Peer Pressure: Does Social Interaction Explain the Disposition Effect?

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Abstract

This paper presents a novel connection between heightened exposure to information via social networks and large increases in the disposition effect. I establish this result using a proprietary database drawn from an investment-specific social network linked to individual-level trading records. To credibly estimate causal peer-effects, I utilize the staggered entry of retail brokerages into partnerships with the social trading platform and compare trader activity before and after exposure to new social conditions. The results appear contrary to the economic concept that more information enables better decisions. However, a framework in which traders strategically bargain and compete to acquire information through mutually-beneficial peer-connections can explain these findings, even when traders are risk-neutral and have well-formed beliefs. More broadly, this paper illustrates that socially-motivated incentives can enhance our understanding of investment puzzles.

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Summary

Financial economists argue that more information enables better decisions. Therefore, behavioral biases should erode when information becomes more broadly available.

In contrast, this paper finds that heightened exposure to information via social networks causes large increases in the disposition effect. I arrive at this result using a proprietary database drawn from an investment-specific social network linked to individual-level trading records. To credibly estimate causal peer-effects, I utilize the staggered entry of retail brokerages into partnerships with the social trading platform. This sets up a panel-data analysis that compares trader activity before and after exposure to new social conditions. Multiple placebo tests and complementary evidence from more widely-used data sources (Barber and Odean (2000)) confirm that the relationship is unrelated to alternative interpretations, while a number of established theories – adverse selection, transaction costs, blame delegation, and a belief in mean-reversion – fail to explain social interaction's influence.

I explain these findings by using an illustrative framework in which traders strategically search for mutually beneficial peer-connections during good times, because it coincides with the peak in their bargaining power and search is more productive. If investors manipulate the manner in which they share information and form connections, the disposition effect arises naturally even when traders are risk-neutral and have well-formed beliefs. In support of this explanation, the empirical results are strongest among inexperienced traders with the most to gain from forming social connections, social-cohort-level variation in the disposition effect can explain much of the variation in the disposition effect across traders, and traders that communicate more selectively have higher levels of the disposition effect. More broadly, these findings illustrate that social considerations can create incentives that enhance our understanding of investment puzzles, and that behavioral phenomena may reflect better resource allocation and increased market efficiency.

> *[T]he time has come to move beyond behavioral finance to 'social finance'* (Hirshleifer (2014))

Economists often argue that individuals are better off when they have access to more information. Therefore, if social connections are information conduits, social networks might be expected to enable better investment choices and reduce behavioral biases. 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. It is possibly the 'Holy Grail' of behavioral investment puzzles, because of its robustness across asset classes and investor types, as well as the difficulty developing an explanation that can reconcile a growing list of stylized facts.[1] Hence, it seems reasonable to suggest that heightened exposure to information via social networks can alleviate behavioral biases.

In contrast to this prediction, this paper presents a novel empirical connection between social interaction and substantial increases in the disposition effect. A lack of suitable data has presumably hindered exploration into this relationship, but this research relies on a new sample of retail traders who participate in a Facebook-style social network, which I call myForexBook. The data includes over two million time-stamped trades and over one hundred thousand time-stamped messages and friendships. More importantly, the social network extracts trading records directly from participating brokerages including records from before joining myForexBook, a distinguishing feature relative to contemporaneous studies that compile self-reported activity from message boards.[2] The data also merit comparison to more widely used brokerage data, namely an extract from a large discount brokerage (Barber and Odean (2000)). Indeed, Barber and Odean (2000)'s data offers empirical tests that compliment my main results.

[1] Kaustia (2010) provides an excellent overview of the literature.

[2] Some examples include Antweiler and Frank (2004), Chen et al. (2014), and Giannini et al. (2014).

Even with detailed network data, empirical researchers find it challenging to identify the causal influence of social interaction, because of endogenous sorting and the reflection problem (Manski (1993)). To overcome this difficulty, I exploit the gradual entrance of new traders into myForexBook over the course of the sample period. This allows for a panel-data analysis that compares a trader's activity before and after exposure to myForexBook. In support of a causal interpretation, a trader is unable to access the network until his or her brokerage has reached legal and technological agreements with myForexBook. The staggered incorporation of new brokerages is similar to an instrumental variable that predicts trader entry, but is likely to be exogenous to the behavior of any individual or group of traders according to empirical evidence. Therefore, traders constrained from entering the social network at any point in time can be considered part of a control group, while traders that enter the network are in the treatment group.

Exposure to myForexBook nearly doubles a trader's susceptibility to the disposition effect. The result is robust to a number of alternative considerations including confounds related to trading style, leverage, time fixed effects, and the use of price-contingent orders, a contributor to the adverse selection problem in markets with retail participants (Linnainmaa (2010)). Additionally, a placebo test that assigns false dates of joining myForexBook and uses a contemporaneous sample of traders that never join myForexBook as a control group, suggests that the results are unrelated to unobservable shocks that differentially affects the underlying heterogeneity that motivates the use of a social networking service. A second placebo test examines retail traders on a discount brokerage (Barber and Odean (2000)) who live in zip codes that were among the first to adopt broadband internet. The introduction of the internet in an era prior to the widespread use of social media does not relate to the disposition effect, which suggests that investor enthusiasm over new technologies is an unlikely confound.

To explain this puzzling empirical result, I conjecture that the disposition effect relates to the manner in which individuals compete and strategically bargain for information. If there is a limited supply of information or there are cognitive bottlenecks, traders have incentive to search for and maintain mutually beneficial peer-connections. Similar to Yuan (2005)'s insight that capital transacts more freely when times are good or to the adage "everybody loves a winner", a trader's search efforts are more productive when the market values her ideas highly. This leads traders to exercise the option to search during good states. Subsequently, a trader's opportunity set expands through her newly acquired social connections and her current portfolio is comparatively less attractive. This increases the likelihood of selling assets held contemporaneously, thereby leading to a disposition effect (under the assumption that the market value of her ideas are correlated with the performance of her investments) even when traders are risk-neutral and make utility-maximizing choices with perfect foresight. The academic job market provides an analogy. A PhD candidate executes her research idea with the highest market value, while downplaying numerous lesser projects, and strategically enters the job market when she expects her match probability to be at its peak.

This illustrative framework conveniently produces additional implications that are empirically verifiable. First, traders with the most to gain from forming social connections – presumably inexperienced traders – see the greatest increase in the disposition effect following exposure to myForexBook. Secondly, myForexBook traders prone to the disposition effect communicate selectively and therefore with less frequency than the average trader whose communications flow at random. Finally, part of the variation in the disposition effect across traders can be explained by cohort-level variation. In support, I examine the matching process between traders by generating a simulated random network that preserves the distribution of the disposition effect across traders. In comparison to the randomly drawn network, the average pair of befriended traders shares and develops a similar level of the disposition effect. Likewise, in an examination of the discount brokerage data (Barber and Odean (2000)), I document that there is ample variation in the disposition effect across plausible social cohorts, namely geographically close traders within a given Metropolitan Statistical Area (MSA).

This explanation also has the advantage of easy reconciliation with a host of stylized facts related to the disposition effect. First, given the robust empirical evidence that social interaction matters to financial market participants, it is reasonable to suggest that the story is viable across asset classes and investor types. It is consistent with the 'v-shape' execution probability found in Ben-David and Hirshleifer (2012). The greater the gains, the greater the bargaining power, while execution in the loss region becomes more likely to reflect down-side constraints such as lost opportunity cost or funding limits. The disposition effect erodes with trader experience (Feng and Seasholes (2005)), consistent with there being less uncertainty over trader quality and more stability in social connections. There is no disposition effect when individuals trade mutual funds (Calvet et al. (2009)), presumably because it is difficult to attribute mutual fund performance to one's acumen. Additionally, since the trading and communication patterns in this illustration reflect a reallocation of resources to more efficient uses, an important and potentially controversial implication is that the disposition effect is related to increased market efficiency. This is unfortunately beyond the data's ability to test, but it would broadly explain why the disposition effect is as persistent across markets and is not arbitraged away.

This research makes a few notable contributions to a growing empirical literature on social interaction in finance. Hampered by data limitations, most empirical papers rely on creative proxies (Heimer (2014b) and Hong et al. (2004)) or spatial analysis (Brown et al. (2008), Kaustia and Knüpfer (2012), Pool et al. (2014), and Shive (2010)) to infer peer interaction. In contrast, this research contains actual revealed linkages between traders. While this alone does not prove that peer-effects exist, the data also allows a panel-analysis that compares pre- and post-exposure to changes in a social environment, an advantage over comparable studies that rely on repeated cross-sectional tests. Outside of conducting a controlled experiment,[3] this approach presumably offers the most compelling causal evidence for financial peer-effects to date.

Additionally, the empirical literature is curiously absent a discussion of the two-sided nature of social interaction and how social considerations shape incentives and affect opportunity sets. Instead, the finance literature focuses on information sharing (Duflo and Saez (2003) and Li (2014)) and explaining cross-sectional correlations of investment choices (Ivković and Weisbenner (2007)). In this respect, this paper is presumably the first to consider the matching process between financial market participants.

The paper also provides a novel explanation for the disposition effect, of which the origins of discourse can be traced to concern over social conditions. According to Shefrin and Statman (1985, pg. 783):

> "...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."

In addition, the disposition effect is found among individual investors on a discount brokerage in the U.S. (Odean (1998)), the population of Finnish (Grinblatt and Keloharju (2001)) and Taiwanese stockholders (Barber et al. (2007)), and day-traders (Jordan and Diltz (2004)). Professional investors are also more likely to hold onto losers (Coval and Shumway (2005) and Locke and Mann (2005)). The disposition effect even exists in controlled laboratory experiments (Weber and Camerer (1998)). Trading of mutual funds is a notable exception

[3]Field experiments on social interaction and financial decision-making include Ahern et al. (2014) and Beshears et al. (2011).

(Calvet et al. (2009)) and the magnitude of the disposition effect varies with respect to investor characteristics Dhar and Zhu (2006).

The pervasiveness of the disposition effect across many assets classes and investor types has prompted a number of proposed explanations. Much of the literature tries to understand the disposition effect through the lens of non-traditional preferences and beliefs, but explanations of this variety have been difficult to reconcile with theoretical (Barberis and Xiong (2009)) or empirical evidence (Barberis and Xiong (2012), Ben-David and Hirshleifer (2012), and Frydman et al. (2014)). This paper's explanation is similar to a contemporaneous narrative on blame delegation (Chang et al. (2014)), as both relate to the attribution of investment successes (Han and Hirshleifer (2013) and Heimer and Simon (2013)). In contrast, I argue that traders have conventional preferences and respond to social incentives, a story that seems widely applicable to both professional and retail investors across asset classes. In this respect, this paper joins a short list of explanations for the disposition effect in which traders are not behaviorally biased (Linnainmaa (2010)).

