders.[6] The result is robust to a number of controls, including trade leverage and calendar time fixed effects. The magnitude of social interaction's effect is unchanged when using trader fixed effects; this account for unobservable differences across traders. Additionally, the regression's identifying assumption is that the brokerage used by the trader causes variation in the time at which traders join myForexBook. The primary concern with this empirical approach is that brokerage-specific features are associated with unrelated changes in the disposition effect. Brokerage fixed effects should address much of this concern, and their inclusion in the regressions does not change the results.

Even though it is often not possible to use empirical methods to distinguish between different theories of social interaction (Manski 2000), I explore one potential reason why social interaction contributes to the disposition effect: impression management. The data contains evidence that the disposition effect is related to strategic efforts to convey a positive self-image after joining myForexBook. Traders can send peer-to-peer messages to one another; doing so attracts attention to one's account. Even after controlling for a trader's integration in the social network, those with the greatest increase in the disposition effect

[5] Examples include Chen et al. (2014) and Giannini, Irvine, and Shu (2014).

[6] The analysis focuses on traders' market orders to distinguish the results from the limit-order effect documented by Linnainmaa 2010.

send messages more selectively. Further, the propensity to feel social pressures is specific to the peer group to which the trader belongs. Evidence suggests these cohort effects matter. The average pair of befriended traders develop correlated levels of the disposition effect, benchmarked against trader networks formed by simulation. I also find that traders with, presumably, the most to gain from their social connections (inexperienced traders) have the greatest increase in the disposition effect.

Much supports the external validity of this paper's findings. First, workhorse data from a large discount brokerage (Barber and Odean 2000b) provides complementary evidence of social interaction's relation to the disposition effect. I show that traders who live near one another have correlated levels of the disposition effect, even within a metropolitan statistical area.[7] Second, using a contemporaneous set of traders who never join myForexBook as a control group, I run placebo tests that assign myForexBook traders false dates of joining the network. The placebo test produces false-positive results infrequently, suggesting that myForexBook traders are no more susceptible to fluctuations in the disposition effect than are traders who do not visit this particular online social network. Furthermore, this paper's findings even have been replicated in controlled laboratory experiments (Goulart et al. 2015).

As a final consideration, other well-supported explanations exist for the disposition effect, such as blame delegation, investor enthusiasm, adverse-selection risk, and mean-reversion beliefs. I conduct empirical tests showing that social interaction's influence on the disposition effect operates independent of these preexisting theories.

This research is, presumably, the first to connect social interaction to investment biases, while also making a few notable contributions to a growing empirical literature on financial peer effects. Hampered by data limitations, most empirical papers use creative proxies for peer interaction, such as background characteristics (Lerner and Malmendier 2013) or geographic variation (Hong, Kubik, and Stein 2005). In contrast, this research contains revealed linkages between traders. The analysis also compares trading before and after exposure to a new social environment, an advantage over past studies, almost all of which have had to rely on repeated cross-sectional tests. Aside from those results collected from controlled field experiments (e.g., Ahern, Duchin, and Shumway 2014; Beshears et al. 2015), this approach is among the most compelling evidence for financial peer effects, to date, comes from this approach. In addition, to the best of my knowledge, no other empirical research has observed connections being made or has witnessed a financial social network grow from infancy to maturity.

Furthermore, this study offers a novel explanation for why social interaction affects household investment decision making: a desire to manage one's self-image. Studies of fund managers (Lakonishok et al. 1991) and loan officers (Hertzberg, Liberti, and Paravisini 2010) argue for the importance of impression-management strategies when it comes time to disclose financial performance to clients, while others model the strategic timing of communication (Grenadier, Malenko, and Malenko 2015). However, similar concepts have not yet been applied to our understanding of household investors, even though evidence suggests external impressions, such as beauty (Duarte, Siegel, and Young 2012; Ravina

[7]This approach to identify peer effects through spatial variation is similar to that of Pool, Stoffman, and Yonker (2015).

2012), matter in financial contexts. Instead, studies of social interaction and household finances have been limited to a search for evidence of information transmission (e.g., Duflo and Saez 2003; Li 2014) via correlated decision making (e.g., Ivković and Weisbenner 2007).

This paper's most notable contribution is its novel explanation for the disposition effect. The advantage of attributing the disposition effect to social interaction is that the explanation is consistent with well-known evidence that social interaction encourages trading. There is also little reason to suspect that the explanation contradicts other stylized facts related to the disposition effect.[8] Notable among these, the disposition effect is found when traders actively manage their investments, but not when portfolio reallocation decisions are delegated (Chang, Solomon, and Westerfield 2016). Chang, Solomon, and Westerfield (2016) credit this finding to self-attribution, which has an intuitive connection to the awareness of one's self-image.

1 Data: A Social Network for Traders

The primary data source used in the empirical analysis was compiled by a social networking Web site that, for privacy purposes, I call myForexBook. Registering with myForexBook – which is free – requires a trader to have an open account with one of roughly fifty retail-specific foreign exchange (forex) brokerages. Once registered, myForexBook can access a trader's complete trading records at these brokerages, even many of the trades they made before joining the network. New trades are executed on the trader's brokerage account, but they are simultaneously recorded in the myForexBook database and are time stamped to the second. Hence, reporting bias or accuracy are not a concern.

[insert Figure 1 about here]

A few features of the myForexBook Web platform are worth describing. Upon joining the network, a trader sets up his homepage, an example of which is displayed in Figure 1, Panel A. The homepage contains some biographical information and a picture of the trader. It also includes links to send personal messages to other traders and post in a discussion forum. Traders agree to form bilateral friendships when one trader sends a friend request and the other agrees to it. A list of traders in the user's "trading team" (friend group) is also presented on the homepage.

Upon forming a friendship, traders can view each other's positions in real time, a feature illustrated in Figure 1, Panel B.[9] A notable feature, this viewing panel marks positions as closed and gives the closing price once the trader's friend executes the trade. Consequently, network peers can distinguish paper gains from realized gains.

[8] For example, see Dhar and Zhu (2006), Kaustia (2010b), and Ben-David and Hirshleifer (2012).

[9] These positions can be only viewed by a trader's friends in the network. Furthermore, those who have not joined myForexBook cannot look at a trader's profile or positions.

1.1 Retail foreign exchange trading and summary statistics

There is not much scholarly research on retail forex traders, but this growing market deserves our attention. Around twenty brokerages are registered with the Commodity Futures Trading Commission (CFTC); over a dozen English-language social networking sites cater to this market; and the daily trading volume worldwide is between \$125 - \$150 billion according to the Bank of International Settlements (King and Rime 2010).

There are many advantages to studying the disposition effect within the market for retail foreign exchange, because the venue is much closer to an experimental setting than are comparable studies of stock market participants. Yet participants trade with their own money, so the usual concerns about experimental studies do not apply. Among these advantages, the market structure alleviates concerns about alternative explanations related to selection across securities based on their characteristics (Kumar 2009), because nearly all of the trading volume takes place on the major currency pairs. Transaction costs are minimal in foreign exchange. Instead of charging a fixed fee, retail brokerages act as market makers, earning the spread, which tends to average just a few pips, where a pip is equal to one unit of the last decimal place in the quoted currency pair. The market is also highly liquid. Therefore, nonexecution risk is not a concern for inference. Furthermore, the data includes both market and limit orders, which are not always distinguishable in data sets drawn from account-level equity holdings.

The traders in this study appear to be representative of the typical retail foreign exchange trader in the United States or in other English-speaking countries. While no other account-level data sets are available for immediate comparison, well over half of the traders in the myForexBook database are unprofitable and a similar number lose in the overall population of retail foreign exchange traders, across the population of brokerages, according to quarterly reports compiled by the CFTC. These findings contrast with widespread evidence suggesting ample opportunity to earn risk-adjusted forex returns comparable to equities, as well as survey evidence that traders expect to earn at least 10% monthly returns.[10,11] Presumably the most reasonable comparison to existing research is to the active traders of common stock analyzed by Barber and Odean (2000b) and many subsequent studies. A key finding from this research is that those who trade a lot tend to underperform relative to standard benchmarks. In this regard, the forex traders studied herein are no different.

1.2 Data trimming and summary statistics

Traders (5,693) in the database made roughly 2.2 million trades, which occurred between early 2009 and December 2010. The sample used in this research is restricted to include only traders for whom data before and after joining the social network is available, and to those who made at least fifty round-trip trades (both market and limit orders). This trimming reduces the set to 2,598 traders for whom 59% of their trades occur after joining the social network. In unreported tests, the trimmed sample is similar to the discarded data with respect to trader's disposition effect.

[10]For example, see Ivanova et al. (2014), who provide a recent overview of the literature.

[11]See http://www.bloomberg.com/news/articles/2015-01-22/currency-broker-fxcm-crippled-by-leverage-in-swiss-shock for survey evidence.

Unless otherwise noted, the sample is restricted to these traders' market orders because it is well known that the connection between the disposition effect and limit orders can largely be attributed to adverse selection risk (Linnainmaa 2010). Moreover, limit orders in the retail market for foreign exchange exclusively refer to take-profit and stop-loss orders. On these transactions, the position is mechanically closed by the brokerage's trading platform. This presumably softens the link between investor psychology and a trade's execution.

Table 1 provides some basic summary statistics about the traders and trades in the trimmed sample (panel A), both before and after exposure to myForexBook (panels B and C, respectively). The table includes the number of trades per account (2,433 total trader accounts after limiting the data to market orders), as well as the number of observations at a gain and that involve a sale. A few variables potentially related to changes in the disposition effect are similar before and after a trader joins myForexBook. Traders are equally likely to take long positions in a currency pair, trade nearly as frequently per day, and trade the same number of distinct currency pairs.

[insert Table 1 about here]

While setting up their user profiles, myForexBook traders respond to a demographic survey. Traders indicate their years of trading experience and are able to choose from one of the following options: 0 - 1, 1 - 3, 4 - 5, or 5+ years. They also specify their preferred trading style, which is classified as technical, momentum, news, fundamental, or none-specific. Traders provide their age at the time of joining the network, as well as their location broadly defined by international region.[12] The nonresponse rate for these questions is as low as 2%.

Traders and their social networking activity can be briefly summarized in the following way: the median trader is thirty-six years old, is from the United States or Western Europe, has one to three years of experience, and is a self-reported technical trader (Table 2). The typical trader sends about five messages per week and has between fifteen and twenty friends.

