Facebook Finance: How Social Interaction Propagates Active Investing

Rawley Z. Heimer* and David Simon†

Brandeis University, International Business School

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Abstract

This research presents empirical evidence of the propagation of active investing strategies within a network of retail traders. We provide support for a model by Hirshleifer (2010) which demonstrates that social interactions contribute to the growth of active strategies. Using new proprietary data compiled through a social network for foreign exchange traders, we verify key assumptions of the model that the willingness of traders to contact other traders is increasing in their short-term returns while trading intensity is increasing in the performance of those from whom they receive communications.

*Corresponding Author: Rawley Z. Heimer, Brandeis International Business School Mailstop 032, P.O. Box 549100, Waltham, MA 02454, USA. e-mail: rheimer@brandeis.edu.

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1 Introduction

This paper provides evidence that social interaction contributes to the growing popularity of active investment strategies among individual investors. Our results support a model by Hirshleifer (2010) in which strategies are transmitted through communications between investors. Traders with good short-term performance are more likely to initiate communications with others and share their investment activity. The better the initiators's recent performance, the more likely the recipients are to adopt the sender's strategy. Owing to their preference for higher variance strategies, active investors have more opportunity to broadcast extreme returns and are thus more effective in persuading other investors to adopt their strategies. Upon doing so, investors misguidedly adopt an approach to trading that is more intensive but not necessarily more profitable. This pattern of communication can explain the prevalence of active investing amongst individual investors.

The participation of active investors in financial markets can have profound effects on market outcomes as well as their own welfare. It has been widely documented since Barber and Odean (2000) that active retail investors lose money on average. More recently, Barber, Lee, Liu and Odean (2009) find that Taiwan's retail investors underperform the market by 3.8 percent and accumulate losses that amount to 2.2 percent of Taiwan's GDP annually. Active retail investors can also influence asset prices, liquidity and volatility by serving as noise traders (DeLong et al. (1990)). Among the empirical studies, Foucault, Sraer and Thesmar (2011) find that increasing the cost associated with active retail trading on Euronext Paris reduces the volatility of daily returns by about a quarter of its standard deviation, while Bender, Osler and Simon (2011) find that a popular technical trading strategy employed by individual investors leads to narrower spreads and higher volumes. Barber, Odean, and Zhu (2009), Kumar and Lee (2006), and Hvidkjaer (2008) also document that trades of individual investors tend to be correlated and therefore may affect asset prices.

The goal of this research is to empirically test the two key assumptions underlying the model in Hirshleifer (2010): (1) the propensity to initiate communications is increasing in own returns and (2) receivers of communications adopt the initiator's strategy in response to hearing of higher returns, and verify a third assumption that (3) the volatility of returns for "Active" traders are greater than those for "Passive". To do so, we introduce new data from a sample of retail foreign exchange traders who are members of a social network that for privacy purposes we call myForexBook.[1] Prior to joining the social network, users must have an open account on one of roughly 45 online brokerages from which myForexBook collects trading activity in real-time. The database contains the detailed trading history and communications of more than 5,500 traders. It includes over two-million time-stamped trades and over 140,000 time-stamped messages and friendships, the majority of which occurred between February, 2009 and December, 2010, allowing us to identify clear links between trading and social activity.

We first verify that the individuals in our dataset are suitable for testing the hypothesis that social interactions promote active investing. We document heterogeneity in individual trading intensity, the frequency with which one trades, and classify traders into two groups: the "Active" and the "Passives". Active traders invest substantial time and resources in foreign exchange trading. They trade several times daily, sometimes even several hundred times per day. Passive traders, by contrast, trade less than once a day on average. The greater commitment of Active traders is also manifest in their larger initial capital base and their persistence in trading despite short-term losses. Notably, Active and Passive traders do not differ

[1] The retail foreign exchange market, which did not exist even a decade ago, has grown tremendously since the advent of online trading. According to King and Rime (2010), worldwide retail foreign exchange trading volume grew over seventy percent during 2007 to 2010 and now exceeds \$125 to \$150 billion per day, roughly the same as daily turnover on the entire NYSE family of stock exchanges (NYSE, Arca and Amex). The venue compares favorably to other asset classes, even the most liquid NYSE stocks, since it offers practically unlimited liquidity, tight spreads, and more than 100x leverage.

in the amount of trading experience they have had which means that we observe individuals who have traded with low frequency for several years. Considering two types of market participants is further justified anecdotally. Whether or not one can earn a living by trading foreign exchange is often a topic of conversation among users of myForexBook and many claim to treat trading like a full-time job.

We find that traders are more likely to initiate communication with others when they experience strong short-term gains. A one standard deviation in weekly log returns results in about a seven percent increase in the probability of contacting other traders in a given week and roughly a six percent increase in the number of individuals contacted. We suggest two candidate explanations for this relationship. Traders may rationally perceive connections made through the social network to be beneficial, such as getting network participants to follow one's trades and provide additional buying pressure, andto gain a following within the network, traders have an incentive to signal only their best performance to others. Secondly, as in Hirshleifer (2010), individuals may exhibit "self-enhancing transmission bias" or the tendency to broadcast one's successes while downplaying their failures.

We address several concerns over proper identification of the emprical relationship between own returns and the propensity to issue communications. First, we control for individual characteristics that may simultaneously drive both higher returns and an increased propensity to send messages. Panel estimation with individual fixed effects also accounts for heterogeneity in individual trading ability. Secondly, market conditions may jointly cause increased chatter between investors as well as higher returns. We show that the empirical relationship between own returns and the probability of communicating holds even after controlling for average returns in the network, a trade-weighted US dollar index, and the average amount of messaging. Lastly, we address the possibility of reverse causality, namely that sending messages results in higher returns. We explain why it is unlikely that individual investors receive higher returns because of the messages they send, namely that the market precludes the possibility of front-running and the difficulty in forecasting exchange rates suggests that individual returns are akin to playing roulette. Empirical support against reverse causality is also offered. Returns are found to Granger-cause message sending, but not vice versa. We also attempt to instrument for returns in several ways. Using the surprise component of macroeconomic news releases fails to reliably predict returns. The VIX positively predicts returns but is a weak instrument. Finally, trader account balance, which proxies for individual wealth, is a candidate instrument, but it fails a DHW test implying that OLS is efficient.

We confirm the second assumption in Hirshleifer (2010) by showing that traders who receive communications increase their trading intensity in response to hearing from those whom have had recent success. A one standard deviation increase in dollar returns by the initiator of communications is associated with about a 33 percent increase in the number of trades issued by the receiver. Likewise, we confirm that our empirical findings hold when controlling for individual characteristics as well as aggregate market activity. This result is in accordance with a body of literature suggesting that individuals tend to choose investments that have performed well in the recent past (Bernatzi, 2001, Choi, Laibson, and Madrian, 2010, and Barber and Odean, 2002). We also find that receiving communications from others reduces one's likelihood of quitting trading.