This paper is organized as follows. Section 1 outlines some theoretical considerations. Section 2 describes the proprietary social network data and the other data sources. Section 3 outlines the identification strategy for the empirical tests in Section 4. Section 5 relates the disposition effect to the development and maintenance of social ties. Section 6 descries some alternative explanations. Concluding thoughts are offered in Section 7.

1 Theoretical Considerations

Consider a simple framework in which a trader makes investment mistakes. According to basic assumptions that underlay models of economic decision-making, innovations that increase access to information about market outcomes enable better choices. Therefore, a straightforward prediction is that when social networks convey new information, they can alleviate trader missteps, for example, the disposition effect.

In contrast, what if information is in limited supply or traders have cognitive limitations? Traders would then need to compete to acquire information, particularly information that best compliments one's own information production. This competition would manifest through the formation and maintenance of bi-lateral social connections between traders, which ultimately must be incentive compatible. Hence, it seems reasonable to evaluate the evolution of investment mistakes and biases through a lens of strategic information sharing and match formation.

Appendix A.1 presents a simple, illustrative framework for understanding how bi-lateral social connections develop and its effect on portfolio decision-making. I assume that there are economies of scale in the production of ideas, which means that traders want to develop and maintain bi-lateral social connections. Agents engage in strategic competition in the matching process to form their connections. The probability of finding a high-quality match is an increasing function of a trader's bargaining power. Bargaining power relates to the market's perception of a trader's investment ideas, which evolves stochastically over time into good or bad states. This gives traders incentive to exercise the option to search for or maintain social connections in good times, while in down states, search is less productive. Hence, traders rely on their priors in down-states, but in good states, resources are allocated to the search process and upon forming a match, the trader's opportunity set expands. These social-search effects increase the likelihood of resource reallocation, because her current portfolio is comparatively less attractive. Since the fluctuation in the market's perception of a trader's investment ideas are correlated with her asset's returns, this clearly implies winning assets get sold more often, which is observationally equivalent to a disposition effect.

A useful analogy is the matching process in the finance job market. A candidate has produced many research ideas throughout her tenure as a PhD student. She executes the idea that is the most promising, making that her job market paper, while holding her other research ideas in reserve. The market's perception of her paper is a noisy signal of her ability to eventually publish successfully, but it is the preeminent factor in the matching process between the position opening and the candidate, with presumably the best jobs matching with the candidate who has the best job market paper. In this market, the match is jointly beneficial to both the candidate and the department in charge of the hire. Moreover, the candidate controls when she searches for a job, because the strategy provides her with the most market-power during the job-search and thus offers the highest long-term payoff. Most PhD programs also have funding constraints that prevent candidates from entertaining infinitely long stays in the program, which means that many candidates have incentive to eventually execute bad projects, but they do so more slowly.

More formally, this explanation for the disposition effect relates to Bergstrom and Bagnoli (1993)'s description of the marriage matching market. In Bergstrom and Bagnoli (1993)'s model, high and low quality individuals compete to find a marriage partner. Bergstrom and Bagnoli (1993) assumes that the individual knows their own quality, but to others it is uncertain and it takes time to be revealed, particularly in relation to lifetime earnings potential. This setting turns time into a choice variable and produces an equilibrium in which high quality individuals strategically wait until their bargaining power is highest to search for a life-partner.

As this process relates to investment decision-making, Appendix A.1 shows that increased access to social networks creates an incentive to engage in trading gambles whose path-dependent, first-best choices yield a disposition effect. This socially inspired tendency to sell winners more quickly than losing assets also produces a few implications that are testable. First, traders who have the highest expected benefit from social interaction are most prone to the disposition effect. Second, traders with a high-level of the disposition effect communicate selectively and therefore less frequently than other traders. Lastly, social-cohort level variation will be responsible for much of the variation in the disposition effect across traders, because the parameters of the matching process are cohort-specific.

It is important to emphasize that this mechanism relates to the learning process about investment ideas and the reallocation of resources to more efficient uses. Much like Berk and Green (2004), competition makes it challenging to observe cross-sectional differences in profitability as a function of the process of information acquisition via social-connections. Therefore, a long-run no-profit condition makes it infeasible to generate ex-post predictions.

2 Data: A Social Network for Traders

The primary data source used in the empirical analysis was compiled by a social networking website 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) brokers. Once registered, myForexBook can access a trader's complete trading record at those brokers, even the trades they made before joining the network. New trades are entered via the retail brokerages but they are simultaneously recorded in the myForexBook database and are time-stamped to the second. Hence, there are no concerns about reporting bias. An example of a myForexBook user's homepage is displayed in Figure 1 and some of the network's features are illustrated in Figure 2.

[insert Fig 1 about here]

[insert Fig 2 about here]

There are 5,693 traders in the database who made roughly 2.2 million trades which occurred between early-2009 and December, 2010. To briefly summarize, the median trader in the untrimmed database is 36 years old, from the USA or Western Europe, has one to three years of experience, and calls herself a technical trader. The typical trader sends about five messages per week and has between 15 to 20 friends. Heimer and Simon (2013) presents a more detailed discussion of the social networking aspects of the database and the trader's performance.

The sample used in this research is restricted to include only traders for whom there is data before and after joining the social network, and to those who made at least fifty round-trip trades (both market and limit orders). The trimmed data includes 2,598 traders who made 965,995 total trades, 59 percent of which occurred after joining the social network. The trimmed sample does not appear to be much different from the rest of the data. In unreported analysis, I separately perform the main disposition effect linear regression using the trimmed sample, pre-myForexBook, and using the sample of traders excluded from the analysis whose trading takes place before joining myForexBook. A Chow test for the null-hypothesis that the disposition effect coefficient is equal across regressions produces a p-value of 0.25, which suggests the two groups are similar.

Retail foreign exchange trading

Despite the lack of scholarly research on retail forex traders, this growing market deserves our attention as there are now around 20 brokerages registered with the CFTC, over a dozen English-language social networking sites catering to this market, and between \$125 - \$150 billion in daily trading volume, worldwide according to the Bank of International Settlements (King and Rime (2010)). Traders in the myForexBook sample tend to underperform relative to reasonable benchmarks, at a rate that is slightly worse than comparable common stock traders (Barber and Odean (2000)) presumably because of the greater availability of leverage in the forex market (Heimer (2014a)). Moreover, the traders in this study appear to be representative of the typical retail foreign exchange trader in the U.S. 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.

However, there are some advantages to studying the disposition effect within the market for retail foreign exchange, which is much closer to an experimental setting than comparable studies of stock market participants. First, the market structure alleviates concern over alternative explanations related to selection across securities based on their characteristics (Kumar (2009)), as 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. The data includes both market and limit orders, which enables tests that are free of concerns over adverse selection (Linnainmaa (2010)). The forex market is large enough such that the cumulative activity of the social network is too small to endogenously affect prices. The market is also highly liquid. Therefore, non-execution risk is not a concern for inference.

Table 1 provides some basic summary statistics on the traders and trades in the trimmed sample (panel A), both before and after exposure to myForexBook (panels B and C, respectively). The summary table includes only market orders, because they are the focus of the primary empirical tests (price-contingent orders execute mechanically and, according to Linnainmaa (2010), for unrelated reasons). The table of summary statistics includes the number of trades per account, as well as the number of observations at a gain and that involve a sale. A few variables that are potentially related to changes in the disposition effect are similar before and after a trader joins myForexBook. Traders are equally likely to be long a currency pair, trade nearly as frequently per day, and trade the same number of distinct currency pairs.

[insert Table 1 about here]

Additional Data Sources

For the purpose of comparison, I incorporate a sample of around 800 retail forex traders obtained by myForexBook who do not conduct any trading within the social network, but trade during the same time period. 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 this data at ten minute intervals, using the nearest tick.

Data from a discount brokerage (Barber and Odean (2000)) widely used to study individual investors augments this study with complementary evidence. The data includes over 70,000 individuals who hold 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. Moreover, I limit the use of the Barber and Odean (2000) data to common stock holdings and to long positions because short-sales are often informed trades (Kelley and Tetlock (2013)). These data trimmings provide a better analogy to the myForexBook sample. For brevity, I direct readers to Chang et al. (2014) for trade-level summary statistics and to Barber and Odean (2001) for a description of demographic characteristics.

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 U.S. The data ranges from 0 - 10 providers. The FCC recoded any value between 1 and 3 as being equal to 2. Lastly, I use a concordance between zip codes and Metropolitan Statistical Areas from the U.S. Census Bureau.

Variables

To study the disposition effect, I follow standard methods used in the literature to determine the trader's response to the price-path of his or her assets. For all variables, the subscript j

refers to the trader, i to the position, and t is time, which is recorded at 10-minute intervals when the myForexBook data is used and monthly the data comes from the discount brokerage sample. The variable, $sale_{ijt}$, equals one if the trader reduces his or her holdings of the asset and is equal to zero otherwise. The variable, $gain_{ijt}$, equals one if the market price at t exceeds the price at which the security was purchased. To capture the effect of the social network, $postFB_{ijt}$ equals one if i is opened after j joins myForexBook.

Several trade-level control variables are included in the analysis. The variable, $leverage_{ijt}$, is the amount of leverage used by the position. Increases in the former indicate that trader beliefs about the value of the asset are highly precise and likely reflect investor overconfidence (Heimer (2014a)). The variable $limit.order_{ijt}$ equals one on any position that executes via a price-contingent order (take-profit or stop-loss). It captures adverse selection risk, which is problematic for less-informed retail traders (Linnainmaa (2010)). It also helps classify trades that execute manually and are therefore less likely to reflect active investor decision-making, an important consideration for any investigation of the disposition effect. Additionally, $holding.period_{ijt}$ is the time since the position opened and $short_{ijt}$ is an indicator for short positions. Currency pair fixed effects are also included in the analysis of the myForexBook data.

myForexBook traders respond to a demographic survey when they join the network. The trader's age at the time of joining the network is age_i. Trading experience is captured by $experience_i$ and traders are allowed to choose from one of the following options: 0 - 1, 1 - 3, 4 - 5, or 5+ years. Traders also specify their preferred trading style, $approach_i$, which is classified as technical, momentum, news, fundamental, or none-specific. The analysis also broadly incorporates the trader's international region, $location_i$.

The demographic file attached to the discount brokerage data (Infobase) contains trader zip codes, which I use to match to $broadband_i$, the number of broadband internet providers per U.S. zip code by the end of 1999.

3 Identification Strategy

For a trader to join myForexBook, his or her brokerage must have first partnered with myForexBook. As illustrated in Fig. 3, new brokerages partnered with myForexBook gradually over the course of the sample period. This staggered process was driven by legal and technological agreements between myForexBook's operators and partnering brokerages. To offer more detail without compromising the identity of the data-provider, myForexBook extracts confidential trading records in real time from a selection of brokerages, all of which have a unique database infrastructure. This means that myForexBook is not only required to reach a nondisclosure agreement with the brokerage, but it also has to make its software compatible with the structure of the brokerage's server.[4]

[insert Figure 3 about here]

The data contains an indicator variable for the brokerage used by the trader and the date at which each new trader enters the network. The former enables the use of brokerage fixed-effects to account for any brokerage-specific factors that could confound the relation between trader entry and trading behavior. The latter allows me to update, when necessary, the set of traders that belong to a trader's peer group as it evolves over the sample period, with confidence that the timing of additions is quasi-random. This is important because random assignment to peer groups counteracts the reflection problem and other endogeneity concerns within social networks (Manski (1993)).