1.3 Additional data sources

To explore the representativeness of the paper's empirical findings, I use two complementary account-level data sources. The first is a sample of 741 retail forex accounts obtained by myForexBook's operators. These traders are not part of the social network, but they trade during the same time period as those in the main sample. The second data set comes from a large discount brokerage and is widely used to study individual investors (Barber and Odean 2000b). The data includes over 70,000 individuals who held common stock between 1991 and 1996. Demographic characteristics are available for roughly 30,000 of these individuals, and I restrict the use of the discount brokerage data to these traders. For

[12] Traders are given the following options: United States, Europe, Asia/Pacific, or no response. Traders provide honest responses. The myForexBook database provides the primary currency – the currency in which a brokerage account was opened – for 68% of all trader's accounts. Only 2% of these traders' primary currency is different from the trader's self-identified location.

brevity, I direct readers to Chang, Solomon, and Westerfield (2016) for trade-level summary statistics and to Barber and Odean (2001) for a description of demographic characteristics. All tests using the discount brokerage data are presented in Appendix A.7.

I obtain forex prices from one of the largest brokerages, Oanda, which operates globally and bases its pricing on a live feed from the interbank market. Oanda publishes these data at ten minute intervals, using the nearest tick. I also use proprietary data from the Federal Communications Commission (FCC) on the number of broadband internet providers per U.S. ZIP code as of the end of the 1999, covering nearly all of the contiguous United States. I merge the FCC data with the discount brokerage data. Lastly, I use a concordance between ZIP codes and metropolitan statistical areas (MSA) from the U.S. Census Bureau.

2 Empirical Strategy

Empirically identifying peer effects is challenging for a few reasons (Manski 1993). The first is selection, whereby individuals choose to associate with their peer group. The second is the reflection problem. The peer group's influence on the individual is potentially indistinguishable from the individual's influence on the group. Third, unobservable shocks can simultaneously affect the individual and the peer group. Fortunately, random or quasi-random assignment of an individual to their peer group alleviates these identification concerns.

The myForexBook data are well positioned to conduct empirical tests that identify peer effects. The database contains many trades executed prior to the time at which the trader joins myForexBook. This feature enables a comparison of trading outcomes before and after traders are exposed to the social network's activity.

[insert Figure 2 about here]

Moreover, the myForexBook database offers a credible source of quasi-random variation in trader exposure to their peers. Agreements between myForexBook and partnering brokerages are a necessary precursor for traders to join the social network and interact with other myForexBook members. As Figure 2 illustrates, new brokerages partnered with myForexBook at a staggered rate over the course of the sample period. The slow process of incorporating new brokerages was caused by the need for legal and technological agreements between myForexBook's operators and partnering brokerages. The myForexBook interface extracts confidential trading records in real time from these brokerages, all of which have a unique database infrastructure. This means that myForexBook is not only required to reach a legal agreement with the brokerage, but it also has to make its software compatible with the structure of the brokerage's server.[13]

These brokerage agreements help identify peer effects, because they strongly predict the time at which traders join myForexBook. An ordinary least-squares (OLS) regression of a trader's join date on an indicator for each brokerage produces an F-statistic of 352.

[insert Table 2 about here]

[13]Providing a discrete example that includes the names of one or more retail brokerages would potentially compromise the identity of our data provider.

Additionally, the introduction of new traders into the network via these brokerage agreements is uncorrelated with observable trader characteristics. Table 2 provides a comparison of early and late entrants into myForexbook. Using *t*-tests for difference in means, I find that traders who join early in the sample are not statistically different from traders who join near the end in terms of trading style, experience, age, or location (Panel A). Probit models provide additional evidence that observable trader characteristics cannot explain which traders are the first to join myForexBook (Panel B). This finding is important for identification because traders who join myForexBook near the beginning of the sample can generally be thought of as being part of a treatment group, while traders who are excluded from joining myForexBook until late in the sample are more often part of the control group. When taking these results together, brokerage agreements appear to be a strong and unbiased predictor of exposure to the social network.

Furthermore, while the empirical strategy is well suited for identifying the effect of social interaction on traders who eventually join myForexBook, I provide evidence that these traders are not much different from other traders who are not members of myForexBook. Appendix A.1 compares trades made prior to joining myForexBook to trades made by the contemporaneous sample of 741 traders who never join myForexBook. Both sets of traders have a similar level of the disposition effect.

3 The Disposition Effect and Social Interaction

3.1 Preliminary evidence

Graphical evidence suggests that social interaction contributes to the disposition effect. Figure 3 plots estimates of a Kaplan-Meier survival function in which the outcome of interest is an indicator variable for closing a position. The survival function shows the cumulative density of executed trades as a function of the position's holding period. I separately plot the survival function for trades that execute at a gain and at a loss. If the fraction of gains sold exceeds the fraction of executed losses, a disposition effect occurs. The size of the vertical spread measures the disposition effect's magnitude.

[insert Figure 3 about here]

The left (right) panel includes trades executed prior to (after) joining myForexBook. A greater percentage of losses, compared with gains, go unsold at any given point in time, a gap that widens as the holding period on the trade increases. The gap between the paper-gain and paper-loss survival function is larger for trades issued after joining myForexBook. This suggests that social interaction is associated with increases in the disposition effect.

3.2 Regression analysis

I use regression analysis to more rigorously test the relation between social interaction and the disposition effect. To conduct the analysis, the following regression models include multiple observations per each trade i, one for every ten minute holding period t until the position closes. The dependent variable *sale* equals one in the period in which the position is closed by trader j and equals zero otherwise. The independent variable *gain* equals one if the current market price is above the asset's purchase price, zero otherwise.

I test for the disposition effect using a Cox proportional hazard model, because the model estimates the time until the occurrence of an event. In the Cox model,

$$h_i(t) = h_0(t)\, exp\left(\beta_1 gain_{ijt} + X'_{ijt}\beta\right) \tag{1}$$

the baseline hazard function is $h_0(t)$, and it measures the time until the trade is closed ($sale = 1$). The coefficient on *gain* reflects the change in the hazard rate when the position is a paper gain. A positive estimate of β_1 implies that traders are more likely to sell positions at a gain than at a loss. This indicates a disposition effect.

[insert Table 3 about here]

Estimates of Equation (1) support the connection between social interaction and the disposition effect (Table 3). For the sample of trades made before joining myForexBook, the rate at which trades are closed increases by 34% if the position is a gain (the odds-ratios in Column 1). Column 2 uses the sample of trades made after joining myForexBook. For these transactions, the rate at which trades are closed increases by 65% if the position is a gain. Both estimates are statistically significant at the 1% error level using standard errors clustered by trader. Column 3 pools both samples and estimates two distinct *gain* coefficients, one for transactions before and one for transactions after joining myForexBook. In addition to the large difference in magnitudes, the coefficients are statistically significantly different at the 5% error level according to a two-sided *t*-test.

The results are similar when I estimate the relation between social interaction and the disposition effect using OLS panel regressions with trader and calendar time fixed effects. The Cox model has a shortcoming: due to the maximum likelihood estimator, which can suffer from incidental parameters problem, incorporating a large number of fixed effects on the right-hand side is difficult (Lancaster 2000). The following OLS regression uses these fixed effects to account for unobserved heterogeneity across traders and calendar time, thereby strengthening the identification of social interaction's impact on the disposition effect:

$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{it}. \tag{2}$$

In Equation (2), trader and calendar time fixed effects are γ_j and γ_t, respectively. The regressions also include a set of indicators for the trade's holding period, one for every ten minute interval until the instrument is sold. The variable *postFB* equals one if the trade is opened after trader j joins myForexBook and is zero otherwise. The coefficient on the interaction term between *gain* and *postFB* measures the extent to which the disposition effect changes as a result of social interaction. As illustrated in Section 2, the staggered introduction of new traders from different brokerages into the myForexBook network suggests that *postFB* is uncorrelated with other trader attributes. Thus, β_3 is presumably an unbiased estimator of the average treatment effect of social interaction on traders' disposition effect.

[insert Table 4 about here]

The panel regression estimates strengthen the evidence that social interaction increases traders' disposition effect (Table 4). Columns (1) and (2) estimate Equation (2) using the sample of trades made prior to and after joining myForexBook, respectively. The coefficient on *gain* in column (1) is equal to 0.021 (SE = 0.002) and this suggests traders are about two percentage points more likely to sell positions at a gain at any given holding period. This implies a disposition effect similar in magnitude to other studies of common-stock holders (Chang, Solomon, and Westerfield 2016). In column (2), the coefficient estimate equals 0.037 (SE = 0.008). Similar to the Cox estimates, the coefficient using the post-entry data is nearly double the size of the coefficient using the pre-entry data.

The difference-in-differences estimates offer further support for social interaction's connection to the disposition effect. In Column (3), the estimate of β_3 is around 0.015 (SE = 0.003). The regression presented in Column (4) contains weekly fixed effects on the right-hand side to account for common, time-invariant shocks that could confound the relationship between social interaction and the propensity to execute trades. Column (5) adds the amount of leverage used on the trade as an independent variable. Trades that use more leverage can reflect a greater degree of confidence in the trader's beliefs about the value of an asset and therefore may correlate with the reluctance to unload losing positions. In both cases, the estimate of β_3 is quantitatively similar to 0.015 and statistically significant at the 5% error level. Relative to the coefficient value of around 0.02 on the pre-myForexBook data, these estimates imply that increased social interaction almost doubles trader susceptibility to the disposition effect.

3.3 Robustness checks

I find similar results when I address concerns about the potential endogeneity of the brokerages and the time at which they partner with myForexBook. Table 5 presents OLS estimates of Equation (2) that replaces trader fixed effects with indicators for the month a trader joins myForexBook (Column 1), brokerage fixed effects (Column 2), and their interaction (Column 3). The coefficient estimates on the interaction between *postCS* and *gain* are not meaningfully different from earlier tests. If changes in the disposition effect are related to brokerage-specific factors, these regression estimates broadly account for this concern.

[insert Table 5 about here]

An instrumental variables (IV) approach also supports the paper's main findings. Appendix A.2 includes IV estimates of Equation (2). These estimates use a trader's brokerage (*broker.id*) to instrument for $postFB$. Specifically, following Balli and Sorensen's (2013) treatment of interaction terms in an IV model, I use *broker.id* as an instrument for $postFB$ and $gain \times broker.id$ to instrument for $gain \times postFB$. Using 2SLS estimation, the coefficient estimates on the interaction term between $postFB$ and *gain* are slightly less than 0.06, more than three times as large as the OLS estimates. In addition, the uninteracted coefficient on *gain* is not statistically different from zero.