To analyze the long-run implications of these results we present a population evolution model derived in Hirshleifer (2010) which shows that as a result of these assumptions the average trader will adopt increasingly active strategies with a rising variance of returns. As predicted, we find that average trading intensity and the variance of returns have both increased over time among participants in the social network. We then address potential concerns over the channels of communication within the network and attempt to rule out other explanations for these trends.

Taken as a whole, our analysis supports Hirshleifer's (2010) conclusion that social interactions propagate active investing.

There is substantial evidence that participation and investor behavior in financial markets are influenced by social interaction (Shiller, 1984, 1989, and, Shiller and Pound, 1989). Hong, Kubik, and Stein (2004), Brown et al. (2008), and Kaustia and Knüpfer (2011) show that social interactions promote stock market participation with the latter showing good returns stimulate entry. Heimer (2011) shows that social individuals are more likely to be active rather passive market participants. Among mutual fund managers, Hong, Kubik, and Stein (2005) demonstrate that portfolios exhibit higher correlation if they are from the same town while Cohen, Frazzini, and Malloy (2008) show that they place greater bets on firms whose board members are from their education network. Correlation across investments in retirement accounts are also observed by Madrian and Shea (2000) and Duflo and Saez (2002, 2003). Researchers document that investors are influenced by the investment decisions of others including famous investors like Warren Buffett (Sandler and Raghavan, 1996), insiders (Givoly and Palmaon, 1985), and readers of the Wall Street Journal's Dartboard column (Barber and Loeffler, 1993). Similar to our research, Shive (2010) uses an epidemic model and data on Finnish stockholdings to study how social contact can predict investor trading. A common thread among studies of social interaction and investing is that it relies on proxies such as geographical proximity to infer variation in the level of communication about investments. This paper enhances the body of evidence by examining incidences of observed communications between investors.

Our study extends the analysis of social forces in two directions. First, it offers an alternative explanation for the over-trading puzzle documented in Barber and Odean (2000) and Barber et al. (2009) whereby individual investors trade actively and lose on average relative to passive benchmarks. The most commonly cited explanation for this phenomena is that they are overconfident (DeBondt and Thaler, 1995, and

Bénabou and Tirole, 2002, among others).[2] Second, our study explores more deeply the little-known world of day-traders as roughly 90 percent of positions in our sample are closed within a day. The literature on day-trading is limited due to a paucity of detailed datasets. Most recent papers confirm our finding that day-traders earn negative excess returns (Odean, 2009, Jordan and Diltz, 2003, and Linnainmaa, 2005, 2010). Among the few exceptions, Mizrach and Weerts (2009), relies on trades that were claimed by chatroom participants which likely adds significant upward bias. Harris and Schultz (1998) find that investors at two day-trading firms are profitable on aggregate yet their small sample may suffer from survivorship bias.

The paper is organized as follows. Section 2 presents the assumptions behind Hirshleifer's (2010) model. Section 3 describes the social network and our proprietary data. Section 4 details our methodology for verifying the assumptions of the model empirically and contains our results. Section 5 presents the implications of these empirical findings and demonstrates that the social network has helped propagate active investing strategies. Section 6 concludes.

2 Theory

Hirshleifer (2010) hypothesizes that social interaction promotes active trading by individual investors. His theory relies on three assumptions: (1) the propensity to initiate communications is increasing in own returns, (2) receivers of communications adopt the initiator's strategy in response to hearing of higher returns, and (3) the volatility of returns for "Active" traders are greater than those for "Passive". Together, these assumptions imply that active strategies will propagate among the population until the cost associated with active trading becomes prohibitive. In this section, we present the assumptions behind Hirshleifer's (2010) model and the testable hypotheses we plan to examine empirical.

[2] Although it is possible that social interactions contribute to overconfidence or vice versa.

2.1 Three Assumptions

Hirshleifer's (2010) model consists of a population of traders that enter as one of two types, Active or Passive, denoted A and P respectively. Active traders are those who pursue more hands-on strategies with higher trading intensity.

2.1.1 Hypothesis 1: sending

When two traders interact one may reveal her investments and if she does, she places emphasis on her greatest successes. This relationship can be generalized by the following linear sending function:

$$s(R_i) = aR_i + b \tag{1}$$

in which s is the probability that an individual discusses her strategies and returns, R is the return of the strategy they transmit, and $i \in \{A, P\}$ is the trader's type. It is assumed that $a > 0$ and since b is the baseline probability of transmission it therefore must be that $b \in [0, 1]$. The positive relationship between short-term returns and revealing strategies can be justified in a few ways. For one, individuals perceive there to be advantages to maintaining strong placement in investor networks and have incentive to signal only their best performance to others. For example, one may get blackballed from the inner circle of an investment club for a bad stock tip. Also, Hirshleifer (2010) and Bénabou and Tirole (2002) draw from extensive psychological research showing individuals tend to attribute their successes to their own skill while blaming their failures on poor luck. This motivates them to broadcast their successes while remaining mute about their failures.Finally, it is possible that traders believe that followers will imitate them and provide incremental price impact to support their trades. The relationship need not always be positive. For one, new traders are likely to engage socially with others with the intention of learning from the more experienced. This would suggest that the worse they perform the more likely they are to seek advice.

> ***Hypothesis 1:*** *Higher own returns result in a greater likelihood of initiating communications with other traders. Likewise, higher own returns result in contacting more traders.*

2.1.2 Hypothesis 2: receiving

When a trader learns of the returns of the person with whom they are in contact, she exhibits some probability, $r(R_i)$ of adopting the sender's strategy and being converted to the sender's type:[3]

$$r(R_i) = cR_i + d \tag{2}$$

Here c is positive if individuals are more likely to be swayed by higher returns and d is the baseline probability.[4] There is strong empirical evidence that investors, faced with the difficult task of having to forecast security returns, choose to extrapolate past returns into the future and invest in securities that have recently performed well. Benartzi (2001) finds that the willingness of employees to invest in their own firm in their retirement accounts is increasing in the performance of its stock but does not predict future returns. In an analysis of online trading, Barber and Odean (2002) find that early adopters switched to online trading after initial good performance, even if they later traded more actively but with weaker performance.In an experimental study, Choi, Laibson, and Madrian (2010) find that investors choose high-fee over low-fee index funds based on annualized returns.

[3]Hirshleifer (2010) uses a quadratic form for the receiver function in order to reflect a greater emphasis on hearing about extreme returns. For simplicity we use a linear form. It does not change the predictions of the model so long as $r'(R_i) > 0$.