The database also contains trading records from prior to entering the network. This feature enables a comparison of trading activity before and after the trader gains access to the social networking features of the web platform. This helps isolate the causal influence of social interaction from contemporaneous factors that potentially confound inference.

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

Empirical evidence offers support for the identifying assumptions. The incorporation of new brokerages is a strong predictor of the time at which a trader joins myForexBook. An OLS regression of a trader's join date on the set of brokerage dummy variables produces an F-statistic of 352.

Additionally, the process by which new brokerages were added to myForexBook is likely uncorrelated with the characteristics of any individual or group of traders. This is important for identification because traders that are the first to join myForexBook 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.

Table 2 provides a comparison of early and late entrants into myForexbook. Using t-tests for difference in means, I find that the two groups are not statistically different (Panel I). In Panel II, several Probit models provide evidence that observable trader characteristics cannot explain which traders are the first to join myForexBook. Taken together, this suggests that brokerage agreements are free of selection bias and other confounds that would invalidate its use as an unbiased predictor of exposure to the social network.

[insert Table 2 about here]

Lastly, I address concerns about sample bias and its relation to trading biases by comparing the pre-myForexBook sample to the contemporaneous sample of roughly 800 traders that never join myForexBook. In a series of unreported tests, the two groups have a similar level of the disposition effect. Anecdotally, it is reasonable to claim that the typical retail participant uses trading resources such as a myForexBook, once one considers the burgeoning empirical literature showing that they are influenced on-average by social interaction and financial media.

4 The Disposition Effect and Social Interaction

Preliminary Evidence

Graphical evidence suggests that social interaction contributes to the disposition effect. Figure 4 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 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, there is a disposition effect, while the size of the vertical spread is indicative of the disposition effect's magnitude.

The left (right) panel includes trades executed prior to (after) joining myForexBook. Among the traders in this study, a greater percentage of losses than gains go unsold at any given point in time, a gap which 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 increases the disposition effect.

[insert Figure 4 about here]

Formal Tests

Regression analysis provides formal tests of the disposition effect while controlling for a number of contemporaneous that potentially shape the difference between pre- and post-myForexBook trading patterns. Similar to Chang et al. (2014), the disposition effect is estimated via the following specification:

$$sale_{ijt} = \beta_0 + \beta_1 \cdot gain_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where $sale_{ijt}$ equals one if the position, i, is sold by trader, j, at a given point in time, t, and is equal to zero otherwise. The independent variable, $gain_{ijt}$, is equal to one if the sale price is above the price at which j purchased the asset. The unconditional average probability of selling the asset is captured by the intercept, β_0. A positive coefficient on $gain_{ijt}$, β_1, implies that traders are more likely to sell positions at a gain than at a loss, which indicates a disposition effect. The equation is estimated using OLS in order to aid in the reader's interpretation of coefficient magnitudes, but is robust to using a logistic model estimated via maximum likelihood as in Grinblatt and Keloharju (2001) (available upon request). Standard errors are double-clustered at the level of the trader and week.

[insert Table 3 about here]

Table 3 presents the results from estimating the disposition effect regressions. Column (1) estimates Equation 1 using the sample of trades made prior to joining myForexBoook, while column (2) estimates the same equation using the sample from after joining. The coefficient on $gain_{ijt}$ in column (1) is equal to 0.021 (s.e. = 0.002), which suggests traders are about two percentage points more likely to sell positions at a gain. This implies a disposition effect that is similar in magnitude to other studies of common-stock holders (Chang et al. (2014)). In column (2), the coefficient is 0.037 and statistically significant at the one percent error level. The coefficient using the post-entry data is nearly double the size of that which uses the pre-entry sample, which provides initial regression evidence that the disposition effect increases following exposure to myForexBook.

The following regression specification causally tests the effect of social interaction on the disposition effect:

$$sale_{ijt} = \gamma_j + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot postFB_{ijt} + \varepsilon_{ijt}, \tag{2}$$

The panel specification includes trader fixed effects captured by γ_j, although the results tend to be insensitive to their inclusion, implying that a random effects model may be more appropriate. The regressor, $postFB_{ijt}$, is an indicator variable equal to one for trades issued after trader j has joined myForexBook, zero otherwise. The coefficient on the interaction term between $gain_{ijt}$ and $postFB_{ijt}$ measures the extent to which the disposition effect changes as a function of social interaction. As illustrated in Section 3, the staggered incorporation of new brokerages into the myForexBook environment counters the argument for time-invariant effects and provides a causal interpretation of β_3 as a result of social interaction.

Column (3) of Table 3 presents estimates of Equation 2, which interacts an indicator variable for trades made after joining the network with an indicator variable for gains. The coefficient estimate is around 0.015 (s.e. = 0.003), implying that changing social conditions can increase trader susceptibility to the disposition effect by as much as double. Column (4) adds the amount of leverage used on the trade as an independent variable. Trades that use more leverage may reflect a greater degree of confidence in one's beliefs about the value of an asset and therefore may correlate with the propensity to hold onto losers. The regression presented in column (5) contains weekly fixed effects on the right-hand side to account for common, time-invariant shocks that may confound the relationship between social interaction and the propensity to execute trades. Column (6) removes the trader fixed effects, but controls for trader experience and self-identified trading style. In all cases, the coefficient on the interaction term, β_3, is quantitatively similar to 0.015 and statistically significant at the five percent error level.

Placebo exercises

I conduct a placebo exercise to see how likely it is that secular trends formed prior to joining myForexBook generate false positive results. The placebo test estimates the empirical model outlined in Equation 2 while re-coding the date at which traders join myForexBook rolling it backwards one week at a time, fifty total times. Each time that I roll back $postCS_{ijt}$ by a week, I estimate the regression model and collect the t-stats from the interaction term on $postCS_{ijt}$ and $gain_{ijt}$. Furthermore, the regressions exclude any positions that are opened following entrance into myForexBook so that the social network's influence does not confound the analysis.

While the treatment group in the placebo exercise is the primary sample of 2,598 myForexBook traders, I use the sample of foreign exchange traders that are not a part the social network as a control group. For this set of traders, $postCS_{ijt}$ is always equal to zero, which requires an estimation without trader fixed effects. However, there are benefits to this approach. Using the contemporaneous sample of traders that never join myForexBook as a control group addresses concern that the results relate to unobservable shocks that differentially affects the underlying heterogeneity that motivates the use of a social networking service. To assist the reader, Figure 5 provides an illustration of the placebo exercise's methodology.

[insert Figure 5 about here]

Figure 6 presents the distribution of t-statistics from the falsification test. The distribution follows a normal distribution with only 2.5 percent producing a t-statistic above 1.96. This suggests that the causal test of social interaction on the disposition effect is unlikely to produce false positive results. The increase in the disposition effect is likely caused by the exposure to new social conditions.

[insert Figure 6 about here]

In a second placebo test, I use the discount brokerage data (Barber and Odean (2000)) to test if the findings are related to the adoption of new technologies rather than the influence of social interaction. Table 4 presents estimates of Equation 1 in which $gain_{ijt}$ is interacted with $broadband_j$, the number of broadband internet providers per U.S. zip code by the end of 1999. The interaction terms captures the marginal contribution of the introduction of the internet on the disposition effect.

[insert Table 4 about here]

Estimation results suggest that the disposition effect does not relate to the adoption of new technologies. In a regression without any additional control variables (Column I), the coefficient on the interaction is negative and statistically insignificant. Column II interacts $gain_{ijt}$ and $broadband_j$ with year dummies. The results are not statistically different over the course of the sample period. The exercise in Column II is informative because the earliest available U.S. data on internet penetration comes from 1999 and the retail brokerage data ends in 1996, which means that measurement error is a concern. However, the estimation is likely to become more accurate as the two data sets get closer to overlapping on the same dates. This implies that a monotonic trend in the interaction coefficient would reflect convergence towards the true parameter value. Column III includes individual demographics, because new technologies may have a stronger influence on certain groups, but the coefficient on the interaction term remains indistinguishable from zero.

Robustness Checks

Appendix A.1 includes instrumental variable (IV) estimates of Equation 2. As outlined in Section 3, a trader's brokerage is a strong predictor of the date in which a trader joins myForexBook and is likely uncorrelated with other investor-level observables that may relate to the disposition effect. Therefore, the 2-stage least squares estimator uses brokerage fixed effects to predict $postFB_{ijt}$. The coefficient estimate on the interaction term between $\widehat{postFB}_{ijt}$ and $gain_{ijt}$ are statistically meaningful, but tend to produce a coefficient estimate that is smaller in magnitude (approximately 0.005). It is reasonable to place less emphasis on these results because, while the brokerage fixed effects are a consistent estimator of $postFB_{ijt}$, by definition, the estimate is biased. Traders are unable to join myForexBook until after the brokerage agreements, which means that the average predicted join date occurs later in the sample. This falsely attributes a greater share of post-myForexBook trades to the pre-myForexBook treatment group, thereby placing a downward bias on the coefficient estimates in the second stage. In light of this statistical hurdle, that the IV estimates still produce supportive results should be interpreted as exceptionally strong evidence in favor of a causal interpretation of social interaction on the disposition effect.

I also conduct some sensitivity analysis, which are unreported but are available upon request by curious readers. The estimation results are quantitatively similar when I sort traders into different age groups and when I divide the data biannually to capture different foreign exchange market conditions. The results also hold when daily implied volatility metrics are included in the regressions. More importantly, Table 1 illustrates that the panel is not quite balanced in terms of the number of trader observations pre- and post-entrance into myForexBook. Using trader fixed effects throughout partially alleviates this concern by estimating a within-trader effect of exposure to the social network. However, I also carefully employ a number of plausible weighting schemes to balance the pre- and post-myForexBook observations. Doing so provides comparable results.

5 Empirical Tests of Strategic Bargaining, Social Considerations, and the Disposition Effect

Increased access to social networks produces large increases in the disposition effect, a result that is consistent with a story in which traders strategically develop and maintain social connections during good states. This explanation, outlined in Section 1, produces a few additional implications, which I examine below.

The disposition effect, social interaction, and trader experience

The first implication is that traders with the most to gain from their social connections are the most likely to have the disposition effect arise through this social-bargaining and signaling mechanism. Novice traders presumably have the most to gain from establishing social connections. Therefore, the social network's effect on the disposition effect is presumably strongest among inexperienced traders.