Furthermore, I test the sensitivity of the regression analysis to different market conditions and find the estimates of the interaction between *gain* and $postFB$ to be mostly unchanged. Presented in Appendix A.3, the effect of joining myForexBook is similar after sorting the data into periods of high and low market volatility, by the day of the week, or by the time of day. These tests provide evidence that the results are unlikely caused by market-based shocks common to these traders.

3.4 A placebo exercise

A placebo exercise measures how likely it is that the difference-in-differences model produces false-positive estimates. The placebo test estimates Equation (2) while recoding the date on which traders join myForexBook, rolling it backwards one week at a time, for a total of fifty regressions. Each time that I roll back $postFB$, I collect the t-stats from the interaction term on $postFB$ and $gain$. These regressions also exclude any trades that are opened following entrance into myForexBook so that the placebo coefficients are uninfluenced by social interaction. I use the sample of foreign exchange traders who never join myForexBook as the control group in this analysis. To assist the reader, Figure 4, panel A, provides an illustration of the placebo test's methodology.

[insert Figure 4 about here]

The placebo exercise provides evidence that the regression tests of social interaction on the disposition effect are unlikely to give false-positive results. Panel B of Figure 4 presents the distribution of t-statistics from the falsification test. The distribution is approximately normal and only 2.5% of t-statistics exceed 1.96.

The results of this placebo exercise address at least two concerns. First, the test provides evidence that the results are not caused by spurious trends in the disposition effect that increase over the course of the sample period, which would deflate the regression model's standard errors (Bertrand, Duflo, and Mullainathan 2004). Second, by using traders who never join myForexBook as a control group, the placebo exercise shows that myForexBook traders are no more or less susceptible to unrelated fluctuations in the disposition effect. The estimates of β_3 could have picked up these fluctuations and falsely attributed disposition effect increases to myForexBook.

4 What Are the Social Mechanisms?

A challenge for empirical research on social interaction is that even after peer effects are identified, it is often not possible to distinguish between different theories of social interaction (Manski 2000).[14] Regardless, I attempt to better understand the empirical connection between social interaction and the disposition effect by using the assumption that social connections benefit traders.

Traders could be better off by making social connections either because they help improve trading performance or there are other, less easily measured utility gains from social interaction. In line with former, Ozsoylev et al. (2014) empirically and theoretically show

[14] Appendix Section A.4 presents an overview of some common theories of social interaction.

that better connected investors earn higher profits, while myForexBook traders earn modestly higher returns after exposure to the network (Appendix Section A.5, Table A.6). In line with latter, some argue that there is "social utility" (Becker 1974) or that social interaction reduces participation costs through informal learning (Hong, Kubik, and Stein 2001). Given these gains from social interaction, it is conceivable that traders' decisions would reflect a desire to build or maintain social connections, particularly if obtaining the benefits of friendship requires the friend's consent. Indeed, traders who experience the largest increase in the disposition effect (the component driven by joining myForexBook) more successfully make connections as measured by the ratio of friendship requests accepted to requests denied (Appendix A.5, Table A.6). Thus, the social finance effects documented in Section 3, could be consistent with an explanation for the disposition effect that has a conceptually different flavor than other disposition effect mechanisms, many of which rely on cognitive mistakes or nonstandard utility functions.

While acknowledging that the empirical results can accommodate a larger set of theories, I further explore further the effect of a desire to present a positive self-image to network peers. To cast oneself favorably, individuals prefer to talk about (conceal) positive (negative) outcomes. Consequently, the option to engage in social interaction amplifies the utility (dis-utility) of gains (losses). A trader is more willing to accept a smaller gain if social benefits can also be exercised. The trader is loss averse because of social norms favoring winning individuals. The following empirical tests are consistent with these impression management strategies contributing to the connection between social interaction and the disposition effect:

IMPLICATION 1: *Traders who expect to benefit most from social interaction are more likely to defer losses and realize gains. They have higher levels of the disposition effect*.

IMPLICATION 2: *Traders from the same community or peer group have correlated levels of the disposition effect*. The likelihood of benefiting from social interaction is a function of the community one belongs to. Therefore, any two traders from the same peer group or community are likely to have similar levels of the disposition effect.

IMPLICATION 3: *Traders with more of a disposition effect communicate selectively and, therefore, less often*. Traders broadcast victories and hide when losing. Suppose gains and losses are equally likely. Then traders who care about their self-image initiate communication half the time. Meanwhile, all traders i have some innate level of chattiness and, therefore, some probability of talking at time t, $Pr_t\left(talk_i\right)$. Therefore, the socially motivated trader communicates with frequency $1/2 \cdot Pr_t\left(talk_i\right)$, which is less than $Pr_t\left(talk_i\right)$.

4.1 The disposition effect, social interaction, and trader experience

The first implication is that traders with the greatest desire to form social connections have the the greatest increase in the disposition effect as a function of social interaction.

Novice traders presumably expect the greatest marginal benefit from establishing social connections. Therefore, the social network's influence on the disposition effect would be strongest among inexperienced traders.

[insert Table 6 about here]

Empirical evidence supports the connection between increases in the disposition effect and trader inexperience. Table 6 presents the results from estimating Equation (2) partitioned by trader experience level. Column (1) includes only traders who have less than one year of experience, and Column (2) includes traders who have one to three years of experience. The coefficient on the interaction term between *gain* and *postFB* is equal to 0.0071 in the former and 0.021 in the latter, and both are statistically significant at the 5% error level. Meanwhile, Column (3) includes traders with four years of experience, and Column (4) includes those with at least five years. The coefficient estimate on the interaction term is not statistically different from zero in Columns (3) or (4).

4.2 Correlated disposition effect within trader subcommunities

The characteristics of a community affect the desire to manage one's self-image. Because a pair of linked (befriended) traders is more likely than unconnected traders to be a part of the same community, connected traders are more likely to be subject to similar social pressures. The empirical implication is that connected traders have correlated levels of the disposition effect, even within a large social network such as myForexBook, graphed in Figure 5.

The following outlines the empirical approach I use to determine whether myForexBook friends have correlated levels of the disposition effect. First, I calculate how susceptible each individual trader is to the disposition effect. Second, I take the absolute difference in the disposition effect between traders who have have formed a friendship. Finally, I compare the distribution of these friendships to a network formed by simulation, in which traders randomly choose their connections. The simulated network provides a statistical benchmark by which to judge how much correlation there would be between befriended traders if the network formed randomly.

To determine how susceptible each trader is to the disposition effect, I estimate the following regression for each trader j:

$$sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it} \; \forall j. \tag{3}$$

The coefficient β_1 represents each trader's idiosyncratic susceptibility to the disposition effect. These estimates of Equation (3) use trades executed after j joins myForexBook.

Next, I quantify the correlation in the disposition effect between each pair of myForexBook friends by using the following equation:

$$DE\,dif_{jk} = |\beta_1(j) - \beta_1(k \neq j)|, \tag{4}$$

where traders j and $k \neq j$ are friends. Values of $DE\,dif_{jk}$ close to zero suggest similar levels of the disposition effect between connected traders.

A social network formed by simulation offers a benchmark for comparison. Friendships in the simulated network are made by drawing any two traders at random with replacement. To make the simulations more realistic, the distribution of the number of friends that a trader has is the same in the simulated data as in the real data. For example, by the end of the sample, sixty-three traders in the myForexBook network have ten friends. In the simulations, I allow sixty-three of the simulated traders to connect with ten friends. I simulate the formation of the network one thousand times. After each simulation, $DE\,dif_{jk}$ is sorted from smallest to largest, and I take the row's average across the simulations.

[insert Figure 6 about here]

Connected traders have correlated levels of the disposition effect according to the empirical results. The left frame of Figure 6 presents the distribution of $DE\,dif_{jk}$. The right frame presents results from the simulations. The histogram of actual friendships has a larger mass concentrated toward zero than the simulated network, and this suggests that traders who are similarly susceptible to the disposition effect tend to form friendships. Indeed, the actual and simulated distributions of $DE\,dif_{jk}$ are statistically different. A Kolmogorov–Smirnov test rejects the hypothesis that the actual distribution of friendships is equal to the simulated distribution of random trader pairings (p-value = 0.00).

I replicate this finding using data from a large discount brokerage (Barber and Odean 2000b). In particular, geographical variation is similar to the community variation within the myForexBook network. Using spatial variation as a proxy for peer effects, Appendix A.7 presents several findings that are consistent with these tests. First, I document statistically meaningful variation in the disposition effect across MSAs. These differences across regions can reflect different preferences or economic shocks, as well as peer effects. To better isolate the component due to peer effects, I adopt Pool, Stoffman, and Yonker's (2015) identification strategy and show that any given pair of traders from the same ZIP code has more correlation in the disposition effect than two traders from different ZIP codes, even within the same MSA. These results enhance the peer effects interpretation, because aggregate shocks are likely to occur at the regional level, while geographically close traders are more likely to have personal interaction.

4.3 Communication and the disposition effect

Traders most susceptible to the disposition effect initiate communication with others less frequently, because they prefer to interact with others when performing well. They also attempt to attract attention from others in the network and the most effective way to do so is via the peer-to-peer messaging device (traders can send peer-to-peer messages to anyone in the network, not just their current friend group).[15]

The following regression model utilizes the issuance and direction of peer-to-peer messages to estimate the relationship between the disposition effect and the intensity of communication:

$$log(1 + messages_j) = \beta_0 + \beta_1 \cdot trader.DE_j + \beta_2 \cdot controls_j + \varepsilon_j, \tag{5}$$

where $messages_j$ is the count of the number of peer-to-peer messages sent (received) by trader j following entrance into the social network. The independent variable, $trader.DE$, is equal to $\beta_1(j)$, a trader's idiosyncratic susceptibility to the disposition effect, estimated using Equation (3). To assist the interpretation of the regression, $trader.DE$ is normalized such that a one-unit increase is equal to a one-standard-deviation increase. The empirical

[15] The data provider did not provide the content of the user messages.

model is estimated with standard errors clustered by the month in which the trader joins myForexBook.