[4]It is important to note that the parameters of the model a, b, c and d do not vary by trader type. This is the case so long as (1) traders do not care about or (2) are unaware of the sender's type.

Hypothesis 2: *The greater the returns of those communicated with, the greater the probability of adopting their strategy.*

2.1.3 Strategy transmission

Taken together, the positive slopes on the sender and receiver functions imply a positive relationship between sender returns and the probability of strategies being transmitted between traders. The probability of the strategy transmitting from an Active sender to a Passive receiver is the joint probability of the sender and receiver functions assuming independence:

$$T_{A,P}(R_A) = r(R_A)s(R_A) \tag{3}$$

By symmetry,

$$T_{P,A}(R_P) = r(R_P)s(R_P) \tag{4}$$

If the assumptions behind the sender and receiver functions hold and s', $r' > 0$, then it is straightforward to show that $T'_{A,P}$, $T'_{P,A} > 0$ as well.

2.1.4 Hypothesis 3: volatility

The higher trading intensity of active traders is associated with a higher variance of returns. This assumption has been verified by other research. Dorn and Huberman (2006) document that in a sample of 2,300 German individual investors between 2000 and 2004 the median volatility of daily returns is 30% and the mean is 35%, significantly higher than the benchmark DAX 100 index that had a volatility of 20%. They find that a significant part of the excess volatility is explained by stated risk-loving by individual investors as well as skewness-loving when owning small portfolios. In the dataset we use to verify Hirshleifer's (2010) assumptions, we also find a positive relationship between trading intensity and the volatility of returns.

3 The Data

3.1 A Social Network for Retail Traders

The data was compiled by a social networking website that, for privacy purposes, we call myForexBook. Registering with myForexBook – which is free – requires a trader to have an open account with one of roughly 45 retail specific foreign exchange 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.

myForexBook, which began registering users in January 2009, had 5,693 individuals who made at least one trade during our sample period, which extends to December 2010.[5] The database includes daily account balances per user and, after cleaning, 2,149,083 opened positions of which 2,144,357 had been closed.[6] For roughly half (1,041,658) of these trades – those submitted to specific brokers – the data includes order types and unfilled limit orders.

In addition to providing a forum for communication between investors, several of myForexBook's features have the potential to aid trader performance. A trader registered with myForexBook has access to a "Dashboard" web-browser window which shows the news plus information specific to the social network, specifically a "Sentiment Index" which compiles the aggregate positions of the entire network in a given

[5] In addition to the 5,693 users whose trades we have records for, there are a few thousand additional users of myForexBook who have not made any trades. These users have either found loopholes through which to register with the network such as using a brokerage practice account or they have not issued any trades on their account. These users will sometimes be involved in the social aspects of the network such as sending messages to other users and posting on forums. They are excluded in all analysis involving trading.

[6] Our initial dataset began with 2,177,747 positions opened. We dropped all duplicate observations and what we believed to be mis-entered data. Observations that we considered to be mis-entered were ones in which the size of the position was negative, the position was closed before it opened, or prices that were not consistent with the historical range of the currency pair.

currency pair. Furthermore, once establishing a bidirectional friendship with another member, both users are able to view each others' trading activity in real-time. Both features are portrayed in Figure 1 and the latter ensures that the vast majority of communication between two users in the network allows for the sharing of returns and strategies.[7]

Our data also includes a complete record of activities within the social network, including the times of logins, friendships established, and messages sent. The median user has made 11.0 logins while the mean has 30.8. Similarly, the median user has 8.0 friends while the mean has 20.9 (Table 1). Care should be taken when referring to these numbers owing to the fact that users enter the database (and potentially quit trading) at uneven times.

The database also contains information on the characteristics of its members. This information is offered voluntarily, but the non-response rate is only around ten percent on any given question. The median trader in our database is 36.2 years old, has one to three years of trading experience, calls herself a technical trader and lives in either the USA or Western Europe.

With respect to their trading activities, myForexBook users have short holding periods in comparison to equity traders. Roughly half of all positions are closed within an hour and only around ten percent last longer than a day. They tend to concentrate on the most liquid pairs with the most frequently traded pair, the EUR/USD, constituting 34.3 percent of all trades. The mean trade size is US$34,580 and they use 8.6x leverage on average after removing outliers that are above 500x and below zero.

[7] It is important to note that traders are unable to place orders with their broker from myForex-Book's website; rather, it may be useful to view simultaneously while trading.

3.2 Active versus Passive Trading

In this section we confirm that the population of traders in the data is suitable for testing Hirshleifer's hypothesis, namely, that traders in the network differ in their level of trading intensity. Trading volume ranges widely among myForexBook users (Table 2). Some registered users made only a few trades in total while others traded almost non-stop. A few users placed several hundred trades a day – even occasionally a few thousand trades (presumably using algorithms). Anecdotal evidence confirms that there is substantial heterogeneity in the level of commitment to trading among myForexBook participants. A frequent topic of conversation on the myForexBook discussion forum is whether it is possible to earn a living by trading. The responses vary from those who claim they do so, others who claim they would be able to if they possessed sufficient capital, and others who say it is unrealistic. For the purposes of illustrating and examining their differences we partition the sample into two groups, the Actives and the Passives, who differ in their level of trading intensity.

Distinguishing these two groups involves a careful balance. Relying solely on the number of trades per individual biases the sample towards those who entered the dataset at an earlier date. Relying instead on the frequency with which individuals trade over-samples individuals who made several trades quickly and then quit. In order to address these concerns, we restrict the Active group according to two criteria: (1) total trades by an individual must exceed the median (128); (2) and the frequency with which they trade during a given week must also exceed the median (32.1).[8] The resulting partition of the sample involves 2,012 Active individuals who made 1,642,262 trades and 3,681 Passives who made 506,821 trades.

[8]This is calculated by taking the total number of trades per individual divided by the number of weeks that pass between their first and last trade. This measure incorporates any lengthy absences from trading making those who take them more likely to be Passive traders.

3.2.1 Distribution of profits

Those who trade the most are not more successful, consistent with the existing literature on active investing. Trades made by myForexBook users are unprofitable on average, losing $6.20 each roundtrip trade. The Actives lose slightly less per trade, but more than make up for it in trading activity so they end up losing more overall. However, the median trade books a $0.22 profit since 63.4 percent are profitable after execution costs. The Actives do however have a much higher hit ratio per trade than Passives traders with positive gains on 65.1 percent of their trades versus only 57.8 percent.