[insert Table 5 about here]

Table 5 presents results from estimating Equation 2 partitioned by trader experience level. Column (1) includes only traders that have zero years experience while column (2) includes traders that have 1 - 3. The coefficient on the interaction term between $gain_{ijt}$ and $postFB_{ijt}$ is equal to 0.0071 in the former and 0.021 in the latter, and both are statistically significant at the five percent error level. Meanwhile, column (3) includes traders with four years of experience and column (4) includes those with 5+ years. The coefficient estimate for the interaction term is not statistically different from zero in either column, which is consistent with the prediction that experienced traders have less incentive to signal through trading.

Trader sub-communities

The illustrative model also predicts that much of the variation in the disposition effect will be driven by social-cohort level variation. This is because the network's characteristics, such as its size and the degree of social trust, govern the probability that traders search for peer-matches. It is not possible to produce a comparative static on this effect, but conveniently, the model implies that there should be more correlation in the disposition effect between traders from similar cohorts than would be predicted by random assignment at the trader level.

To assess the correlation in the disposition effect between traders within social cohorts, I begin by estimating the following regression for each individual j

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

and collect the coefficient β_1, which represents each trader's idiosyncratic susceptibility to the disposition effect. The regression is estimated using only post-myForexBook data and includes the same controls as earlier regressions, which suggests the distribution of β_1 accounts for a number of contemporaneous factors which may explain friendship formation among like-pairs. For the sample of traders used in the regression analysis, the coefficient β_1 has a mean of 0.038, standard deviation of 0.16, skewness equal to 1.1, and kurtosis equal to 18.8. I use these parameters to conduct a thousand simulations of a randomly-drawn network composed of 15,030 friendships, the same number in the actual data when restricted to those in the trimmed sample. This simulation is equivalent to the null-distribution from the hypothesis that networks form at random and that there are no peer-effects.

[insert Figure 7 about here]

The left panel in Figure 7 presents a histogram of

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

which is the absolute difference in the idiosyncratic disposition effect for any pair of traders. The right panel presents the results from simulating the network. I sort $DE\,dif_{jk}$ in each simulation in order from smallest to largest and take the row-average across the thousand simulations. The histogram of actual friendships (left frame) has a larger mass concentrated towards zero than the simulated network (right frame), which suggests that traders who are similarly susceptible to the disposition effect tend to cluster together.

Appendix A.2 presents complementary results using the discount brokerage data from Barber and Odean (2000). I use equation 3 to estimate each trader's idiosyncratic disposition effect and I match the trader's zip code to a table of MSAs provided by the U.S. Census Bureau. I restrict the analysis to traders with enough activity to reliably estimate a within-trader disposition effect and to MSAs that have at least one-thousand traders.

In a first test, I demonstrate that there is substantial variation in the average level of the disposition effect across MSAs. It is smallest in the Seattle, WA area (0.6) and largest in San Jose-Santa Clara, CA (1.0). More formally, an F-test for differences in means across MSAs produces a p-value of 0.00, which suggests that geography can explain much of the variation across traders.

To address concern that the averages reflect common geographic shocks rather than peer-effects, I employ an identification strategy similar to Pool et al. (2014) who note that a pair of traders who live fairly close are more likely to engage in social interaction than any two traders that are geographically distant within an MSA. Hence, I assume that any two traders within a zip code form a friendship and compare the trader-pair correlation in the disposition effect (equation 4) to a simulated null distribution under the hypothesis that, within an MSA, traders randomly sort and form peer-connections. In all MSAs, a Kolmogorov–Smirnov rejects the hypothesis that the actual distribution of friendships is equal to the simulated distribution of random trader pairings. Moreover, the actual distribution of within-zip code trader-pairings merits comparison to Figure 7, in which the mass of the actual distribution is concentrated close to zero. Generally, this suggests that there is too much geographical clustering in levels of the disposition effect to be explained by random chance.

Talking and Disposition Effect

The social bargaining story predicts that traders most susceptible to the disposition effect issue fewer communications on average. The myForexBook platform allows traders to send peer-to-peer messages to one another, which enables empirical tests of this prediction. The following regression model estimates the relationship between the disposition effect and communications:

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

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, $trader.DE_j$, is equal to $\beta_1(j)$, a trader's idiosyncratic susceptibility to the disposition effect, as outlined in the previous sub-section. To ease interpretation, $trader.DE_j$ is normalized about its standard deviation, such that a one unit increase is equal to a one standard deviation increase. The empirical model is estimated with standard errors clustered by the month in which the trader joins myForexBook.

Table 6 presents estimates of equation 5, which broadly finds a negative relationship between issuing communication and the disposition effect. 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 (s.e. = 0.030). This implies that a standard deviation increase in the disposition effect is association with seven percent fewer messages sent to other traders. Column (2) includes a set of dummy variables for the month trader j joins the social network, which accounts for variation in the time spent using myForexBook. Column (3) includes a set of individual-specific control variables including trader experience, region, and approach. The estimate of β_1 remains negative and statistically meaningful in both alternative specifications.

The negative relationship between sending messages and the disposition effect could instead reflect a trader's response to communications directed at her. Similar to a placebo exercise, 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. The coefficient estimate of β_1 is not statistically different from zero, implying that receiving communication is independent of the disposition effect.

[insert Table 6 about here]

6 Alternative Explanations for the Disposition Effect

Blame Delegation

In recent research, Chang et al. (2014) show that investors exhibit a reverse disposition effect in their ownership of delegated assets. By entering the social network, it is possible that traders adopt other traders' strategies. Doing so would suggest that traders can assign blame to others, which would make them more willing to realize losses, contrary to this paper's results.

Adverse Selection

Adverse selection concerns are important for markets with retail participants. Linnainmaa (2010) demonstrates that traders who use limit orders provide a free option to informed market participants. Since retail traders tend to be less-informed, their limit orders frequently execute unexpectedly, a process that mechanically produces a disposition effect. Hence, not sorting trades by order type can mischaracterize the empirical results.

Table 7 presents estimates of equation 2 augmented to include all positions that include a price-contingent order (stop-loss or take-profit). As indicated by the coefficient on $limit.order_{ijt}$, these trades are unconditionally less likely to execute, but when they do, they are more likely to produce a gain (the coefficient on the interaction between $gain_{ijt}$ and $limit.order_{ijt}$). For the purposes of evaluating the effect of social interaction on the disposition effect, the coefficient on the interaction between $gain_{ijt}$ and $postFB_{ijt}$ remains positive, statistically significant and is quantitatively similar to the corresponding regression specifications in Columns (3) - (6) of Table 3. In general, the ability to account for and separately estimate an effect for price-contingent orders is an improvement over many empirical studies of the disposition effect.

[insert Table 7 about here]

Transaction Costs

Transaction costs are minimal in foreign exchange. There are no fixed fees. Brokerages act as market makers earning the spread on each transaction, which tends to average no more than a few pips on major currency pairs. Thus, transaction costs are constant before and after a trader joins myForexBook

Mean-Reversion

Social interaction may exacerbate a belief in mean-reversion. The traders in myForexBook state their preferred trading strategy upon joining the social network. myForexBook limits the responses to *News, Momentum, Technical, Fundamental,* and *None Specific.* The strategies can roughly be ranked in order of a revealed belief in mean-reversion. Fundamental traders believe the most in mean-reversion, while Momentum traders believe the least. Technical and News-based strategies would presumably fall somewhere in between.

[insert Table 8 about here]

Table 8 presents estimates of the regression in Equation 2 sorted by a trader's preferred strategy. The coefficient on the interaction term between $gain_{ijt}$ and $postFB_{ijt}$ is positive in all regressions. The coefficient estimate is statistically significant at the five percent error level when the trader chooses fundamental, technical, or does not have one specific strategy. While positive in both cases, the estimate is not statistically different from zero when the trader follows news or momentum strategies. However, it is difficult to rule out the possibility that this result is caused by a loss of statistical power when clustering the standard errors by trader, for which there are far fewer observations. It is therefore unlikely that the social network affects the belief in mean-reversion.

7 Conclusion

This paper finds that social interaction contributes to investment behavior that is seemingly biased. In particular, social interaction increases the magnitude of the disposition effect, a puzzling deviation from rational trading behavior found frequently across many types of investors and on a variety of asset classes. I document this relationship using the introduction of an online social networking platform into the world of retail trading. The social networking features were introduced to traders on different brokerages at a staggered rate over time, which enables unique causal tests of peer-effects.

This paper suggests a number of avenues for future research. The disposition effect is among the most robust behavioral findings, which makes it ripe for studying, but a number of other behavioral phenomena are potentially influenced by social forces. For example, some have suggested that overconfidence develops through social interaction (Burks et al. (2013) and Heimer (2014a)). Furthermore, this paper highlights the difficulty studying the mechanisms underlying peer-effects. There have been a few recent attempts at this endeavor either through field experiments (Bursztyn et al. (2014)) or in the laboratory (Frydman (2014)), but there is much room for additional research.

As a final consideration, this paper contributes to a growing literature which suggests that potentially welfare-improving changes to the financial sector can amplify harmful behavior among household or individual investors. Mullainathan et al. (2012) provides evidence that financial advisers reinforce the behavioral biases of their clients. Ahmed et al. (2013) suggests that allowing individuals greater choice over the allocation of their retirement funds may cause the social security system to be underfunded. This paper finds seemingly comparable empirical results: new information provided via social networks increase rather than alleviate a prominent behavioral bias. In contrast, I demonstrate that increased access to social networks may create incentives that lead to a disposition effect. In this sense, behavioral biases may reflect perfectly rational decision-making.

Appendix

A.1 An Illustrative Framework for Bi-Lateral Matching with Strategic Signaling

Setup and assumptions

Consider a risk-neutral trader i who gets utility from consumption. Traders have the option to produce investment ideas, x_i, and chooses the time, t, in which she reallocates resources other activities. The trader can participate in the non-degenerate gamble X, which means that the trader's optimization problem is equivalent to

$$U(c) = \max_{t} \quad max\left(\mathrm{E}\left[X(t,\ \Phi)\right],\ 0\right) \tag{6}$$

where zero is the payout to not participating. For convenience, X can be called *socially motivated* trading, because as I show, trading occurs with the intention of capturing surplus achieved through establishing mutually beneficial social connections. The trader's information set about the market is captured by Φ, which is exogenous and could include factors such as the number of market participants and the complementary nature of investment ideas. It is beyond this paper's scope to model Φ, but other research, such as Bergstrom and Bagnoli (1993), prove the existence and uniqueness of two-sided matching market equilibrium when t is a strategic variable and there is quality uncertainty. I refer readers to Bergstrom and Bagnoli (1993) for a formal theoretical treatment. The trader is also endowed with an asset v that is in fixed supply. While I do not generalize this exercise to include multiple asset holdings, a similar intuition would apply, particularly if an individual's portfolio-weights are more strongly correlated with their good ideas.