[insert Table 7 about here]

There is a negative relationship between initiating communication and the disposition effect, according to estimates of Equation 5 (Table 7). Columns (1) through (3) use the number of messages sent as a dependent variable. Column (1) estimates the binary relation between the variables of interest and produces an estimate of β_1 equal to -0.070 (SE = 0.030). This implies that a standard deviation increase in the disposition effect is associated with about 7% fewer messages sent to other traders.[16] Column (2) includes a set of dummy variables for the month j joins the social network, and this accounts for the variation in the time spent using myForexBook. Column (3) includes a set of individual-specific control variables, including trader experience, region, and approach. The estimates of β_1 are negative and statistically meaningful in both alternative specifications.

The relationship between the disposition effect and sending messages does not simply capture a trader's integration into the network. The negative relationship between sending messages and the disposition effect could instead reflect a trader's response to communications directed toward him. Columns (4) through (6) estimate specifications identical to columns (1) through (3), but the dependent variable is instead the number of peer-to-peer messages received by trader j. These estimates of β_1 are not statistically different from zero.

5 Alternative Explanations for the Disposition Effect

This section examines – in alphabetical order – several alternative explanations for the disposition effect, while considering how these explanations could relate to the effect of social interaction.

5.1 Adverse selection

Retail traders are often considered less informed than their institutional counterparts. Because of these information asymmetries, retail traders are subject to adverse selection risk. When information shocks occur, price-contingent orders are a free option to informed market participants. Therefore, limit orders issued by retail traders are likely to execute following new information about fundamentals and do not execute otherwise. This pattern mechanically produces a disposition effect (Linnainmaa 2010).

[insert Table 8 about here]

Social networks potentially change the information about market conditions available to each trader. This new information could influence traders' order submission strategies vis-à-vis the limit order effect documented by Linnainmaa (2010). As a consequence,

[16] The estimated effect of $trader.DE_j$ on $messages_j$ is equal to e^{β}.

the effect of social interaction would be entangled with adverse selection risk, causing differences in the disposition effect before and after joining the social network.

According to the evidence in Table 8, social interaction's impact on the disposition effect is likely to be distinct from the limit order effect. Table 8's tests include all transactions – both market and limit orders – made by the set of traders who survive the data filtering outlined in Section 1. After pooling both transaction types, the coefficient on *gain* and $postFB$ for market orders remains about equal to 0.015 and is statistically significant, even with trader fixed effects and standard errors clustered by trader. On the other hand, the social network does not affect the execution probability of limit orders for gains or losses according to evidence from these tests.

5.2 Cognitive dissonance and blame delegation

Cognitive dissonance is another explanation for the disposition effect (Chang, Solomon, and Westerfield 2016). The theory is supported by evidence that investors are more willing to unload delegated assets when they underperform, because blame can be assigned to an asset manager. Simultaneously, these individuals have a self-attribution bias, which means they struggle to admit having made poor decisions about their self-managed trades.

[insert Table 9 about here]

Evidence that blame delegation does not explain myForexBook's relation to the disposition effect comes from an examination of different relationship types between connected traders. Social interaction's impact on the disposition effect would primarily affect novice traders who are friends with experienced traders, because the relationship is presumably comparable to that of an investor's reliance on a portfolio manager for guidance. Table 9 presents the estimates of β_3 after sorting the data along two dimensions: j's trading experience and the average experience of j's friends. These estimates of β_3 exhibit no clear patterns. Therefore, myForexBook's influence on the disposition effect is independent of the relationship types that form.

Alternatively, this paper's findings are likely to complement the cognitive dissonance theory. Self-attribution increases the reluctance to admit trading mistakes. In the context of this paper, traders want credit for trading victories, because it conforms with the desire to present a positive self-image. This mechanism is similar in spirit to a self-attribution bias.

5.3 Mean reversion beliefs

A belief in mean reversion can cause the disposition effect (Odean 1998). Social interaction could reinforce these beliefs. I test this explanation by exploiting variation in traders' revealed trading strategies.

The traders in myForexBook state their preferred trading strategy upon joining the social network, and these strategies can be roughly ranked in order of a revealed belief in mean reversion. The myForexBook interface allows the following responses: *News, Momentum, Technical, Fundamental,* and *NonSpecific.* Fundamental traders believe the most in mean reversion, while momentum traders believe the least. Traders who use technical and news-based strategies would presumably fall somewhere in between.

[insert Table 10 about here]

If social interaction increases beliefs in mean reversion, there should be strong differences in the effect on traders who use momentum and fundamental strategies, but there is no evidence to support this hypothesis. Table 10 presents estimates of Equation 2 after sorting trades by a trader's preferred strategy. I include limit orders in these regressions, because they play an important role in certain trading strategies, such as technical analysis. The coefficient on the interaction term between *gain* and *postFB* for market orders is positive in all regressions. The coefficient is equal to 0.015 (SE = 0.007) when the regression includes trades from fundamental traders (Column 1) and 0.011 (SE = 0.07) for momentum traders (Column 2). Moreover, these coefficient magnitudes are not larger or smaller than the effect on traders with other strategies. The effect of social interaction is weakest for traders who use news or technical strategies (β_3 is approximately equal to 0.006 in both columns 3 and 4) and strongest for those with no specific strategic preference ($\beta_3 = 0.028$ in column 5).

5.4 Trader enthusiasm from realized gains

Another alternative explanation is that temporary good performance (more realized gains) makes traders more interested in trading and everything related to it, including the use of social networking platforms like myForexBook. Hence, the same factors that caused increased portfolio turnover following the introduction of online trading (Barber and Odean 2002), would cause spurious correlation between myForexBook and the disposition effect.

Increases in the disposition effect are better explained by social interaction than by investor enthusiasm. First, investor enthusiasm would cause an initial burst of excitement around the time of joining myForexBook that ultimately diminishes over time as a trader experiences some losses. Figure 7 examines how the magnitude of the disposition effect changes over time within a trader's account. The figure presents estimates of β_1 from Equation (2) after sorting trades by distance (trade time) since joining myForexBook. For example, the first quartile includes the first 25% of trades issued chronologically within each trader's account after joining the network.[17] The coefficient estimate has a discrete jump in the quartile after joining myForexBook. Following the discrete increase, there is a slight upward trend in the disposition effect in subsequent quartiles. Thus, social interaction's influence on the disposition effect is persistent and this refutes this alternative explanation.

[insert Figure 7 about here]

The Appendix provides further evidence that increases in the disposition effect are not related to the introduction of online trading or the adoption of new trading technologies. I merge the discount brokerage data (Barber and Odean 2000b) with geographic variation in broadband internet penetration in the late 1990s. Using regression analysis, I interact

[17] The use of "trade-time" rather than calendar time addresses concern over variation in the degree to which different traders cluster or spread out their trading activity over time. It roughly balances the contribution of each trader to each regression estimate.

gain with *broadband*, the number of broadband internet providers per U.S. ZIP code. The coefficient on the interaction term captures the effect of increased internet access on the disposition effect. The coefficient's magnitude is small and not statistically different from zero across a reasonable set of specifications. Thus, there is scant evidence that new trading technologies can explain why traders exhibit the disposition effect.

6 Conclusion

The disposition effect – the tendency to sell winning assets and the reluctance to let go of losing assets – is considered a deviation from rational trading behavior. It is widely found across asset classes and even among traders who are not typically considered to be behaviorally biased. Most puzzling is that those most likely to exhibit the disposition effect seem to be the least likely to trade, according to leading theories. Social interaction is often linked to increased trading, and this paper provides evidence that social interaction jointly contributes to the disposition effect. I document the relationship between social interaction and the disposition effect using the introduction of an online social networking platform into the world of retail trading. The social networking features were made available to traders on different brokerages at a staggered rate over time and this enabled causal tests of peer effects.

These findings suggest a number of avenues for future research. The disposition effect is among the most robust findings in the literature on trading, which makes it ripe for studying. Yet solutions to other behavioral puzzles are potentially rooted in social interaction. For example, some have suggested that overconfidence develops when individuals compare themselves to their peers (Burks et al. 2013).

Furthermore, this paper highlights the difficulty in using observational data to distinguish between different theories of social interaction. Considering the empirical challenges, there have been a few recent attempts using field experiments (Bursztyn et al. 2014) and the laboratory (Frydman 2014), but there is much room for additional research. In particular, this paper tries to understand why social networks contribute to the disposition effect by arguing that peers may have a more favorable view of traders with recent wins relative to those with recent losses. This peer pressure motivates traders to worry about their self-image and alter their trading decisions.

Table 1: **Trader and trade-level summary statistics**

This table presents summary statistics for the myForexBook database. The data are trimmed to include traders who make trades both before and after joining myForexBook and who have executed at least fifty trades (both market and limit orders). This table presents summary statistics for the sample of these traders' market orders. For the variables "observations at a gain" and "observations involving a sale", the unit of observation is a trade-holding period observation, one for every ten minutes until the trade is closed, inclusive.

	Mean	SD	Median	*N*
A. All trades				
Trades per account	159.27	792.33	66.0	2,433
Fraction trades long per account	0.54			2,433
Distinct currency pairs traded at least once per account	5.66	3.16	6.0	2,433
Trades per account/day	4.00	13.03	2.0	96,770
Observations at a gain	0.40			2,912,925
Observations involving a sale	0.073			2,912,925
B. Pre-myForexBook				
Trades per account	80.88	177.86	35.0	2,164
Fraction trades long per account	0.54			2,164
Distinct currency pairs traded at least once per account	4.61	3.00	4.0	2,164
Trades per account/day	3.75	5.06	2.0	46,716
Observations at a gain	0.41			1,301,466
Observations involving a sale	0.075			1,301,466
C. Post-myForexBook				
Trades per account	97.91	775.48	24.0	2,170
Fraction trades long per account	0.54			2,170
Distinct currency pairs traded at least once per account	4.46	2.98	4.0	2,170
Trades per account/day	4.23	17.40	2.0	50,256
Observations at a gain	0.40			1,611,459
Observations involving a sale	0.072			1,611,459

Table 2: **A comparison of the first and last traders to join myForexBook**

This table compares the first 250, 500, and 1,000 traders to join myForexBook ($first_i$) to the last 250, 500, 1,000 traders to join ($last_i$). The data-provider chose the categories used by the following variables. The survey responses are obtained while traders sign up for myForexBook. Panel A includes a comparison of means. Panel B estimates a probit model in which the dependent variable $first_i$, is equal to one if a trader is among the first set of traders to join myForexBook and equal to zero if the trader is among the last to join. Standard errors are in parentheses, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