In examining profitability per trader we find that 21.0 percent of the total sample and only 17.8 percent of the Actives are profitable as of December 2010. The average trader has accumulated $2,335 in losses while the average Active trader has lost $4,776. The 95 percent confidence interval for cumulative profits of individual traders is [$-11,751; $1,382]. In support of the assumption in Hirshleifer's (2010) model (Hypothesis 3), the standard deviation of log weekly returns to Active traders, 61.2 percent, is statistically higher than the corresponding variance for the Passives, 47.4 percent. 75.7 percent of Active traders have negative skewness of weekly returns versus 64.0 percent of Passive traders.

3.2.2 Starting capital

We find that at least some differences between the groups can be accounted for by different levels of initial investment. As shown in Table 4, the median starting balance among myForexBook traders is US$983. This is substantially lower than Finnish day traders in Linnainmaa (2003) where the median is €17,525, or approximately US$25,000. Active traders have a median starting account balance of $1,938, compared to $612 for Passives. The mean for both groups is substantially higher, $8,512 for the Actives and $1,101 for the Passives. A student's t-test indicates that the difference is significant at the one percent level.

3.2.3 Trader lifespan

Another substantial difference between the two groups is their reaction to large losses. Table 5 displays results from estimating Cox-proportional hazard models in which the regressors are zero-one indicators for the decile of weekly returns. Consistent with Linnainmaa (2005), we proxy for having left the market if a trader has been inactive for the last month of the dataset. If a user is found to have quit trading then we say they quit at the time of their last observable activity in the dataset. According to this definition, roughly 75 percent of all participants in our sample quit trading. This fact is not surprising considering that the mean trade is unprofitable regardless of user type. Overall, Active traders are slightly more likely to continue trading than Passive traders, but all of this difference is eliminated if the trader makes it past two weeks.[9]

The results from our tests suggest that for both Active and Passive traders a week of good performance reduces the probability of quitting; a week in the highest decile of returns reduces the probability by roughly 40 percent. Active and Passive traders however react differently to poor performance. While a performance in the lower deciles for Passive traders increases the likelihood of quitting by anywhere from 20 to 60 percent, it has little to no effect on the likelihood of quitting for the Actives. Attempts to account for this difference by including proxies for sunk costs such as their initial balances failed to change these results.

[9] When plotting hazard rates we find very little difference between Active and Passive investors in their underlying probability of quitting over time. All of the difference is eliminated when excluding traders who failed to last past two weeks.

4 Empirical Analysis

In this section, we use the data compiled by myForexBook to test the two hypotheses presented in Section 2. First, the propensity to initiate communications is increasing in own returns. Secondly, receivers of communications increase their trading intensity in response to hearing of higher returns. We address concerns about identification and causality following the baseline estimation of each relationship.

4.1 The Sending Function

In order to confirm that traders are more likely to initiate communications the greater their returns, we use our data to generate weekly[10] returns per individual and indicator variables for whether or not individual i initiated communication with another member of the social network via a user-message. Weekly returns R in time t are defined as:

$$R_{i,t} = \log\left(\frac{V^e_{i,t}}{V^b_{i,t}}\right) \tag{5}$$

where V^b is the balance at the beginning of the week and V^e is the end of week balance (excluding net deposits) sampled between consecutive Saturdays at midnight, GMT.

Table 6, panel I, displays odds-ratios from estimating a logit model of the form in Equation 1

$$logit(p^s_{i,t}) = \beta_0 + \beta_1 * R^s_{i,t} + \beta_2 * X^s_i + \beta_3 * X^s_{i,t} + \beta_4 * t + \varepsilon_{i,t} \tag{6}$$

in which the dependent variable is an indicator that is equal to one if the trader sent a message during the week and the independent variable of interest is weekly

[10]Considering that much of the activity in this market centers around the release of economic news and that weekends are comparably silent, we believe that week-to-week returns best capture the mindset of these traders.

returns. The coeficient on weekly returns, β_1, is positive and statistically significant even when controlling for factors that are fixed across time for each trader, X_i^s, (where the superscript s denotes that the characteristics belong to the sender of communications) such as trader age, experience, and factors that vary across time, $X_{i,t}$, such as trading intensity and length of time since joining the social network, We also include a time trend which captures growth in the size of the network. Furthermore, the relationship holds when we remove outliers (log returns that are in the outer fifth percent on either tail of the distribution), use robust standard errors, cluster the errors by individual and time, and use log dollar returns as the regressor rather than the specification in Equation 1.

We also confirm the presence of a positive relationship between sender returns and the *number* of messages sent. In the second panel of Table 6, we use OLS to regress the number of messages sent on log returns of the sender conditional on having sent at least one message.

$$message\,count_{i,t}^s = \beta_0 + \beta_1 * R_{i,t}^s + \beta_2 * X_i^s + \beta_3 * X_{i,t}^s + \beta_4 * t + \varepsilon_{i,t} \tag{7}$$

The relationship is positive, but significant only at the ten percent level. The lack of a strong statistically significant relationship may be caused by using OLS to predict count data. To account for this potential model misspecification, in the third panel of Table 6, we present results from estimating the same relationship using a zero-truncated Poisson regression. The coefficient in this specification is again positive, but is now strongly statistically significant implying that the better an individual's returns the more communications they issue.

Furthermore, we also use panel estimation with individual fixed effects to estimate all of the preceding regressions and find that it does not change our results. This specification accounts for the possibility that there is substantial heterogeneity in individual trading skill that in the previous regressions is only captured in the error term. Therefore, returns and the propensity to communicate may be jointly determined by unobserved differences in trading skill. The fixed effects regressions soak up the difference across individuals and allows the variable returns to be a deviation around a baseline per individual. We find that the fixed effects regressions do not lesssen the significance nor the magnitude of our results; in fact, the relationship between returns and the number of messages sent is now strongly positive.

In order to assess magnitudes, we calculate marginal effects and find that a one standard deviation increase in log returns results in about a seven percent increase in the probability of contacting other traders in a given week when evaluated at the means. Likewise, it increases the number of messages sent by about six percent according to the Poisson regression. Put another way, an individual who doubles their money is 17 percent more likely to tell other individuals and tells 14 percent more people than someone who loses 90 percent of their money.

Upon examining how the relationship between returns and communications varies by trader experience, we find evidence that the structure of the network plays an important role in the propensity to communicate. The most experienced traders – those who claim to have been trading for at least four years – display the strongest tendency to initiate social contact following weeks of good performance (Table 6). Traders at the center of the distribution (one to three years) also have a positive coefficient, but it is smaller and only significant at the ten percent level. Those with the least amount of self-declared experience (zero to one years) when joining the network have a negative and insignificant coefficient. Since the least experienced traders perform significantly worse than other groups, this might be a sign that beginner traders send messages seeking advice. On the other hand, the more experienced traders may be attempting to gain a following within the network and thus strategically communicate only after good returns.