The trader's investment idea can be in one of three monotonically preferred states – *bad*, *uncertain*, or *good*. The idea's intrinsic value is $\tilde{x}$, but the market's perception of the idea has a stochastic component, σ_x. The intrinsic value is evenly distributed meaning that the median value is *uncertain* when $t = 0$. The stochastic component governs the evolution over time of the market's perception of the idea and has the following transition matrix:

$$\sigma_x = \begin{bmatrix} 1 - p(u=1) & p(u=1) & 0 \\ 1 - p(u=1) & 0 & p(u=1) \\ 0 & 1 - p(u=1) & p(u=1) \end{bmatrix} \tag{7}$$

which has the state-space $\{1 = \textit{bad},\ 2 = \textit{uncertain},\ 3 = \textit{good}\}$ and does not change over t. The probability that x_i's value increases is represented by $p(u = 1)$, with $u \in \{0, 1\}$. Since i chooses t, which is finite, the current state is a noisy signal of the initial state and thus the intrinsic value of x_i. To briefly demonstrate that the current state reflects $\tilde{x}$, consider the mass of ideas perceived to be *good* in $t = 1$. The transition matrix dictates that half of the *uncertain* ideas become *good*, while half of the *good* ideas remain *good*. The idea has a finite lifespan for exogenous reasons, such as liquidity constraints or opportunity costs, and is therefore abandoned after two periods.

Furthermore, suppose there are other traders, j, who develop their own investment ideas, z_j, whose stochastic process, σ_z, is independent of σ_x. The ideas of j are complimentary to i's ideas, implying that joint knowledge production produces an expected benefit to i equal to $E_i\left[V(z_j)\right] > 0$. There are a few ways to interpret the assumption that the expected benefit is positive, all of which are reasonable. For one, there can be benefits to diversification across investment ideas. Another story suggests that if there are bottlenecks to producing or interpreting information (e.g. time constraints or attention is a scarce resource), there can be benefits to sharing the burden. In line with this story, recent theoretical research shows that when retail traders with limited attention compete for profits against institutions, they are motivated to form trading coalitions (Davies (2014)). Moreover, this illustration provides the same intuition whether or not the social network actually benefits the trader, what matters is the investor's *beliefs*. Considering the growing and prominent empirical literature that finds that social interaction influences investment choices, as well as the explosive growth of online investment forums and chatrooms, it seems reasonable to assume that traders believe that social connections are valuable.

A second feature of the model is that after each round, bilateral connections are formed one at a time, in hierarchical order, with probability $q(x_i, \Phi) \in [0, 1]$ that a trader can find a match. When a trader chooses to search for a match, the probability she produces one is increasing in x_i, because matches are bilateral and their formation has to be incentive compatible. To illustrate, if it is costless to search through potential matches, the trader whose idea is valued most highly by the market has the most bargaining power and will choose to match with the trader whose idea has the most value-added, and so forth. This mechanism is similar to Yuan (2005)'s argument that it is less costly for investors to raise capital in good states.

After developing a social connection with another trader, i reallocates all or part of her portfolio holdings to more efficient uses in order to capture $E_i[V(z_j)]$. The performance of the trader's portfolio holdings, v, are correlated with the fluctuations in the market value of her idea, $cov(v, x_i) > 0$. Therefore, the reallocation produces realized gains or realized losses depending on the underlying stochastic process and the timing in which the trader chooses to develop or reaffirm social connections.

A numerical example and solution

Since this amounts to an optimal stopping problem, solving the model requires backward induction and a calculation of the trader's path-dependent choices. I can reduce the problem to a decision rule based on the random evolution of the investment idea in the first period. For exposition, I set the match probability equal to:

$$q(x_i) = \begin{cases} 0, & x_i = bad \\ \delta \in (0,1), & x_i = uncertain \cdot \\ 1, & x_i = good \end{cases} \tag{8}$$

I also set $p(u = 1) = 0.5$. The idea's payoff, v, is correlated with the fluctuations in the transition matrix, and for convenience, I set it to increase (decrease) by 1 when $u = 1$ ($u = 0$). I assume that when a trader searches for a match and succeeds in finding one, she reallocates all of her resources to joint information production, which means that if she finds a match in $t = 1$, position v is executed and it no longer accrues or loses value. Lastly, I set $\tilde{x} = uncertain$, but the two other initial conditions produce similar results.

Solution in the up state. Searching for a match is a dominant strategy when $u = 1$. In $t = 1$, $v = 1$ and $x_i = good$. If she searches for a match she does so with certainty and enjoys the benefits of joint information production. Her final payout $1 + E_i\left[V(z_j)\right]$. If she waits to search she receives $0.5(\delta \cdot E_i\left[V(z_j)\right]) + 0.5(2 + E_i\left[V(z_j)\right])$, which simplifies to $1 + \frac{1+\delta}{2} \cdot E_i\left[V(z_j)\right]$. Since $1 + E_i\left[V(z_j)\right] > 1 + \frac{1+\delta}{2} \cdot E_i\left[V(z_j)\right]$, engaging in joint production is strictly preferred, which implies selling assets when $v = 1$.

Solution in the down state. When $u = 0$, it is beneficial to wait and search for a match until forming one becomes more likely. In $t = 1$, $v = -1$ and $x_i = bad$. Since $p(x_i) = 0$, searching at $t = 1$ is unproductive and so her total utility equals -1. Holding out for a better match produces $0.5(\delta \cdot E_i\left[V(z_j)\right]) + 0.5(-2)$, which can be rearranged as $-1 + \frac{\delta}{2} \cdot E_i\left[V(z_j)\right]$. Since $-1 + \frac{\delta}{2} \cdot E_i\left[V(z_j)\right] > -1$, the trader prefers to search for joint production in $t = 2$, which implies that she does not reallocate her resources when $v = -1$. In other words, traders prefer to hold unrealized losses.

The trader's utility maximizing solution. Returning to Equation 6, the expected benefit of the gamble X must exceed zero or else she prefers not to engage in *socially motivated* trading. The expected value of X is equal to one-half times the payoff in the down state plus one-half times the payoff in the upstate, which is equal to

$$^1/_2\left(1+\frac{1+\delta}{2}\cdot E_i\left[V(z_j)\right]\right)+{}^1/_2\left(-1+\frac{\delta}{2}\cdot E_i\left[V(z_j)\right]\right)=\frac{1+2\delta}{4}\cdot E_i\left[V(z_j)\right]. \tag{9}$$

The expression is greater than zero so long as $\delta\cdot E_i\left[V(z_j)\right]>0$. Broadly, this means that economies of scale in the production of investment ideas leads to socially inspired trading and the disposition effect.

Implications

In addition to showing that social interaction is causally related to the disposition effect, the model provides some additional intuition on the margin, which I outline as follows.

Implication 1: *Traders with the highest valuation of their social connections are most susceptible to the disposition effect.*

The probability the trader participates in *socially motivated* trading is equal to $Pr\left(X\right)=Pr\left(\frac{1+2q(x_i,\Phi)}{4}\cdot E_i\left[V(z_j)\right]>0\right)$. When i chooses X she adopts a strategy that produces a disposition effect. Clearly, $Pr\left(X\right)$ is an increasing function of $E_i\left[V(z_j)\right]$,

$$\frac{\partial Pr\left(\frac{1+2q(\cdot)}{4}\cdot E_i\left[V(z_j)\right]>0\right)}{\partial E_i\left[V(z_j)\right]}=\frac{1+2q(\cdot)}{4}>0 \tag{10}$$

which means that when a trader has a high valuation of their social connections, they are more likely to have a disposition effect.

Implication 2: *There are different equilibrium levels of the disposition effect across social cohorts.*

A simple interpretation of $q(x_i, \Phi)$ is that it relates to the concept of social trust (Guiso et al. (2004)). However, the effect on the propensity to engage in X is ambiguous, because the matching process is two-sided,

$$\frac{\partial Pr\left(\frac{1+q(\cdot)}{4} \cdot E_i\left[V(z_j)\right] > 0\right)}{\partial q(\cdot)} = \left(\underset{+}{\frac{\partial Pr(\cdot)}{\partial q}} \frac{\partial q}{\partial x_i} + \underset{?}{\frac{\partial Pr(\cdot)}{\partial q}} \frac{\partial q}{\partial \Phi}\right) \frac{E_i\left[V(z_j)\right]}{2}. \tag{11}$$

The trader can control her own bargaining power, and benefits when it is stronger, meaning the effect of $q(x_i, \Phi)$ on $Pr\,(X)$ through x_i is strictly positive. On the other hand, exogenous market factors that affect the match probability, Φ, interact with the trader's decision rule in an ambiguous manner. For example, when trust is high, the uncertainty over the match falls, but this also means that weaker signals are required to form matches, thereby lowering the need to wait until *good* states occur to form matches. However, since Φ is a parameter specific to the market or community of traders, the motivation to engage in gamble X differs across social cohorts.

Implication 3: *The relation between the disposition effect and the propensity to communicate with others is negative.*

To illustrate, a trader can either communicate with others or remain silent, $s = \{0, 1\}$. The unconditional probability of communication is equal to $Pr\,(s = 1) \in [0, 1]$, which reflects the degree to which a typical individual likes to talk without motive. Therefore, when i does not choose X, she communicates with a frequency $Pr(s = 1)$ each period. Meanwhile, the probability of communication for a trader who chooses X also includes a component that is based on their expected utility, $Pr(\mathrm{E}\,[U(t)]) \in [0, 1]$. Consider i's decision-rule when $t = 1$. The trader selectively talks in the good state and is mute in the down state, so $Pr\,(\mathrm{E}\,[U(t = 1)]) = 0.5$. Since $Pr\,(s = 1)$ is independent of $Pr(\mathrm{E}\,[U(t)])$, the probability of communicating when $t = 1$ is equal to $Pr(s = 1) \times Pr(\mathrm{E}\,[U(t = 1)])$. This is by definition less than or equal to the unconditional probability. Hence, traders that are prone to the disposition effect communicate less frequently than a trader drawn at random who has no expectation of benefiting from her social connections.

A.2 Instrumental Variable Estimates

This section presents the following instrumental variables estimation using two-staged least squares (2SLS):

$$
\begin{aligned}
sale_{ijt} &= \beta_0 + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot \widehat{postFB}_{ijt} + \beta_3 \cdot gain_{ijt} \cdot \widehat{postFB}_{ijt} + \varepsilon_{ijt} \\
postFB_{ijt} &= \gamma_0 + \gamma_1 \cdot broker.id_j + \gamma_2 \cdot gain_{ijt} + \mu_{ijt}
\end{aligned} \tag{12}
$$

where the excluded instrument is $broker.id_j$, trader j's brokerage. As demonstrated in Section 3, $broker.id_j$ is a strong predictor of $postFB_{ijt}$; a simple OLS regression produces an F-statistic of over 300. It is also uncorrelated with other trader characteristics, which implies that $broker.id_j$ satisfies the necessary exclusionary restrictions and does not suffer from the problem of being a weak instrument. However, $broker.id_j$ predicts $postFB_{ijt}$ with upward bias. This is because it is not possible to have observations where $postFB_{ijt} = 1$ until after the brokerage and myForexBook partner, even though the true distribution's mean of intended join dates is presumably centered about the brokerage's partnership date. An upwardly biased estimate of $postFB_{ijt}$ falsely attributes too large a share of trades to the pre-myForexBook group, which places a downward bias on the 2SLS estimates of β_2 and β_3. It is unfortunately beyond the data's means to determine the extent of the bias. A second issue is that 2SLS is under-identified with two endogenous regressors and one exogenous.