***A*. Difference in means between first and last to join myForexBook**

First/last network entrants	250			500			1,000		
Variable	$first_i$	$last_i$	t^a	$first_i$	$last_i$	t^a	$first_i$	$last_i$	t^a
age_i	36.384	35.216	*1.31*	35.797	35.406	*0.61*	36.488	36.198	*0.63*
$experience_i^{\dagger}$									
0 - 1	0.364	0.36	*0.09*	0.372	0.356	*0.53*	0.340	0.329	*0.52*
1 - 3	0.460	0.452	*0.18*	0.448	0.446	*0.06*	0.471	0.462	*0.40*
3 - 5	0.072	0.092	*-0.81*	0.078	0.086	*-0.46*	0.091	0.074	*1.38*
5 +	0.100	0.080	*0.78*	0.096	0.100	*-0.21*	0.094	0.128	*-2.42*
$trading.approach_i^{\ddagger}$									
momentum	0.056	0.048	*0.40*	0.066	0.062	*0.26*	0.058	0.058	*0.00*
news	0.036	0.024	*0.79*	0.026	0.030	*-0.38*	0.022	0.026	*-0.58*
technical	0.648	0.676	*-0.66*	0.622	0.650	*-0.92*	0.706	0.632	*3.53*
not specific	0.204	0.220	*-0.44*	0.238	0.210	*1.06*	0.175	0.232	*-3.17*
$location_i^{\xi}$									
Asia/Pacific	0.192	0.184	*0.23*	0.218	0.218	*0.00*	0.176	0.184	*-0.47*
Europe	0.424	0.404	*0.45*	0.412	0.412	*0.00*	0.404	0.454	*-2.26*
United States	0.364	0.380	*-0.37*	0.348	0.350	*-0.07*	0.406	0.345	*2.82*

[a] Test of equality of means among $first_i$ and $last_i$ to join myForexBook

***B*: Probit model estimates of being among the first to join myForexBook**

First/last network entrants:	250		500		1,000	
Dep var: $first_i = 1$	Coef	(SE)	Coef	(SE)	Coef	(SE)
age_i	0.00691	(0.0058)	0.00262	(0.0040)	0.00139	(0.0028)
$experience_i^a$						
0 - 1	0.889	(0.69)	0.526	(0.45)	0.320	(0.39)
1 - 3	0.908	(0.69)	0.511	(0.45)	0.284	(0.39)
3 - 5	0.760	(0.72)	0.442	(0.47)	0.405	(0.40)
5 +	1.016	(0.71)	0.468	(0.46)	0.0681	(0.40)
$trading.approach_i^b$						
momentum	-0.238	(0.37)	0.0184	(0.24)	0.162	(0.18)
news	-0.0820	(0.44)	-0.105	(0.30)	0.0554	(0.23)
technical	-0.380	(0.29)	-0.0406	(0.19)	0.256*	(0.14)
not specific	-0.386	(0.30)	0.0702	(0.20)	-0.000292	(0.15)
$location_i^c$						
Asia/Pacific	0.215	(0.40)	-0.123	(0.30)	0.0248	(0.24)
Europe	0.235	(0.38)	-0.122	(0.29)	-0.0193	(0.23)
United States	0.131	(0.38)	-0.139	(0.29)	0.164	(0.23)
$constant$	-0.976	(0.77)	-0.458	(0.52)	-0.571	(0.45)
Number of traders	500		1000		2000	
Pseudo R^2	0.012		0.0026		0.012	

[a]Omitted category is *no response*

[b]Omitted category is *fundamental*

[c] Omitted category is *nonspecific*

Table 3: **Social interaction and the disposition effect: Hazard estimates**

This table presents estimates of the determinants of the hazard rate to closing a position using the following Cox-proportional hazard model:

$$h_i(t) = h_0(t)\, exp\left(\beta_1 gain_{ijt} + X'_{ijt}\beta\right).$$

The model includes multiple observations per each trade *i*, one for every 10-minute holding period until the position closes. The baseline hazard function $h_0(t)$ measures the time until the trade is sold. The variable, *gain*, equals one if the position is a paper gain in period t, and $preFB$ ($postFB$) equals one if *i* was opened before (after) trader *j* joined myForexBook. All specifications stratify the baseline hazard function by calendar date (weekly). The pre-(post-)myForexBook samples are the set of trades executed before (after) each trader *j* joined myForexBook. Standard errors in parentheses are clustered by trader, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	Pre-myForexBook		Post-myForexBook		Full sample	
	(1)		(2)		(3)	
	Coef	[*odds-ratio*]	Coef	[*odds-ratio*]	Coef	[*odds-ratio*]
Gain ...	0.295***	[*1.343*]	0.503***	[*1.654*]	-	
	(0.019)		(0.08)		-	
... × preFB					0.294***	[*1.342*]
					(0.019)	
... × postFB					0.501***	[*1.651*]
					(0.08)	
PostFB					-0.130	[*0.878*]
					(0.088)	
Observations	1,301,466		1,611,459		2,912,925	
Number of trades	177,511		215,359		392,870	

Table 4: **Social interaction and the disposition effect: Panel estimates**

This table presents results from using the myForexBook data to estimate the following OLS regression:

$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{ijt}.$$

The regression model includes multiple observations per each trade *i*, one for every ten minute holding period until the position closes. The dependent variable *sale* equals one if trader *j* closes position *i* in period *t*. The independent variable *gain* equals one if the position is a paper gain in period *t*, and *postFB* equals one if the position was opened after *j* joined myForexBook. Trader and calendar time fixed effects are γ_j and γ_t, respectively. The regressions include holding period fixed effects, which is a set of indicator variables for every ten minute interval starting after the position opens. Standard errors are double clustered by day and trader, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	Pre-myForexBook	Post-myForexBook	Full sample		
Sale	(1)	(2)	(3)	(4)	(5)
Gain	0.0213***	0.0367***	0.0226***	0.0226***	0.0224***
	(0.0020)	(0.0084)	(0.0017)	(0.0017)	(0.0017)
PostFB			-0.00842	-0.00768	-0.00756
			(0.0052)	(0.0048)	(0.0048)
Gain × postFB			0.0140**	0.0146**	0.0149**
			(0.0077)	(0.0074)	(0.0075)
Leverage					0.00400***
					(0.00075)
Holding period FE	x	x	x	x	x
Currency pair FE	x	x	x	x	x
Trader FE	x	x	x	x	x
Week FE				x	x
Observations	1,301,466	1,611,459	2,912,925	2,912,925	2,874,465
Number of trades	177,511	215,359	392,870	392,870	387,312
Adj. R^2	0.0016	0.0048	0.031	0.032	0.031

Table 5: **Social interaction and the disposition effect with brokerage fixed effects**

This table presents the results from using the myForexBook data to estimate the following OLS regression:

$$sale_{ijt} = \gamma_m + \gamma_b + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{ijt}.$$

The estimates include fixed effects for the month trader j joins myForexBook (γ_m) and fixed effects for j's brokerage (γ_b), and their interaction. All columns include holding period, currency pair, and week fixed effects. The setup of the data, as well as the other variables, is described in previous tables. Standard errors are double clustered by day and trader, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Sale	(1)	(2)	(3)
Gain	0.0227***	0.0223***	0.0234***
	(0.00079)	(0.00082)	(0.0012)
PostFB	-0.00886**	-0.00512	-0.00469
	(0.0043)	(0.0041)	(0.0033)
Gain × postFB	0.0137**	0.0141**	0.0139**
	(0.0066)	(0.0069)	(0.0066)
Month join network FE	x		
Brokerage FE		x	
Month join network × brokerage FE			x
Observations	2,912,925	2,912,925	2,912,925
Number of trades	392,870	392,870	392,870
Adj. R^2	0.032	0.032	0.037

Table 6: **The disposition effect by trader experience**

This table presents the OLS estimates from the regression,

$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{ijt},$$

using data from the myForexBook database. Regressions are estimated after sorting the data by trader experience. The operators of myForexBook chose the year categories used to sort the traders. The setup of the data, as well as the variables, have been described in the previous tables. Standard errors are double clustered by day and trader, and ***, **, and * denote significance at $p < 0.010$, $p < 0.05$, and $p < 0.01$, respectively.

	Trading experience (years) =			
	0-1	1-3	4	5+
Sale	(1)	(2)	(3)	(4)
Gain	0.0236***	0.0232***	0.0192***	0.0210***
	(0.0024)	(0.0027)	(0.0034)	(0.0034)
PostFB	-0.00807**	-0.00593	0.0130	-0.00691
	(0.0033)	(0.0045)	(0.0086)	(0.0062)
Gain × postFB	0.00702**	0.0207**	-0.00114	0.00651
	(0.0032)	(0.0074)	(0.0044)	(0.0044)
Holding period FE	x	x	x	x
Currency pair FE	x	x	x	x
Trader FE	x	x	x	x
Week FE	x	x	x	x
Observations	710,872	1,563,267	206,683	412,464
Number of trades	102,714	203,152	29,363	55,016
Adj. R^2	0.034	0.030	0.038	0.030

Table 7: **The disposition effect and communication between traders**

This table presents the results from using the myForexBook data to estimate the following OLS regression:

$$log(1+messages_j) = \beta_0 + \beta_1 \cdot trader.DE_j + \beta_2 \cdot controls_j + \varepsilon_j,$$

where *messages* is the number of peer-to-peer personal messages sent (received) by trader j. The independent variable $trader.DE$ is equal to $\beta_1(j)$ from the following regression individually estimated for each trader j, $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$. I normalize $trader.DE$ so that a one-unit increase is equal to a one-standard-deviation increase (Z). Standard errors are clustered by trader experience, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	$log\,(sent.messages_j)$			$log\,(received.messages_j)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Trader.DE (Z)	-0.0700**	-0.0667**	-0.0607**	-0.0216	-0.0199	-0.00665
	(0.030)	(0.029)	(0.029)	(0.018)	(0.016)	(0.015)
Log number of trades			0.0998***			0.190***
			(0.028)			(0.015)
Constant	x	x	x	x	x	x
Month join network FE		x	x		x	x
Trading region FE			x			x
Trading experience FE			x			x
Trading approach FE			x			x
Number of traders	2,598	2,598	2,598	2,598	2,598	2,598
R^2	0.0022	0.032	0.043	0.00056	0.17	0.29

Table 8: **The disposition effect accounting for adverse selection risk**

This table presents results from using the myForexBook data to estimate the following regression using OLS:

$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \beta_4 \cdot limit.order_{ijt} + \beta_5 \cdot gain_{ijt} \times limit.order_{ijt} \ldots$$
$$\ldots + \beta_6 \cdot postFB_{ijt} \times limit.order_{ijt} + \beta_7 \cdot gain_{ijt} \times postFB_{ijt} \times limit.order_{ijt} + \varepsilon_{ijt}.$$