4.1.1 Sender function robustness

A primary concern is that average chatter increases during times of high performance in the network leading to a spurious correlation between individual returns and their probability of sending messages. We address this concern by creating a variable called *"average chatter"*, which is equal to the total number of messages sent in the network over the total number of users in the network at time t (excluding those who are deemed to have quit trading) and including it in the preceding regressions (Table 8). We find that when average chatter within the network increases both the probability of sending a message and the number of messages sent by the individual also increase. The inclusion of *average chatter* does not however negate the effect of own returns on the likelihood of sending a message or the number of messages sent.

Similarly, it could be that favorable market conditions are driving both individual returns and increased chatter. Individuals are more likely to be engaged in trading activity because of high returns and their heightened attention to trading makes them more likely to be at their computers, hence more likely to be issuing communications with other traders. We control for these potential confounding factors by including two variables that capture aggregate market performance. The first variable, *"community performance",* is the average dollar gains per trade for all trades made within the week at time t (Table 8). The second variable, *"USD index",* is the trade-weighted US dollar index, a measure of the value of the US dollar relative to other world currencies in time t obtained from Thomson Reuters. The relationship between idiosyncratic returns of sender i and their issuance of communications is not affected by the inclusion of these variables.

4.1.2 Sender function causality

It is unlikely that the positive relationship between returns and issuing communications suffers from reverse causality. In other words, investors are not profiting from the communications they issue. First, we outline why it is unlikely that traders are directly benefiting from messaging others. Secondly, a Granger causality test suggests that returns are driving the propensity to communicate. Thirdly, we present attempts to instrument for returns using exogenous factors that are thought to drive exchange rates such as macro fundamentals and volatility, and using trader account balance which proxies for wealth. Lastly, to lessen concerns over feedback from messages to returns, we employ the lagged dependent variable as an instrument.

The argument for reverse causality appears unlikely since there is often considerable lag between sender initiated communications and recipients accessing the communications, while the median holding period on any round-trip trade is under an hour. Information in the foreign exchange market is short-lived and there would need to be near immediate receipt of information for traders to directly benefit. Furthermore, while front-running (buying (shorting) an asset and instigating followers to buy (short) as well to push up (down) prices) is a candidate explanation for reverse causality in other settings it is unlikely that the aggregate community of traders in myForexBook has sufficient market power to influence prices. King and Rime (2010) indicate that retail trading constitutes only around 10 percent of daily volume in foreign exchange markets. Additionally, the volume of trading in the entire lifespan of myForexBook, which amounts to approximately two years of data, is roughly equivalent to half of one day's worth of trading by the aggregate retail market, $125 to $150 billion.

More plausibly, traders may issue messages and then glean from the recipient a trading strategy that remains profitable. This would imply that strategies become more correlated after traders contact each other. As we show in detail in Section XX, there is an increase in correlated trading or "herding" after messaging, but the magnitude is small enough to suggest that it cannot explain our findings. In addition, it is not possible to discern whether it is the sender or receiver of communications that contributes most to the increase in correlated trading. Of course, if it is the latter then it would not influence the observed relationship between own returns and the propensity to communicate. Furthermore, considering the well-documented difficulty in reliably forecasting exchange rates (see below in our attempts to instrument for returns), it is even more far-fetched to believe that individual traders are able to fully comprehend and implement such a model provided via communications within the network. This leaves the most plausible explanation: individual investors returns in foreign exchange are akin to playing roulette, they arrive exogenously.

We further investigate whether there is reverse causality empirically, first by checking for Granger-causality between sending a message and returns in the next period. The results show that while returns Granger-cause sending a message, sending a message does not Granger-cause returns.

We also attempt to instrument for sender returns. Our first pass involves taking the surprise component of economic news releases to forecast individual investor returns. We are unable to reliably instrument for returns in this manner for the following reason: macro variables are poor predictors of exchange rate movements at short horizons and thus there is a high variance in individual performance around these events. Other aggregate variables, VIX and a US Dollar Index, display slightly more explanatory power, but prove to be weak instruments.

A more promising instrument is trader account balance which proxies for individual wealth. Bonaparte and Fabozzi (2011) show that wealthy investors utilize more productive search efforts – for instance, they can acquire the services of financial professionals – and this advantage has a substantial positive impact on profitability. On the other hand, account balance can be excluded from the second stage regression since there is no a priori reason to suspect that wealth correlates with the propensity to communicate within a network of traders. We find that account balance is closely correlated with returns, with a first-stage F-value of 89.7. However, the Durbin-Hausman-Wu test indicates that this instrument is inefficient and the original regression provides better estimates.

One last instrument we employ is the lagged dependent variable, sender returns in $t-1$. If the instrument is uncorrelated with the error term in the main regression and the empirical relationship between returns and communications hold, it will alleviate concerns over communications causing higher returns. Results from using an instrumental variables approach are presented in Table 9 and they support the hypothesis that there is a causal relationship from high returns to the issuance of communications. Furthermore, the magnitude of the effect of returns on communications is stronger in this specification than in the baseline logistic model we present in Section 4.1. A one standard deviation increase in log returns increases the probability of sending a message by 22 percent.

4.2 The Receiving Function

In this section we verify that traders increase their trading intensity in response to hearing from individuals who have had good returns. In the theory presented in Section 2, we include the simplification that there are only two types of traders, Active and Passive, who differ in their level of trading intensity. Conversion between the two types occurs through communications that are instigated by good short term performance. Identifying incidences of conversion from Passive to Active (and vice versa) in our dataset is cumbersome owing to the fact that trading intensity of individuals is not a binary variable and highly dependent on our ad hoc criteria for distinguishing between trader types (Section 3.2). We therefore proxy for conversion to active investing by calculating the number of trades issued in a given week by the recipient of communication.

We are confronted with three challenges when attempting to identify the empirical relationship between sender returns and recipient activity: (1) how does an individual respond to receiving messages from more than one individual in a given period, (2) what unit of measurement for presenting one's returns does an individual respond to most, and (3) how do we account for the lag between receiving and reading a message along with the possibility that messages go unread? In order to address the first issue we calculate the max, mean, and sum of sender returns and estimate the effect of each separately. To combat the second complication, we calculate dollar returns rather than the specification for log returns presented in Equation 5. Conversations about dollar returns are presumably more salient to individuals. Furthermore, responding to log returns requires a recipient of communications to have prior knowledge of the initiator's opening balances, a proposition we assume unlikely. We address the third issue by matching the time of the sent message with the time of the nearest login by the receiver that occurs after the message had been sent. The database also contains an indicator for whether or not the message was read by the receiver allowing us to exclude all unread messages.