Regardless, Table A.1 presents the estimates from the 2SLS approach. The results are largely consistent with the paper's findings that social interaction increases the disposition effect. The instrumental variables estimate of β_3 tends to be around 0.005 and statistically significant at the five percent error level. As expected, this implies that the magnitude falls to around a quarter of the unconditional disposition effect, the estimate for β_1.

Table A.1: **Instrumental Variables, Social Interaction, and the Disposition Effect**
Description: This table presents results from using the myForexBook data to estimate the following 2SLS model: $sale_{ijt} = \beta_0 + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot \widehat{postFB}_{ijt} + \beta_3 \cdot gain_{ijt} \cdot \widehat{postFB}_{ijt} + \varepsilon_{ijt}$. It uses the variable $broker.id_j$, trader j's brokerage, as an instrument. Standard errors are clustered by trader.

$sale_{ijt}$	(1)	(2)	(3)
$gain_{ijt}$	0.0157***	0.0160***	0.0151***
	(0.0025)	(0.0025)	(0.0030)
$postFB_{ijt}$	-0.0142	-0.0129	-0.0116
	(0.022)	(0.020)	(0.028)
$gain_{ijt} \times postFB_{ijt}$	0.00540**	0.00520**	0.00531**
	(0.0025)	(0.0023)	(0.023)
constant	x	x	x
holding period FE	x	x	x
week FE		x	x
experience FE			x
approach FE			x
N	2,057,515	2,057,515	2,057,515
R^2	0.030	0.030	0.031

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3 Within Community Clustering in the Disposition Effect

Pool et al. (2014) illustrates that aggregate shocks occur at the level of the community, while peer-effects can be identified by examining the correlations among geographically close pairs within a community unit. In other words, social interaction is important if two neighbors have more similar behavior than a pair of individuals that are geographically distance.

I apply this empirical approach to the discount brokerage data used in Barber and Odean (2000). To preserve statistical power in my tests, I restrict the sample to traders in the six MSAs that contain more than one thousand traders. I use the following regression

$sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}\ \forall j$, to estimate each trader's idiosyncratic susceptibility to the disposition effect, $\beta_1(j)$. Since the demographic file does not contain precise addresses, only zip codes, I assume that each trader within a given zip code forms a bilateral connection with every other trader in the zip code and collect the distribution of pair-wise disposition effect differences, $DE\,dif_{jk} = |\beta_1(j) - \beta_1(k \neq j)|$. Then for each MSA, I generate a simulated network in which traders are paired at random. I calculate $DE\,dif_{jk}$, sort the distribution in ascending order, and take the row average for 1,000 simulated distributions.

Table A.2 presents a comparison of means across MSAs (Panel I), as well as a comparison of the distribution for geographically close traders against a simulated random network (Panel II). Panel I demonstrates that there are significant differences in the disposition effect across MSAs, which alone does not prove social interaction matters, but is informative. Panel II shows that geographically close pairs have more correlated levels of the disposition effect than any randomly drawn pair from a given MSA. These findings support the hypothesis that there are different equilibrium levels of the disposition effect across social cohorts.

Table A.2: **Geographic Peer-effects and the Disposition Effect**

Description: This table uses data on common stock trading from a large discount brokerage Barber and Odean (2000), matched to zip codes from Infobase and to statistical MSAs from the U.S. Census Bureau. For both panels, I estimate the following regression for each individual in the data, $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$, where i is a position and t is monthly, and record estimates of β_1 for each individual j. Call $\beta_1(j) = DE_j$, which captures each individual's susceptibility to the disposition effect.

Panel I includes means and standard deviations of DE_j, as well as an F-test for the null hypothesis that all statistical MSAs yield the same mean level of the disposition effect.

Panel II conducts a within MSA study of the geographical correlation in the disposition effect across traders. It defines a friendship as a pairing of any two traders that reside in the same zip code. $DE\,dif_{jk}$ is the absolute difference between $\beta_1(j)$ and $\beta_1(k)$ for $k \neq j$, for each possible within zip code pair. The simulated comparison randomly draws any two traders form the MSA. Each simulation includes N friendships. I estimate 1000 simulated networks per MSA. Panel II also contains results from a Kolmogorov-Smirnov test for the null hypothesis that the actual and simulated distributions are equivalent.

	Panel I: across MSA variation		**Panel II:** within MSA trader correlations ($DE\,dif_{jk}$)			
statistical MSA	mean DE_j[†] (std dev)	N traders	actual median[‡]	simulated median[‡]	K-S test $p-value$	N friendships[ξ]
New York-Northern New Jersey-Long Island, NY-NJ-PA	0.0722 (0.182)	3,106	0.539	0.603	0.00	14,714
San Francisco-Oakland-Fremont, CA	0.0791 (0.200)	2,711	0.563	0.642	0.00	37,846
Los Angeles-Long Beach-Santa Ana, CA	0.0740 (0.197)	2,017	0.518	0.688	0.00	12,178
Chicago-Naperville-Joliet, IL-IN-WI	0.0660 (0.183)	1,656	0.529	0.751	0.00	10,967
San Jose-Sunnyvale-Santa Clara, CA	0.103 (0.219)	1,388	0.581	0.693	0.00	31,057
Seattle-Tacoma-Bellevue, WA	0.0621 (0.183)	1,068	0.523	0.657	0.00	8,357
$p-value$ from F-test	0.00					

[†] $DE_j = \beta_1$ from trader-level estimates of $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$

[‡] Trader-pair level calculation of $DE\,dif_{jk} = |\beta_1(j) - \beta_1(k \neq j)|$

[ξ] A friendship is a pairing of any two traders in a given zip code

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Table 1: **Trader and Trade-level Summary Statistics**

Description: This table presents summary statistics from the myForexBook database. The data has been trimmed to include only traders who have at least fifty trades and who trade both before and after joining myForexBook. This cut of data excludes any positions that include a price-contingent order (stop-loss or take-profit) and therefore only market orders are presented below.

	mean	std dev	median	N
Panel A: *All trades*				
Trades per account	159.27	792.33	66.0	2433
Fraction trades long per account	0.54	0.22	0.54	2433
Distinct currency pairs traded at least once per account	5.66	3.16	6.0	2433
Traders 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
Panel B: *Pre-myForexBook*				
Trades per account	80.88	177.86	35.0	2164
Fraction trades long per account	0.54	0.26	0.54	2164
Distinct currency pairs traded at least once per account	4.61	3.00	4.0	2164
Traders 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
Panel C: *Post-myForexBook*				
Trades per account	97.91	775.48	24	2170
Fraction trades long per account	0.54	0.26	0.54	2170
Distinct currency pairs traded at least once per account	4.46	2.98	4.0	2170
Traders 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**

Description: 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, $last_i$. Panel I includes a comparison of means. Panel II 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.

Panel I: Difference in means between first and last entrants

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*
$experience_i$									
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*
$trading.approach_i$									
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*
$location_i$									
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

Panel II: Probit model estimates of being among the first entrants

first/last network entrants:	(a) 250		(b) 500		(c) 1,000	
dep var: $first_i = 1$	coef	(s.e.)	coef	(s.e.)	coef	(s.e.)
age_i	0.00691	(0.0058)	0.00262	(0.0040)	0.00139	(0.0028)
$experience_i^{\dagger}$						
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)
$trading.approach_i^{\ddagger}$						
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)
$location_i^{\xi}$						
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)
N	500		1000		2000	
pseudo R^2	0.012		0.0026		0.012	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

†omitted category is *no response,* ‡omitted category is *fundamental,* $^{\xi}$ omitted category is *none specified*

Table 3: **Social Interaction on the Disposition Effect**

Description: This table plots the results from using the myForexBook data to estimate the following regression: $sale_{ijt} = \gamma_j + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot postFB_{ijt} + \varepsilon_{ijt}$, in which $sale_{ijt}$ is an indicator variable for closing a position, $gain_{ijt}$ is an indicator for a paper gain, and $postFB_{ijt}$ is an indicator if the position was opened after trader j joined myForexBook. Trader fixed effects are represented by γ_j. Standard errors are double-clustered by trader and week.

	pre-social network	post-social network	full sample			
$sale_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)
$gain_{ijt}$	0.0213***	0.0367***	0.0226***	0.0225***	0.0224***	0.0222***
	(0.0020)	(0.0084)	(0.0017)	(0.0017)	(0.0017)	(0.0016)
$postFB_{ijt}$			-0.00842	-0.00829*	-0.00756	-0.00552
			(0.0052)	(0.0053)	(0.0048)	(0.0034)
$gain_{ijt} \times postFB_{ijt}$			0.0140**	0.0143**	0.0149**	0.0150**
			(0.0077)	(0.0071)	(0.0075)	(0.076)
$leverage_{ijt}$				0.00371***	0.00400***	0.00410***
				(0.00070)	(0.00075)	(0.00085)
$constant$	0.0665***	0.0571***	0.151***	0.151***	0.159***	0.143***
	(0.0033)	(0.0067)	(0.0066)	(0.066)	(0.075)	(0.015)
holding period FE	x	x	x	x	x	x
trader FE			x	x	x	
week FE					x	x
experience FE						x
approach FE						x
N	1,301,466	1,611,459	2,912,925	2,874,465	2,874,465	2,874,465
adj. R^2	0.0016	0.0048	0.031	0.030	0.031	0.033

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: **Broadband Internet Placebo Test**

Description: This table plots the results from using the discount brokerage data (Barber and Odean (2000)) to estimate the following regression: $sale_{ijt} = \beta_0 + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot broadband_j + \varepsilon_{ijt}$, in which $sale_{ijt}$ is an indicator variable for closing a position, $gain_{ijt}$ is an indicator for a paper gain, and $broadband_i$ is the number of broadband internet providers in j's zip code by the end of 1999. Standard errors are double-clustered by trader and month.