The variable $limit.order$ is an indicator for positions closed mechanically by the brokerage's trading platform using a price-contingent order, either a stop-loss or take-profit. The setup of the data, as well other variables, have been described in previous tables. Standard errors are double-clustered by day and trader, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Sale	Sample of limit orders (1)	Pooled sample, market and limit orders (2)
Gain	-	0.0224***
		(0.0018)
PostFB	-	-0.00858
		(0.0053)
Gain × postFB	-	0.0143**
		(0.0071)
Limit order	-	-0.0147***
		(0.0032)
Gain × limit order	0.0263**	0.00371
	(0.0018)	(0.0023)
PostFB × limit order	0.00315	0.0116**
	(0.0024)	(0.0057)
Gain × postFB × limit order	-0.00142	-0.0154**
	(0.0022)	(0.0073)
Holding period FE	x	x
Currency pair FE	x	x
Trader FE	x	x
Week FE	x	x
Observations	4,550,158	7,463,083
Number of trades	571,029	963,899
Adj. R^2	0.019	0.024

Estimates of sale probability predicted by model (2)

Order type	$Pr(sale\|gain) - Pr(sale\|loss)$ PostFB = 1	PostFB = 0	Difference
Market:	0.0366***	0.0224***	*0.143***
	(0.0075)	(0.0018)	*(0.0071)*
Limit:	0.0249***	0.0261***	*-0.00116*
	(0.0017)	(0.0018)	*(0.0022)*

Table 9: **The disposition effect and relationship types in the network**

This table presents estimates of β_3 from the following OLS regression:

$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{ijt}.$$

Prior to each regression, the data is sorted as follows. The columns indicate the fraction of trader j's friend group constituted by traders with at least four years of experience. Traders with the lowest fraction of friends with at least four years of experience are placed in the first quartile, and a trader with highest fraction of friends with at least four years of experience are included in the fourth quartile. The rows sort traders j by their own trading experience as described in Table 6.

Coefficient on interaction term from disp. effect regression

		Percent of trader j's friends w/ $\geq$ 4 years experience (quartiles)			
		1st	2nd	3rd	4th
	0 - 1	0.00549	0.0120	0.00454	0.00703
Trader j's	1 - 3	0.0122	0.00422	0.0303	0.00532
Trading experience (years)	4	-0.00598	0.00419	0.000949	-0.00956
	5+	0.00816	0.00607	0.00641	0.00247

Table 10: **The disposition effect by trading strategy**

This table presents the results from using the myForexBook data to estimate the following regression:

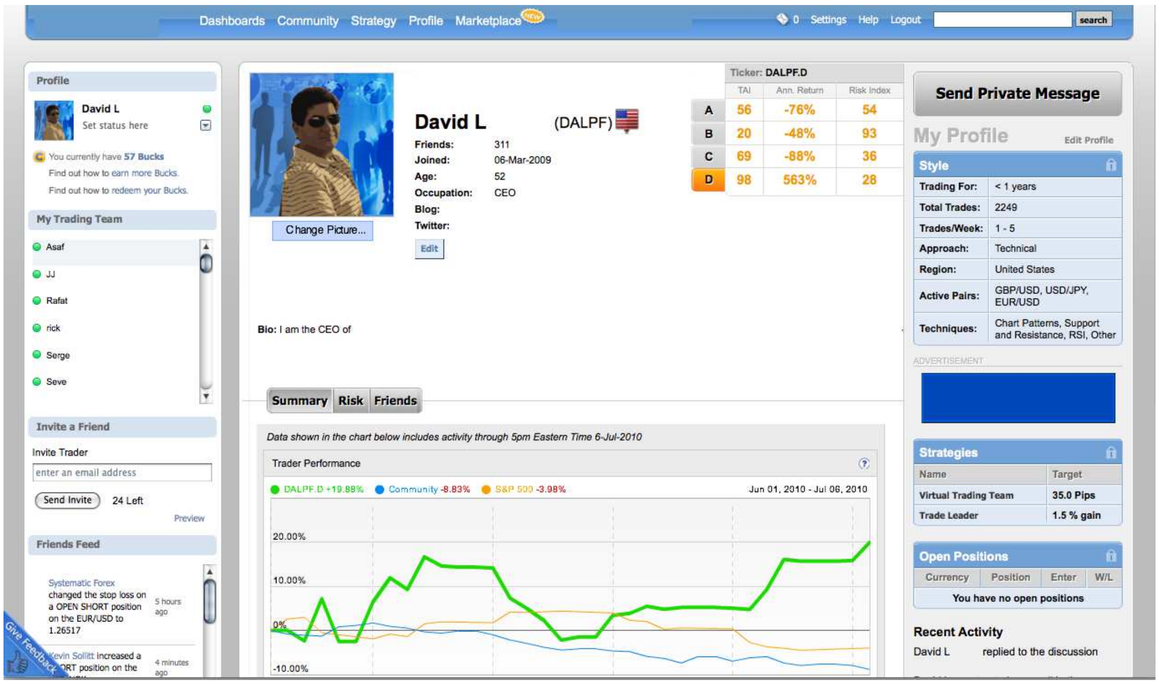
$$sale_{ijt} = \gamma_j + \gamma_t + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \times postFB_{ijt} + \varepsilon_{ijt}$$

using OLS. Regressions are estimated after partitioning the data by self-identified trading strategy. myForex-Book's operators chose the categories of trading strategy. The setup of the data, as well as the variables, have been described in previous tables. The sample includes market and limit orders, but the coefficients presented below correspond to the effect on market orders. Standard errors are double clustered by day and trader, and ***, **, and * denote significance at $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

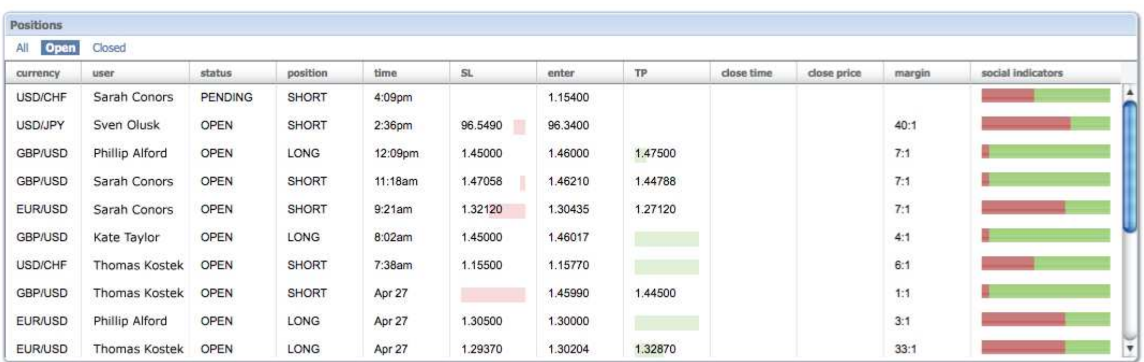
	Trading strategy =				
	Fundamental	Momentum	News	Technical	Nonspecific
Sale	(1)	(2)	(3)	(4)	(5)
Gain	0.0137***	0.0281***	0.0243***	0.0200***	0.0301***
	(0.0041)	(0.0060)	(0.011)	(0.0020)	(0.0042)
PostFB	-0.0256**	0.0102	-0.0104	-0.00204	-0.0111
	(0.0084)	(0.0076)	(0.0081)	(0.0040)	(0.0036)
Gain × postFB	0.0152**	0.0111	0.00603	0.00598**	0.0275**
	(0.0069)	(0.0074)	(0.011)	(0.0026)	(0.0112)
Holding period FE	x	x	x	x	x
Currency pair FE	x	x	x	x	x
Trader FE	x	x	x	x	x
Week FE	x	x	x	x	x
Limit order	x	x	x	x	x
Limit order × gain	x	x	x	x	x
Observations	306,054	314,996	125,425	4,703,473	1,416,744
Number of trades	37,901	42,809	16,789	609,844	176,148
Adj. R^2	0.027	0.030	0.031	0.024	0.027

Figure 1: **myForexBook user homepage**

A. This figure displays the user homepage for a member of myForexBook. Users are able to form bilateral friendships with other traders and communicate via private message or in the chat forum.