Table 10 displays results from estimating the relationship between returns and trading intensity via OLS:

$$trade\,count^r_{i,t} = \delta_0 + \delta_1 * R^s_{i,t} + \delta_2 * X^r_i + \delta_3 * X^r_{i,t} + \delta_4 * t + \varepsilon_{i,t}$$

The dependent variable is the log number of trades issued in the week (or the week after) the trader received and read at least one user message (the superscript r indicates a variable that belongs to the receiver of communications). The independent variable is log dollar returns of the sender, $R^s_{i,t}$. In all instances, the coefficient of interest, δ_1, is positive and statistically significant even after controlling for the same set of controls listed in section 4.1 (X^r_i, $X^r_{i,t}$, and t). In this case, the controls belong to the receiver of communications rather than the issuer. The result holds in both the week the individual receives the message and the week after with the strongest effect being on the latter. We also estimate the relationship using a zero-truncated Poisson regression in which the dependent variable is the number of trades issued. The results are presented in Table 11, and they are in accordance with the results using OLS.

In order to assess the magnitude of the relationship between receiving communication about returns and trading intensity, we calculate marginal effects using the results from the zero-truncated Poisson regression (when the independent variable is the log of summed returns) and find that a one standard deviation increase in sender returns is associated with about a 33 percent increase in the number of trades issued by the receiver. Since the mean number of trades in a week is around 29, this amounts to an additional 10 trades made per week. It is interesting to note that the max and sum of the sender's returns are associated with increased trading by the receiver while the mean of the sender's returns is less strongly correlated. The coefficient in this specification (Table 10, column IV) is smaller than all others and only significant at the ten percent level. Since low returns bring down the weekly averages we calculate, this result may indicate that receiving communication from individuals with poor performance can offset some of the increase in trading intensity brought about by hearing of good returns.

4.2.1 Receiving function robustness

The empirical relationship between sender returns and the trading activity of the receiver may stem from overall market performance at time t. In other words, the increase in activity by the receiver upon receiving news of high returns is not caused by communications between investors; rather the presence of high returns in the market motivates an overall increase in trading by all investors. In order to address this concern we attempt to identify the idiosyncratic component of sender returns and its effect on receiver activity. We include in all specifications two additional variables that attempt to control overall market performance. The variables, *"community performance"* and *"USD index"*, are described in Section 4.1.1 and we include them in all regressions. Likewise, it may be that average community chatter is driving both sender returns and increased trading activity amongst all users of the social network leading to a spurious correlation between the two. We include the variable *"average chatter"* presented in Section 4.1.1.

Another concern is that the performance of the receiver motivates the sender to initiate communications. If receiver and sender returns are correlated, then it could explain the observed relationship between sender returns and receiver activity. We include a variable for receiver performance in time t to control for this potential confounding factor. One last concern is that senders of communications simply target their messages to those who trade more. This requires us to control for pre-existing activity by the receiver. Therefore, we include a variable for the number of trades issued by the receiver in the week prior to sending the message.

We find that after including these controls, the results are still highly statistically significant when estimating a zero-truncated Poisson regression (Table 14). However, when estimating the relationship using OLS, the inclusion of the number of trades the receiver placed the previous week or the returns of the receiver during the previous week cause the coefficient on sender returns to lose its significance (Table 13).

4.2.2 Receiving function causality

Reverse causality is less of a concern when we assess the relationship between sender returns and receiver trading activity. The majority of messages arrive without being prompted by the receiver. This reinforces the notion that sender returns is an exogenous regressor and that higher sender returns result in more trading activity by the receiver.

4.2.3 Receiving messages and attrition

We find that not only are traders more likely to increase their trading intensity upon receiving messages from traders with recent strong performance, but that it also influences the extensive margin: traders are less likely to quit trading when contacted even after controlling for realized returns. In Table 12, we present hazard rates from including indicator variables in the analysis described in Section 3.2.3. The event in the survival analysis is an indicator variable for whether or not an individual quit trading. The independent variables are indicators for whether or not the trader initiated or received and read communications from another individual during the week in question.

We find that those who receive communications are less likely to quit trading while those who initiate them are more likely. The latter result appears to be evidence against the relationship between social interactions and investing; however, this empirical finding does not imply causality and may reflect other factors. We suspect that the decision to quit trading is associated with a greater propensity than the average week to contact other traders since individuals may be motivated to maintain ties when leaving the network. For example, a trader may be planning a move to a different asset class and wishes to remain in contact should the receiver change as well. The trader may also wish to maintain contact should they decide to return to trading at some point beyond our sample.

The model further suggests that individuals are about 30 to 40 percent less likely to quit trading after receiving communications. This result reinforces the findings of Hong, Kubik, and Stein (2004) and Kaustia and Knüpfer (2011) that social interaction promotes market participation. While their results specifically refer to market entry, our results bolster their argument by examining the rate of attrition. In considering its implications on the average market participant, if we were to consider a dynamic setting of the model proposed in Section 2, in which the population of traders includes entry and exit, incorporation of this finding would point towards further exacerbation of trends towards active investing.

5 Implications

Taken together, the two novel empirical findings presented in this paper, together with the fact that the standard deviation of log weekly returns to Active traders, 61.2 percent, is statistically higher than the corresponding variance for the Passives, 47.4 percent support a theory in which social interaction promotes active investment strategies. In this section, we provide a simplification of Hirshleifer's (2010) model and proceed to show that the average change in the fraction of active investing is positive so long as: (1) on average, the propensity to initiate communications is increasing in own returns, (2) receivers of communications increase their trading intensity in response to hearing of higher returns, and (3) the volatility of Active strategies is greater than that of Passive. We present evidence that the social network, myForexBook, has helped propagate active investing among its membership.

5.1 Population Dynamics

This section is a recapitulation of section 2.1 in Hirshleifer (2010). In each period, two randomly drawn traders of type i meet and have the opportunity to share their strategies. The population of traders is finite and equal to n, and the fraction of traders f who are of type A is:

$$f = \frac{n_A}{n} \tag{8}$$

For simplicity, we do not allow traders to exit the market so the fraction of A and the fraction of P traders sums to one in every period.