$sale_{ijt}$	I	II	III
$gain_{ijt}$	0.0483***	0.0906***	0.0480***
	(0.0022)	(0.0051)	(0.0025)
$broadband_i$	0.0000864	0.00105**	0.000176
	(0.00031)	(0.00052)	(0.00040)
$gain_{ijt} \times broadband_i$	-0.000447	0.000977	-0.000179
	(0.00051)	(0.0012)	(0.00056)
$gain_{it} \times broadband_i \times year1992_t$		0.000152	
		(0.0013)	
$gain_{it} \times broadband_i \times year1993_t$		-0.000944	
		(0.0013)	
$gain_{it} \times broadband_i \times year1994_t$		-0.00117	
		(0.0014)	
$gain_{it} \times broadband_i \times year1995_t$		-0.00245*	
		(0.0014)	
$gain_{it} \times broadband_i \times year1996_t$		-0.00152	
		(0.0014)	
log age			-0.00758**
			(0.0038)
male			0.0165***
			(0.0023)
female			0.0203**
			(0.010)
year FE		x	
marital status			x
constant	x	x	x
N	1,277,026	1,277,026	862,847
R^2	0.0070	0.010	0.0077

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **The Disposition Effect by Trader Experience**

Description: This table presents estimates from the following regression $sale_{ijt} = \gamma_j + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot postFB_{ijt} + \varepsilon_{ijt}$ using the myForexBook database. Regressions are estimated by trader experience which is the response to a survey administered by myForexBook. The myForexBook operators grouped traders into the following buckets. Standard errors are double-clustered by trader and week.

	experience (years) =			
	0	1-3	4	5+
$sale_{ijt}$	(1)	(2)	(3)	(4)
$gain_{ijt}$	0.0233***	0.0231***	0.0187***	0.0204***
	(0.0024)	(0.0028)	(0.0045)	(0.0035)
$postFB_{ijt}$	-0.00862**	-0.00701	0.0151*	-0.00782
	(0.0034)	(0.0052)	(0.0089)	(0.0063)
$gain_{ijt} \times postFB_{ijt}$	0.00707**	0.0210**	-0.000724	0.00690
	(0.0033)	(0.010)	(0.0076)	(0.0044)
$constant$	0.153***	0.122***	0.120***	0.117***
	(0.0091)	(0.0082)	(0.017)	(0.016)
holding period FE	x	x	x	x
week FE	x	x	x	x
trader FE	x	x	x	x
limit order	x	x	x	x
N	1,833,847	3,822,824	658,284	1,100,307
adj. R^2	0.027	0.023	0.030	0.022

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **The disposition effect and communication between traders**

Description: This table plots the results from using the myForexBook data to estimate the following regression: $log(1 + messages_j) = \beta_0 + \beta_1 \cdot trader.DE_j + \beta_2 \cdot X_j + \varepsilon_j$, in which $messages_i$ is the number of peer-to-peer personal messages sent (received) by trader i. The independent variable $trader.DE_j$ is equal to $B_1(j)$ from the following regression estimated individually for each trader j, $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$. Standard errors are clustered by the month the trader joins myForexBook.

	$log.sent.messages_j$			$log.received.messages_j$		
	(1)	(2)	(3)	(4)	(5)	(6)
$trader.DE_j$ (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)
$trade.count_j$			0.0998***			0.190***
			(0.028)			(0.015)
constant	x	x	x	x	x	x
join month FE		x	x		x	x
trading region FE			x			x
experience FE			x			x
approach FE			x			x
N	2598	2598	2598	2598	2598	2598
R^2	0.0022	0.032	0.043	0.00056	0.17	0.29

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Accounting for Adverse Selection**

Description: This table presents results from using the myForexBook data to estimate the following regression: $sale_{ijt} = \gamma_j + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot postFB_{ijt} + \beta_4 \cdot limit.order_{ijt} + \beta_3 \cdot gain_{ijt} \cdot limit.order_{ijt} + \varepsilon_{ijt}$, in which $sale_{ijt}$ is an indicator variable for closing a position, $gain_{ijt}$ is an indicator for a paper gain, $postFB_{ijt}$ is an indicator if the position was opened after trader j joined myForexBook, and $limit.order_{ijt}$ is an indicator for positions that include either a stop-loss or take-profit order. Trader fixed effects are captured by γ_j. Standard errors are double-clustered by trader and week.

$sale_{ijt}$	(1)	(2)	(3)	(4)
$gain_{ijt}$	0.0213***	0.0223***	0.0221***	0.0213***
	(0.0020)	(0.0017)	(0.0017)	(0.0020)
$postFB_{ijt}$	-0.00938	-0.00695*	-0.00683*	-0.00602
	(0.0058)	(0.0039)	(0.0039)	(0.0058)
$gain_{ijt} \times postFB_{ijt}$	0.0154**	0.0143**	0.0146**	0.0158**
	(0.0077)	(0.0071)	(0.0072)	(0.071)
$limit.order_{ijt}$	-0.0174***	-0.0146***	-0.0145***	-0.0185***
	(0.0036)	(0.0030)	(0.0031)	(0.0035)
$gain_{ijt} \times limit.order_{ijt}$	0.00652**	0.00380*	0.00402*	0.00666***
	(0.0026)	(0.0023)	(0.0023)	(0.0025)
$leverage_{ijt}$			0.00400***	
			(0.00065)	
$constant$	0.0665***	0.122***	0.121***	0.146
	(0.0033)	(0.014)	(0.014)	(0.098)
holding period FE	x	x	x	x
trader FE	x	x	x	
week FE			x	x
experience FE				x
approach FE				x
N	7,463,083	7,463,083	7,390,840	7,463,083
adj. R^2	0.0036	0.025	0.025	0.0047

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: **The Disposition Effect by Trading Strategy**

Description: This table presents results from using the myForexBook data to estimate the following regression: $sale_{ijt} = \beta_0 + \beta_1 \cdot gain_{ijt} + \beta_2 \cdot postFB_{ijt} + \beta_3 \cdot gain_{ijt} \cdot postFB_{ijt} + \varepsilon_{ijt}$. Regressions are estimated by self-identified trading strategy which is limited to the following categories by the operators of the social network. Standard errors are double-clustered by trader and week.

	trading strategy =				
	fundamental	momentum	news	technical	none specific
$sale_{ijt}$	(1)	(2)	(3)	(4)	(5)
$gain_{ijt}$	0.0137***	0.0281***	0.0243***	0.0200***	0.0301***
	(0.0041)	(0.0060)	(0.011)	(0.0020)	(0.0042)
$postFB_{ijt}$	-0.0256**	0.0102	-0.0104	-0.00204	-0.0111
	(0.0084)	(0.0076)	(0.0081)	(0.0040)	(0.0036)
$gain_{ijt} \times postFB_{ijt}$	0.0152**	0.0111	0.00603	0.00598**	0.0275**
	(0.0069)	(0.0074)	(0.011)	(0.0026)	(0.0112)
$constant$	0.165***	0.150***	0.156***	0.170***	0.162***
	(0.010)	(0.013)	(0.014)	(0.019)	0.014
holding period FE	x	x	x	x	x
week FE	x	x	x	x	x
trader FE	x	x	x	x	x
limit order	x	x	x	x	x
N	306,054	314,996	125,425	4,703,473	1,416,744
adj. R^2	0.027	0.030	0.031	0.024	0.027

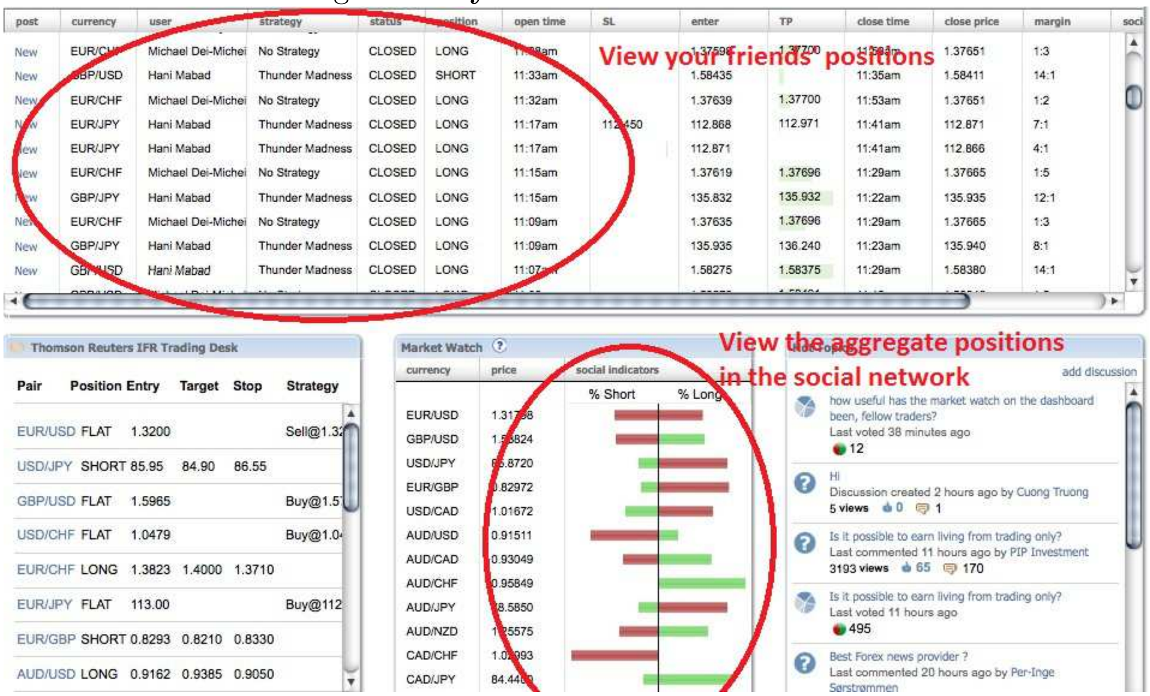
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: **myForexBook User Homepage**

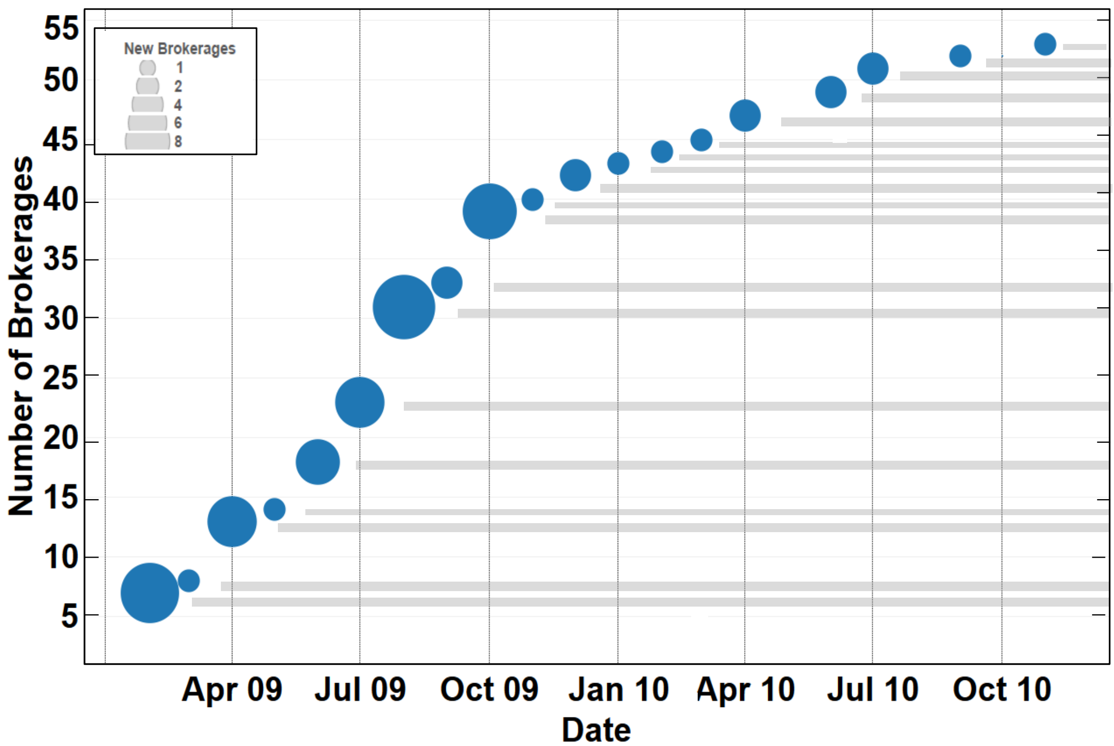
Description: This figure displays the user homepage for a member of myForexBook. Users are able to form bi-lateral friendships with other traders and communicate via private message or in the chat forum.