B. myForexBook users are able to view their friends' positions in real-time.

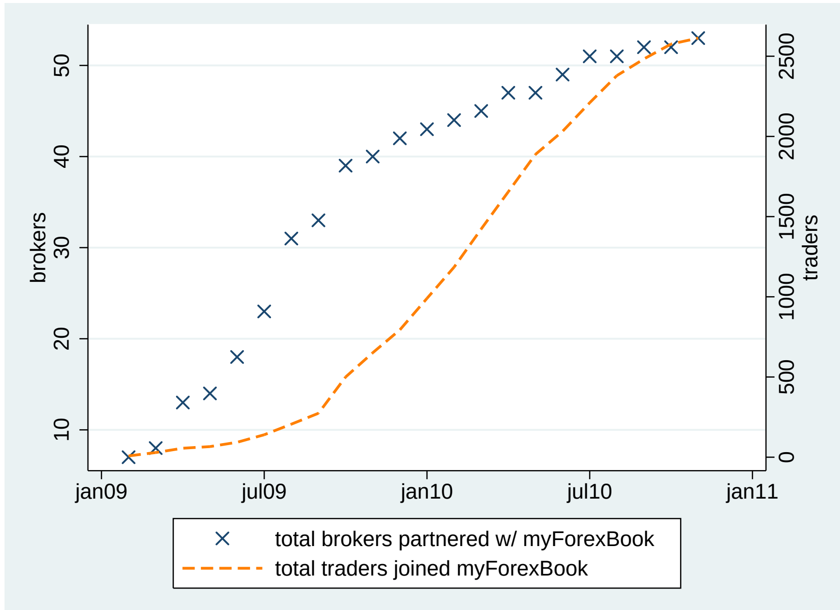


Positions

All Open Closed

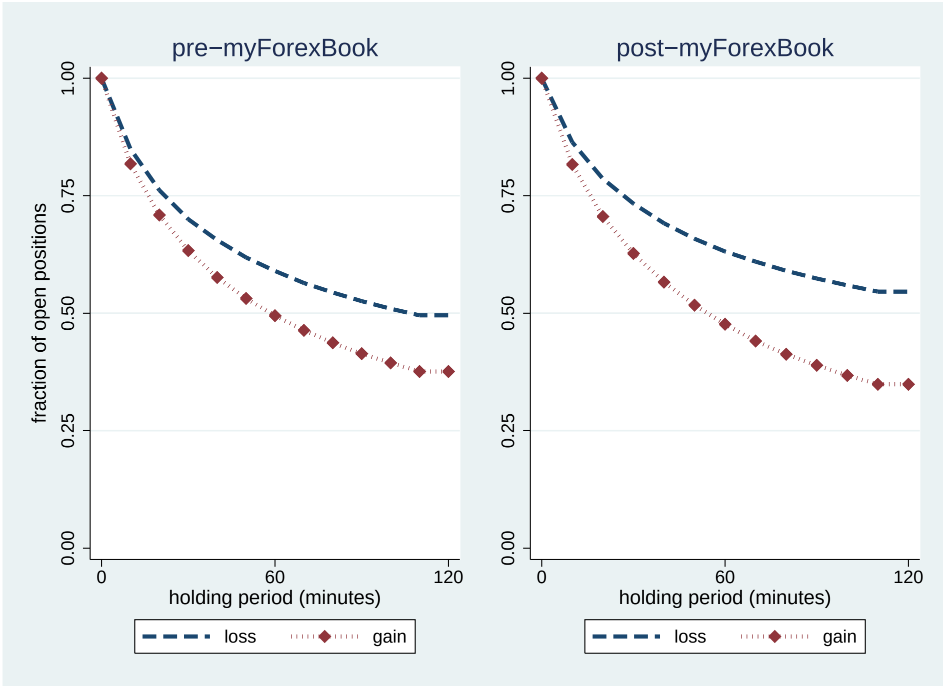
currency	user	status	position	time	SL	enter	TP	close time	close price	margin	social indicators
USD/CHF	Sarah Conors	PENDING	SHORT	4:09pm		1.15400					
USD/JPY	Sven Olusk	OPEN	SHORT	2:36pm	96.5490	96.3400				40:1	
GBP/USD	Phillip Alford	OPEN	LONG	12:09pm	1.45000	1.46000	1.47500			7:1	
GBP/USD	Sarah Conors	OPEN	SHORT	11:18am	1.47058	1.46210	1.44788			7:1	
EUR/USD	Sarah Conors	OPEN	SHORT	9:21am	1.32120	1.30435	1.27120			7:1	
GBP/USD	Kate Taylor	OPEN	LONG	8:02am	1.45000	1.46017				4:1	
USD/CHF	Thomas Kostek	OPEN	SHORT	7:38am	1.15500	1.15770				6:1	
GBP/USD	Thomas Kostek	OPEN	SHORT	Apr 27		1.45990	1.44500			1:1	
EUR/USD	Phillip Alford	OPEN	LONG	Apr 27	1.30500	1.30000				3:1	
EUR/USD	Thomas Kostek	OPEN	LONG	Apr 27	1.29370	1.30204	1.32870			33:1	

Figure 2: **New partnerships between myForexBook and retail brokerages**



This figure illustrates the formation of partnerships between myForexBook and different retail foreign exchange brokerages. Each x is a new brokerage that partners with myForexBook. The dashed line is the cumulative number of traders to have joined myForexBook. Traders are not able to join the social network until their brokerage has agreed to partner with myForexBook.

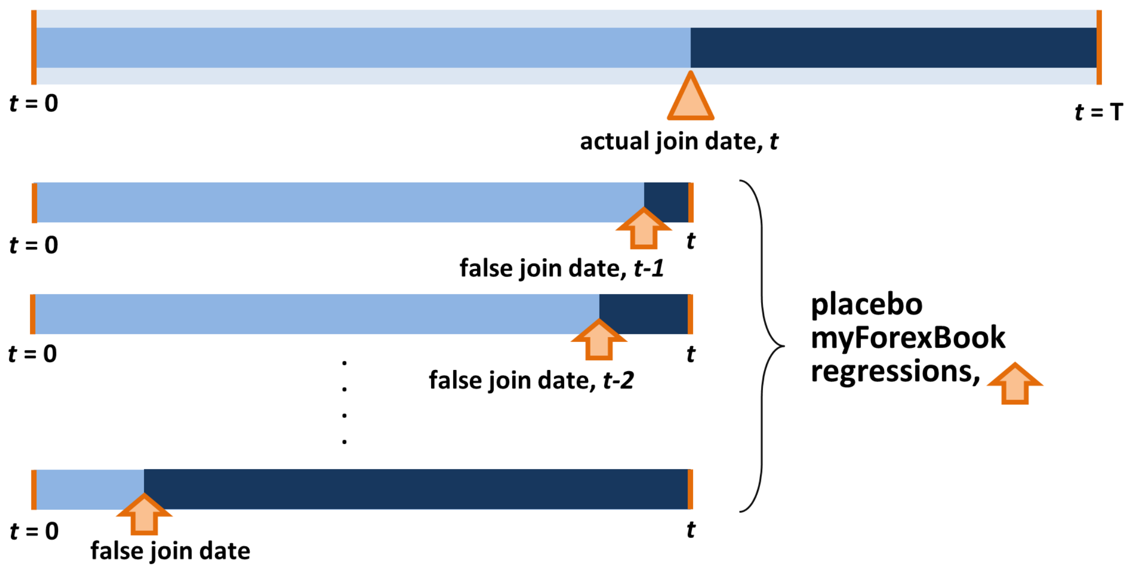
Figure 3: **Holding period of gains/losses and social interaction**



This figure plots estimates of a Kaplan-Meier survival function in which the outcome of interest is an indicator variable for closing a position. Both graphs separate the survival function by paper gains and paper losses. The graph on the left uses trades executed prior to joining myForexBook, and the graph on the right uses post-myForexBook trades. The data only includes market orders. Confidence intervals are not presented, because the survival functions are precisely estimated and the confidence bands are difficult to visually distinguish from the point estimates.

Figure 4: **Placebo test of the disposition effect**

A. This figure outlines the placebo exercise described in Section 3.



B. This figure presents estimates of the t-statistic on the interaction term between $gain$ and $postFB$, while using false dates for $postFB$. The falsification exercise uses the sample of traders who never use the social network as a control group.

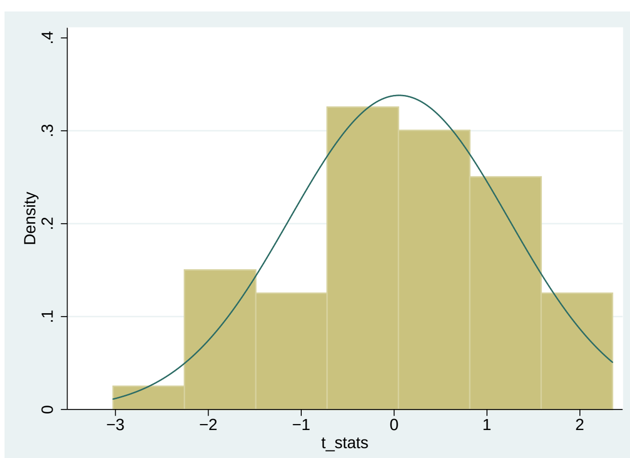
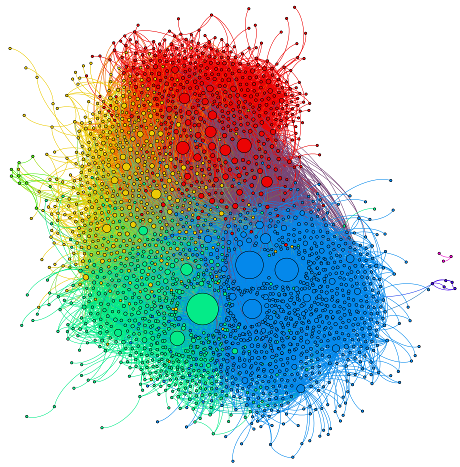
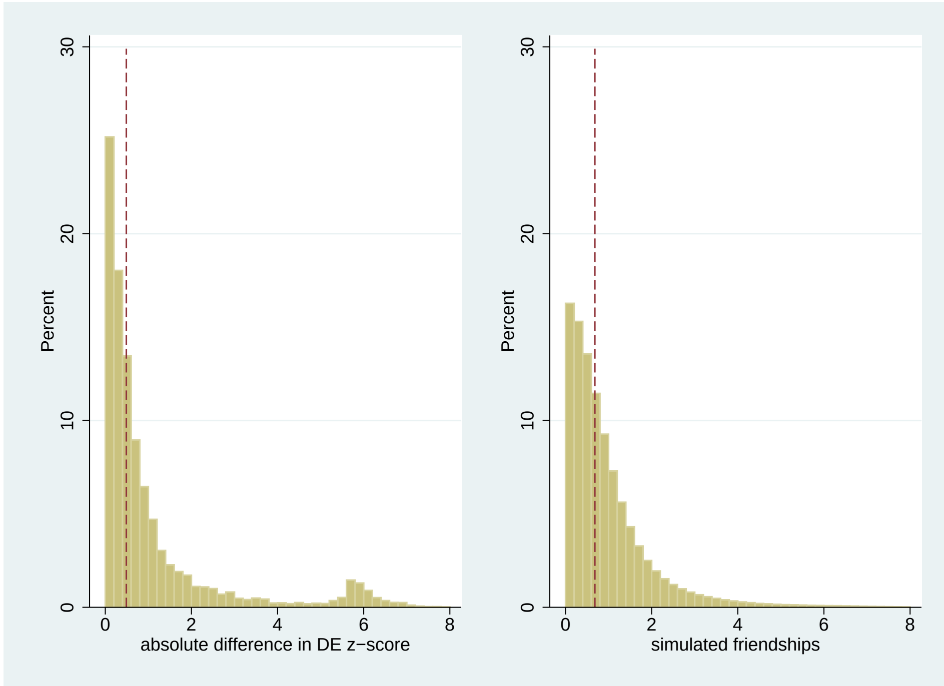


Figure 5: **Friendship connections in the myForexBook network**



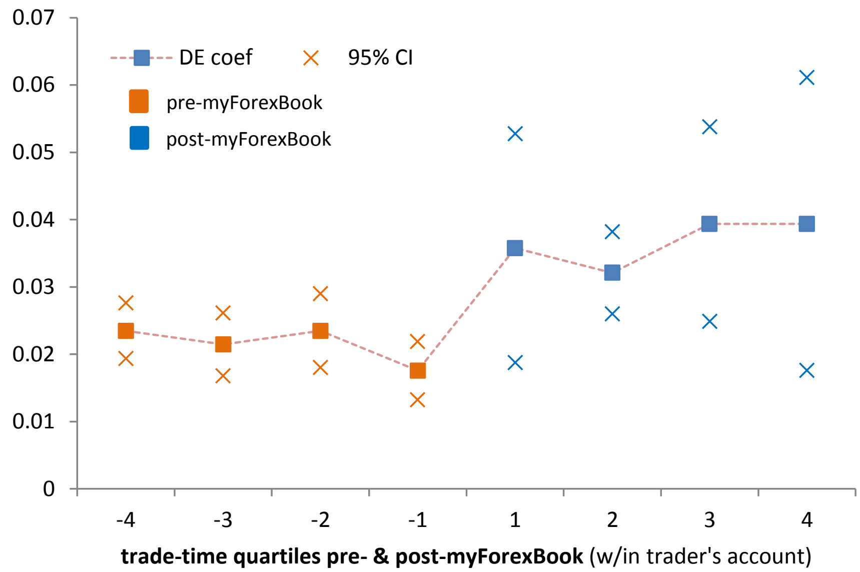
This figure presents the entire set of connections (bilateral friendships) in the myForexBook social network. The size of each node represents the number of friendships a trader has. The colors represent different communities within the network using the Louvain algorithm for community detection. The image was generated using the network software Gephi.