Since homogeneous pairings do not impact the strategies of the traders, we seek to define the probability of drawing one A and one P at random. If the probability of first choosing a A is $\frac{n_A}{n}$ then the probability of drawing a P is $\frac{n-n_A}{n-1}$. Likewise, the probability of first choosing a P is $\frac{n-n_A}{n}$ and the probability of following that with a A is $\frac{n_A}{n-1}$. Together, they yield the total probability χ that a A/P pairing is drawn:

$$\chi = \left(\frac{n_A}{n}\right)\left(\frac{n-n_A}{n-1}\right) + \left(\frac{n-n_A}{n}\right)\left(\frac{n_A}{n-1}\right) \tag{9}$$

or,

$$= \frac{2nf(1-f)}{(n-1)} \tag{10}$$

The probability that the number of traders of either type increases by one in any given period is a function of both the probability of drawing a cross-pairing and the probability that the strategy transmits from one trader to the other. We denote the following period with a $*$ and therefore:

$$Pr(n_A^* = n_A + 1, n_P^* = n_P - 1) = \left(\frac{\chi}{2}\right) T_{A,P}(R_A)$$

$$Pr(n_P^* = n_P + 1, n_A^* = n_A - 1) = \left(\frac{\chi}{2}\right) T_{P,A}(R_P) \tag{11}$$

The change in the fraction of A traders can be defined as: $\triangle f = f^* - f$, which is equal to the set $\frac{1}{n}$ with probability $\frac{\chi T_{A,P}(R_A)}{2}$, $-\frac{1}{n}$ with probability $\frac{\chi T_{P,A}(R_P)}{2}$, and 0 with probability $1 - \frac{\chi T_{A,P}(R_A)}{2} - \frac{\chi T_{P,A}(R_P)}{2}$. The expected change in the fraction of A traders in a given period is thus:

$$\left(\frac{2n}{\chi}\right) E\left[\triangle f\right] = E\left[T_{A,P}(R_A)\right] - E\left[T_{P,A}(R_P)\right] \tag{12}$$

The intuition behind Equation 12 is that so long as the transition rate from P to A is greater than the transition rate from A to P, then on average the fraction of

Active traders in the market will be increasing.

5.2 Expected Population Trends, Communication, and Idiosyncratic Volatility

In this section, we diverge from Hirshleifer (2010) and present a condition necessary for the population to trend towards Active trading. We show that the average change in the fraction of active investing is positive so long as: (1) on average, the propensity to initiate communications is increasing in returns, (2) receivers of communications increase their trading intensity in response to hearing of higher returns, and (3) the volatility of A returns is greater than that of P traders. This setup incorporates the realistic assumption in item (3) above. It suggests that recipients of communications are responding to the right tail of the sender's distribution of returns. Accordingly, A's are more persuasive since they have more opportunities to broadcast extreme returns.

Suppose that A and P traders share some common component to their returns , $\bar{R}$, with $E\left[\bar{R}\right] = 0$ and variance, $\sigma^2_{\bar{R}}$ (as mentioned by Hirshleifer (2010), this could be the market portfolio). Strategies may differ in their sensitivity to the common factor, β_i. There is also an idiosyncratic component to their strategies, ε_i, which is mean zero as well, $E\left[\varepsilon_i\right] = 0$.[11] The variance of the idiosyncratic portion of their trading activities is assumed to be greater for the A's, $\sigma^2_A > \sigma^2_P$. Therefore, if we assume that these components are uncorrelated and there is no penalty to being an A trader , realized returns are as follows:

$$R_A = \beta_A * \bar{R} + \varepsilon_A$$

$$R_P = \beta_P * \bar{R} + \varepsilon_P \tag{13}$$

[11]Note that both $\bar{R}$ and ε_i do not have to be drawn from a normal distribution. As in Hirshleifer (2010), their distributions may be skewed.

Substituting the returns structure depicted in Equation 13, into Equation 12, gives an expression for the expected change in the fraction of A traders (see Section 1 of the Appendix for the derivation):

$$\left(\frac{2n}{\chi}\right) E\left[\triangle f\right] = ac\left((\sigma_A^2 - \sigma_P^2) + (\beta_A^2 - \beta_P^2)\sigma_{\bar{R}}^2\right) \tag{14}$$

This expression is positive so long as $\sigma_A^2 > \sigma_P^2$, $|\beta_A| \geq |\beta_P|$ (or the linear combination of the differences in the expression are greater than zero) , and a and c, the coefficients in the sender and receiver functions, are positive.

The model implies that the fraction of Active traders in a market will increase on average provided that their returns have a wider variance than the average market participant and high realized returns bring about conversation and conversion.[12] This result is intuitively appealing: those with more extreme positive outcomes to discuss will be more influential. It further implies that individuals respond to the positive tail of a distribution. They may falsely attribute a few observations as representing the mean of the entire sample or simply have preferences towards these sorts of gambles (Kumar, 2009). Hirshleifer (2010) points out a variety of phenomena which can be explained by the relationship between social interactions and volatility. In the following sections of this paper we examine whether this theory applies in communications between investors.

5.3 Social Networking and Active Investing Over Time

The model presented above suggests that communications between investors can lead to the growth of active investing. We find that features consistent with the predictions of the model are present in our data.

[12]Without shocks to the parameters, the model predicts convergence towards all traders becoming active investors. Including a penalty to active investing prevents this from occurring particularly if the penalty is increasing in the fraction of active investing. See Section 2 of the Appendix for further discussion of the consequences of including a penalty to trading actively.

First, we verify that the average participant in the social network has increased their trading intensity. This requires us to determine which individuals in our sample are participants in the market at any given time t. Accordingly, we define a user's time of entry as their first observable action in the dataset and quitting is defined as in Section 3.2.3. This means that the total number of surviving users in our dataset at any given time t is derived as follows:

$$survivors_t = \sum_{t=1}^{T} (entrants_t - quitters_{t-1}) \tag{15}$$

We then calculate the average number of trades issued per surviving user each month as: $\frac{\#\, trades_t}{survivors_t}$. This measure, rather than the number of trades over the the number of users who issued them in a given month, incorporates individuals who take breaks from trading. The corresponding time series is plotted in Figure 2. We find that the average trading intensity per myForexBook user has increased over the course of the sample from roughly 40 trades per month for most of 2009 to roughly double that by late 2010.

We also find that average volatility of returns has increased among participants. We regress the standard deviation of log weekly returns against time (Figure 6) finding that it increases by about 0.2 percent (statistically significant at the one percent level) per week over the life of the social network. This implies an increase in the standard deviation of around 20 percentage points in less than two years.

5.4 Discussion

In this section we address three potential concerns that would either offer an alternative explanation of our findings that the average market participant possesses more active strategies or weaken our assertion that social interaction is contributing to the trend: (1) does communication in the network travel along a channel that would promote active strategies, (2) can uneven entry and exit explain the empirical finding that the average trader has increased their activity over time, and (3) is the level of social networking activity sufficient to sustain these trends?