Figure 2: **myForexBook Dashboard**



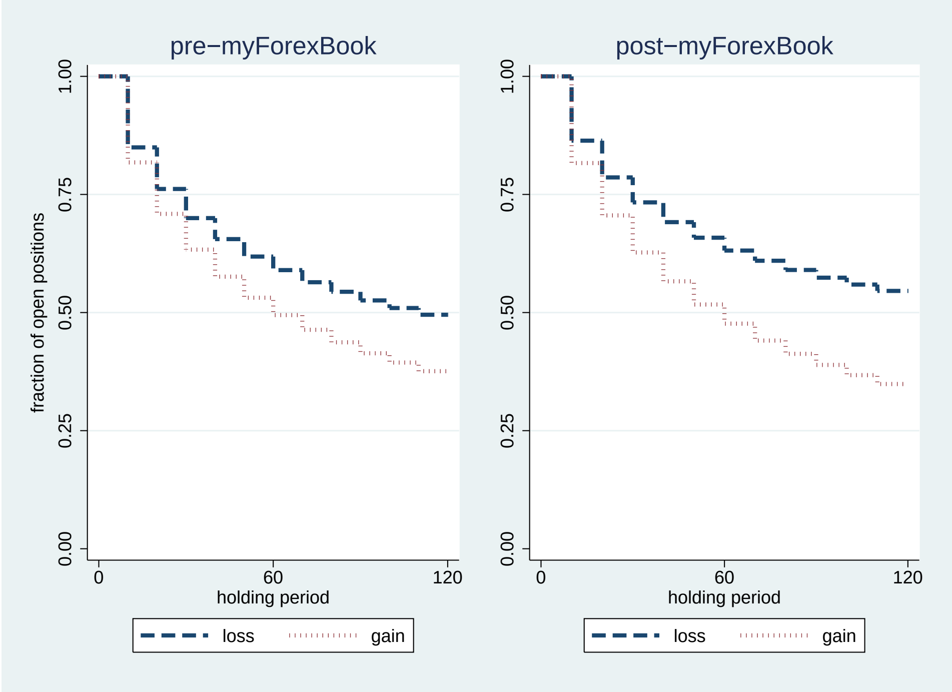
Description: This figure displays a customizable webpage dashboard available to members of myForexBook. Users are able to view their friends' positions in real-time, the aggregate positions within the network, and chat in web-forums, among other options.

Figure 3: **New Partnerships Between myForexBook and Retail Brokerages**



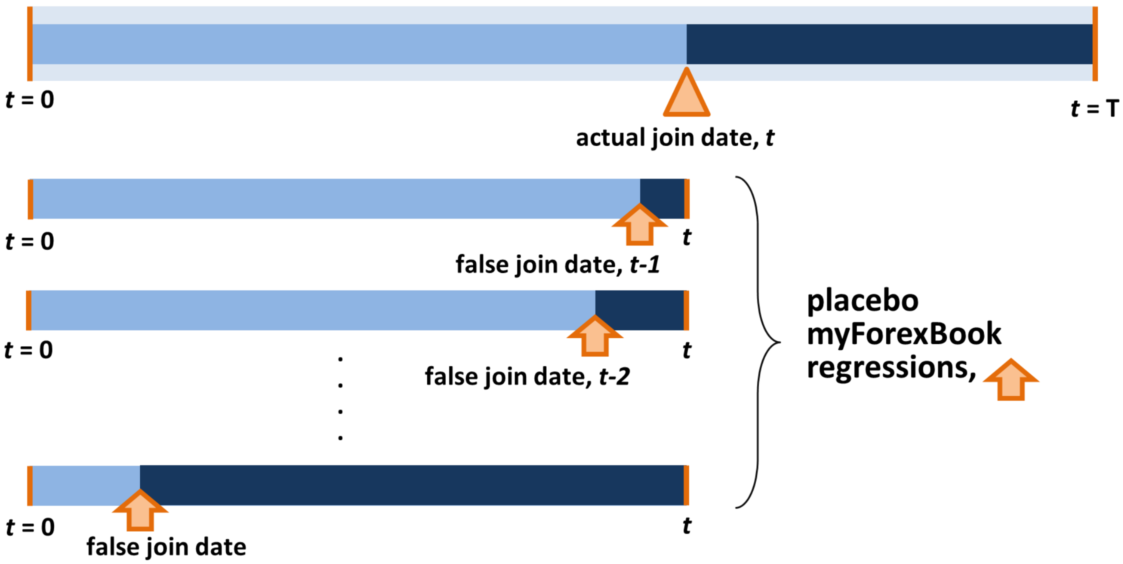
Description: This figure illustrates the formation of partnerships between myForexBook and different retail foreign exchange brokerages. The dots represent the date at which the first trader from each new brokerage joins myForexBook. Traders are not able to join the social network until their brokerage has agreed to partner with myForexBook.

Figure 4: **Holding Period of Gains/Losses and Social Interaction**



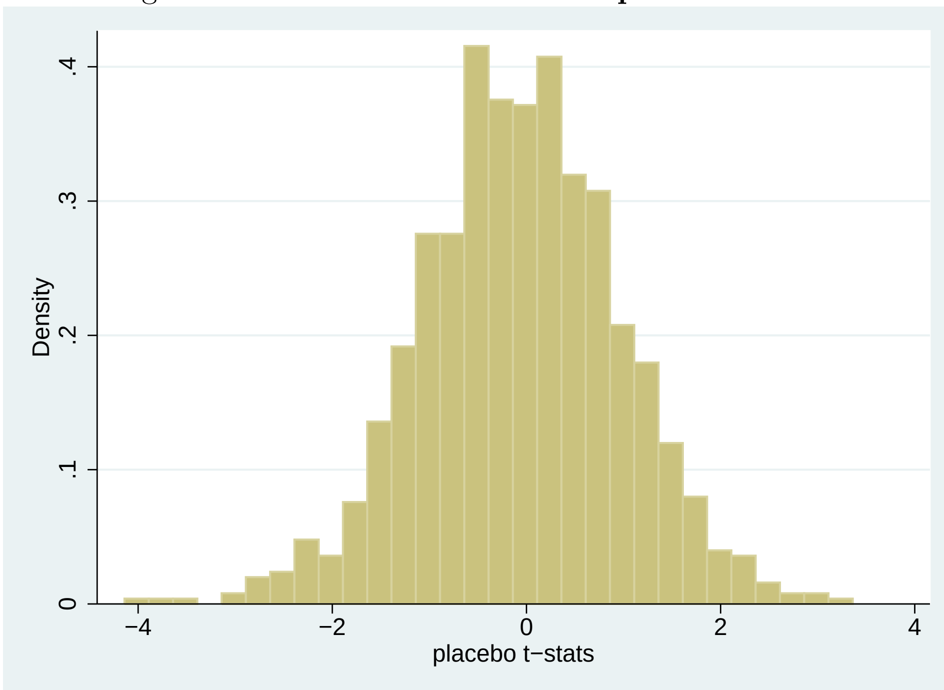
Description: This figure plots estimates of a Kaplan-Meier survival function in which the outcome of interest is an indicator variable for closing a position. Both graphs separate the survival function by paper gains and paper losses. The graph on the left is estimated using data from prior to joining myForexBook, while the graph on the right uses post-myForexBook data. The data is restricted to just market orders.

Figure 5: **Placebo Test of the Disposition Effect**



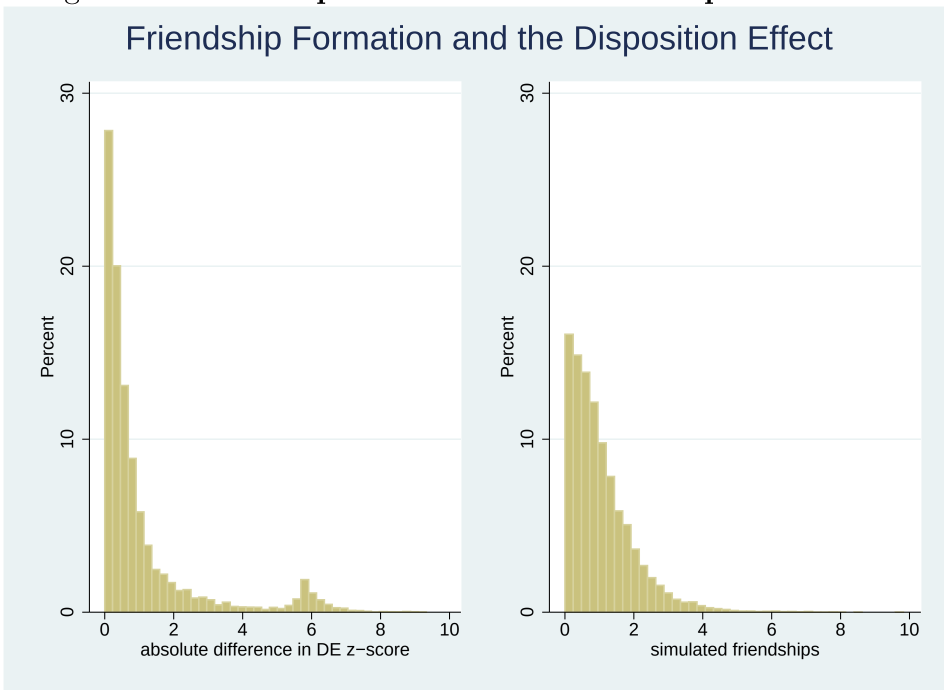
Description: This figure outlines the placebo exercise described in Section 4.

Figure 6: **Placebo Test of the Disposition Effect**



Description: This figure presents estimates of the t-statistic on the interaction term between $gain_{ijt}$ and $postFB_{ijt}$, while using false dates for $postFB_{ijt}$. The falsification exercise uses the sample of traders who never use the social network as a control group.

Figure 7: **Friendship Formation and the Disposition Effect**



Description: Using the myForexBook database, 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 $sale_{it} = \beta_0 + \beta_1 \cdot gain_{it} + \varepsilon_{it}$. The right hand panel presents a similar histogram drawn from a simulated random network, which is parametrized using the same number of friendships and the same distribution (up to the fourth moment) of $\beta_1(j)$.