Figure 6: **Friendship formation and the disposition effect**



This figure uses data from myForexBook. The left panel presents a histogram of $DE\,dif_{jk} = |\beta_1(j) - \beta_1(k \neq j)|$, where $\beta_1(j)$ is a coefficient measuring the idiosyncratic disposition effect for trader j estimated using the regression, $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$ over the sample of j's trades. After estimating $\beta_1(j)$, it is normalized so that one unit is equal to one standard deviation. The right panel presents a similar histogram of the connections formed by simulating the network's topology. To generate the simulated network, connections between traders are established by drawing two traders at random (with replacement). Each simulation contains the same number of traders who have the same number of friends as in the actual data. The histogram's bins have a width equal to 0.2, and the red dashed lines indicate the median of the distribution.

Figure 7: **The disposition effect over the account's life-cycle**



This figure plots the point estimate of β_1 and its 95 percent confidence interval from the following regression: $sale_{ijt} = \beta_0 + \beta_1 \cdot gain_{ijt} + \varepsilon_{ijt}$, using the data from myForexBook. Prior to estimating each regression, the data is sorted into pre- and post-myForexBook trades. These trades are then sorted according to trade-distance since joining myForexBook. Trade-distance is a sequential ordering over time of trades (i) within each trader's (j) account. For example, when the x-axis equals one, the regression is estimated using the first 25 percent of trades opened after joining myForexBook from each trader j's account.

References

Ahern, K. R., R. Duchin, and T. Shumway. 2014. Peer effects in risk aversion and trust. *Review of Financial Studies* 27:3213–40.

Balli, H. O., and B. E. Sorensen. 2013. Interaction effects in econometrics. *Empirical Economics* 45:583–603.

Barber, B. M., and T. Odean. 2000a. Too many cooks spoil the profits: Investment club performance. *Financial Analyst Journal* 17–25.

———. 2000b. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55:773–806.

———. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics* 116:261–92.

———. 2002. Online investors: Do the slow die first? *Review of Financial Studies* 15:455–88.

Barberis, N., and W. Xiong. 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. *Journal of Finance* 64:751–84. ISSN 1540-6261.

Becker, G. S. 1974. A theory of social interactions. *Journal of Political Economy* 82:pp. 1063–1093.

———. 1991. A note on restaurant pricing and other examples of social influences on price. *Journal of Political Economy* 99:1109–16.

Ben-David, I., and D. Hirshleifer. 2012. Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. *Review of Financial Studies* 25:2485–532.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics* 119:249–75.

Beshears, J., J. J. Choi, D. Laibson, B. C. Madrian, and K. L. Milkman. 2015. The effect of providing peer information on retirement savings decisions. Working Paper 3.

Brown, J. R., Z. Ivkovic, P. A. Smith, and S. Weisbenner. 2008. Neighbors matter: Causal community effects and stock market participation. *Journal of Finance* 63:1509–31.

Burks, S. V., J. P. Carpenter, L. Goette, and A. Rustichini. 2013. Overconfidence and social signalling. *Review of Economic Studies* 80:949–83.

Bursztyn, L., F. Ederer, B. Ferman, and N. Yuchtman. 2014. Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica* 82:1273–301.

Chang, T., D. H. Solomon, and M. M. Westerfield. 2016. Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *Journal of Finance* 71:267–302. ISSN 1540-6261.

Chen, H., P. De, Y. J. Hu, and B.-H. Hwang. 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27:1367–403.

Davies, S. W. 2014. Retail traders and the competitive allocation of attention. *working paper* .

Dhar, R., and N. Zhu. 2006. Up close and personal: Investor sophistication and the disposition effect. *Management Science* 52:726–40.

Duarte, J., S. Siegel, and L. Young. 2012. Trust and credit: The role of appearance in peer-to-peer lending. *Review of Financial Studies* 25:2455–84.

Duflo, E., and E. Saez. 2003. The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quarterly Journal of Economics* 118:815–42.

East, R., K. Hammond, and M. Wright. 2007. The relative incidence of positive and negative word of mouth: A multi-category study. *International Journal of Research in Marketing* 24:175–84.

Frydman, C. 2014. What drives peer effects in financial decision making? Neural and behavioral evidence. *working paper* .

Georgarakos, D., and G. Pasini. 2011. Trust, sociability, and stock market participation. *Review of Finance* 15:693–725.

Giannini, R. C., P. J. Irvine, and T. Shu. 2014. Do local investors know more? A direct examination of individual investors' information set. *working paper* .

Goulart, M., N. C. da Costa, E. B. Andrade, and A. A. Santos. 2015. Hedging against embarrassment. *Journal of Economic Behavior & Organization* 116:310–8.

Grenadier, S. R., A. Malenko, and N. Malenko. 2015. Timing decisions in organizations: Communication and authority in a dynamic environment. *Stanford University Graduate School of Business Research Paper* 15.

Han, B., and D. Hirshleifer. 2013. Self-enhancing transmission bias and active investing. *AFA Annual Meetings Paper* .

Heimer, R. Z. 2014. Friends do let friends buy stocks actively. *Journal of Economic Behavior & Organization* 107:527–40.

Heimer, R. Z., and D. Simon. 2013. Facebook finance: How social interaction propagates active investing. *AFA 2013 San Diego Meetings Paper* .

Hertzberg, A., J. M. Liberti, and D. Paravisini. 2010. Information and incentives inside the firm: Evidence from loan officer rotation. *Journal of Finance* 65:795–828.

Hirshleifer, D. A. 2015. Behavioral finance. *Annual Review of Financial Economics* 7:133–59.

Hong, H., W. Jiang, N. Wang, and B. Zhao. 2014. Trading for status. *Review of Financial Studies* 27:3171–212.

Hong, H., J. D. Kubik, and J. C. Stein. 2001. Social interaction and stock-market participation. NBER Working Papers 8358, National Bureau of Economic Research, Inc.

———. 2004. Social interaction and stock-market participation. *Journal of Finance* 59:137–63.

———. 2005. Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *Journal of Finance* 60:2801–24.

Hwang, B.-H., S. Huang, and D. Lou. 2015. Does word of mouth communication affect trading? *working paper* .

Ivanova, Y., C. J. Neely, D. E. Rapach, and P. A. Weller. 2014. Can risk explain the profitability of technical trading in currency markets? *Federal Reserve Bank of St. Louis* Working Paper.

Ivković, Z., and S. Weisbenner. 2007. Information diffusion effects in individual investors' common stock purchases: Covet thy neighbors' investment choices. *Review of Financial Studies* 20:1327–57.

Kaustia, M. 2010a. Disposition effect. In H. K. Baker and J. R. Nofsinger, eds., *Behavioral finance: Investors, Corporations, and Markets*, 169–89. John Wiley and Sons, Inc.

———. 2010b. Prospect theory and the disposition effect. *The Journal of Financial and Quantitative Analysis* 45:pp. 791–812.

Kaustia, M., and S. Knüpfer. 2012. Peer performance and stock market entry. *Journal of Financial Economics* 104:321–38.

King, M. R., and D. Rime. 2010. The $4 trillion question: What explains FX growth since the 2007 survey? *BIS Quarterly Review* .

Kumar, A. 2009. Hard-to-value stocks, behavioral biases, and informed trading. *Journal of Financial and Quantitative Analysis* 44:1375–401. ISSN 1756-6916.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishnyi. 1991. Window dressing by pension fund managers. *American Economic Review Papers and Proceedings* 81:227–31.

Lancaster, T. 2000. The incidental parameter problem since 1948. *Journal of Econometrics* 95:391–413.

Lerner, J., and U. Malmendier. 2013. With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *Review of Financial Studies* 26:2411–52.

Li, G. 2014. Information sharing and stock market participation: Evidence from extended families. *Review of Economics and Statistics* 96:151–60.

Linnainmaa, J. T. 2010. Do limit orders alter inferences about investor performance and behavior? *Journal of Finance* 65:1473–506.

Manski, C. F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60:531–42.

———. 2000. Economic analysis of social interactions. *Journal of Economic Perspectives* 14:115–36.

Nofsinger, J. R., and R. W. Sias. 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54:2263–95.

Odean, T. 1998. Are investors reluctant to realize their losses? *Journal of Finance* 53:1775–98. ISSN 1540-6261.

Ozsoylev, H. N., J. Walden, M. D. Yavuz, and R. Bildik. 2014. Investor networks in the stock market. *Review of Financial Studies* 27:1323–66.

Pool, V., N. Stoffman, and S. Yonker. 2015. The people in your neighborhood: Social interactions and mutual fund portfolios. *Journal of Finance* 70:2679–732.

Ravina, E. 2012. Love and loans: The effect of beauty and personal characteristics in credit markets. *working paper* .

Shefrin, H., and M. Statman. 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance* 40:pp. 777–790.

Shiller, R. J. 2000. *Irrational exuberance*. Princeton University Press.

Shiller, R. J., and J. Pound. 1989. Survey evidence on diffusion of interest and information among investors. *Journal of Economic Behavior and Organization* 12:47 – 66.

Tversky, A., and D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* 5:297–323.