A key consideration necessary to confirm that social interactions are contributing to the growth of active strategies is to establish that the channels of communication travel in directions that would promote this trading behavior. In the model, communications between individuals of different type, Active and Passive, leads to the transmission of active strategies. The probability of the two types communicating with one another is a function of the percentage of each type in the population, but is otherwise random. In reality, individuals make choices about whom to communicate with and if there is a high degree of homophily – the tendency of individuals to bond with those who possess like characteristics – among myForexBook participants then strategies are unlikely to spread. In Figure 4, we plot against time the number of new user friendships established among participants in the social network. While the number of friendships made by the users of the social network is roughly constant over time, the prevalence of Active/Passive pairings, 53.2 percent of all friendships, is striking considering that Active traders constitute only one-third of the population. According to Equation 10, the Actives/ Passive would form 45.7 percent of all friendships if they occur completely at random. This finding implies a network structure in which Active traders establish a central location within the social network and encourage the Passives to adopt more active strategies.[13]

Another concern is that uneven entry and exit may explain the time series, Figure 2, showing that the average trader has increased their activity over time. In particular, an influx of high activity traders at the end of the sample period could explain this empirical finding. Contrary to this argument, bias is more likely to run in the opposite direction because Active traders are surely more attuned to media

[13]Another unexplored possibility is that Active/Passive pairings simply reinforce and aggravate bad trading behavior.

intended to improve trading performance (a notion reinforced by the fact that the average Active is more involved in the social networking aspects of myForexBook) and therefore more likely than the Passives to be among the early participants in the network. Secondly, a sharp decrease in Passives at the end of the sample could explain the time series, but this is likely to be offset by new participants. Our belief that entry and exit of individuals is not at the heart of our findings is reinforced when, in Figure 5, we plot entrants and exits of each type and the number of surviving users in the dataset over time. The ratio of Active to Passive traders remains roughly constant over time and while there is a spike in exits among Passives at the end of the sample period it is unlikely to discount much of our findings.

One last consideration is that unless the impact on one's trading activity caused by receiving communications about high returns is extremely persistent, then the trend towards active investing will stagnate. Therefore, social networking usage must also have increased over the time frame in question. In Figure 6, we plot the number of logins per user to the social network on a monthly basis, a key proxy for social networking usage, and find that it has nearly doubled over the course of the sample from around five to close to ten.

6 Concluding remarks

Our analysis of a new dataset on the activities of retail foreign exchange traders who are participants in a social network supports our hypothesis that social interactions promote the growth of active investment strategies. We apply a population evolution model in which strategies are transmitted through communications between investors and their adoption is motivated by the promise of high returns. The model predicts that the average individual employs increasingly active strategies so long as (1) the propensity to reveal one's strategies is increasing in realized returns, (2) receivers of communication increase their trading intensity in response to hearing of higher returns, and (3) the volatility of returns for those who are characterized as being active traders are greater than those for whom are not. We confirm the assumptions behind the model by documenting two novel empirical findings: on average, individual investors are more likely to initiate communications with other investors the greater their returns and they increase their trading intensity upon hearing of good returns.

Our research is the first to use detailed data on communications between investors rather than proxies to document its impact on financial behavior, thereby strengthening the empirical literature on the role of social interactions in financial markets. It provides greater insight into the process of diffusion of strategies and news about returns. Our findings also contribute to the disagreement over how increased flow of information contributes to efficient outcomes. While in most standard theory the flow of information within networks leads to better performance among market participants, we find that communications between investors may reinforce and even promote reckless trading behavior. This is largely driven by bias found among traders in which they develop forecasts of future returns that are merely extrapolations of the recent performance of assets. This leads them to follow strategies with occasional outstanding results, but that are less profitable on average.A final thought to discuss is that while our analysis considers the influence of peer-to-peer communications the traders we studied are participants in an entire network, one that contains over one-hundred thousand direct linkages between traders. There may be substantial network effects that we fail to account for in this research. For example, our findings may stem from "group-think" among clusters of traders whose activities have become correlated. Traveling down this road may answer questions about the contribution of social interactions within networks to many puzzles of asset pricing including the formation of bubbles, propagation of herding, and attention-grabbing.

Appendix

Section 1

In this section we derive the result in equation 14.

Substituting equations 3 and 4 into equation 12 yields:

$$\left(\frac{2n}{\chi}\right) E\left[\triangle f\right] = E\left[r(R_A)s(R_A)\right] - E\left[r(R_P)s(R_P)\right] \tag{16}$$

$$= E\left[(aR_A + b)(cR_A + d)\right] - E\left[(aR_P + b)(cR_P + d)\right] \tag{17}$$

and since, a, b, c, and d are constants,

$$= acE\left[R_A^2\right] + (ad + bc)E\left[R_A\right] - acE\left[R_P^2\right] - (ad + bc)E\left[R_P\right] \tag{18}$$

Further substituting the returns structure from the equations in 13 into the equation above yields:

$$= acE\left[(\beta_A * \bar{R} + \varepsilon_A)^2\right] + (ad+bc)E\left[\beta_A * \bar{R} + \varepsilon_A\right] - acE\left[(\beta_P * \bar{R} + \varepsilon_P)^2\right] - (ad+bc)E\left[\beta_P * \bar{R} + \varepsilon_P\right] \tag{19}$$

and since $E\left[\bar{R}\right] = E\left[\varepsilon_i\right] = 0$,

$$= ac\left(E\left[(\beta_A * \bar{R} + \varepsilon_A)^2\right] - E\left[(\beta_P * \bar{R} + \varepsilon_P)^2\right]\right) \tag{20}$$

After expanding out the expressions in parentheses and zeroing out any term with $E\left[\bar{R}\right]$or $E\left[\varepsilon_i\right]$:

$$= ac\left(E\left[\varepsilon_A^2\right] - E\left[\varepsilon_P^2\right] + (\beta_A^2 - \beta_P^2)E\left[\bar{R}^2\right]\right) \tag{21}$$

Since $E\left[\varepsilon_i^2\right] = \sigma_i^2$ and $E\left[\bar{R}_i^2\right] = \sigma_{\bar{R}}^2$,

$$\left(\frac{2n}{\chi}\right) E\left[\triangle f\right] = ac\left((\sigma_A^2 - \sigma_P^2) + (\beta_A^2 - \beta_P^2)\sigma_{\bar{R}}^2\right) \tag{22}$$

which is what we wanted to show.

Section 2

In this section, we modify the returns structure to include a penalty (or premium) to being an Active trader exactly as suggested in Hirshleifer (2010).

$$R_A = \beta_A * \bar{R} + \varepsilon_A - D$$

$$R_P = \beta_P * \bar{R} + \varepsilon_P \tag{23}$$

Following the same set of steps as in Section 1 of the Appendix brings us to the result:

$$\left(\frac{2n}{\chi}\right) E\left[\triangle f\right] = ac\left((\sigma_A^2 - \sigma_P^2) + (\beta_A^2 - \beta_P^2)\sigma_{\bar{R}}^2\right) + \left(acD^2 - (ad + bc)D\right) \tag{24}$$

Having already discussed the first term on the right hand side of equation 24, we turn our attention to the second set of outermost parentheses. This term governs how the change in the fraction of Active traders responds to the return penalty (or premium) to being an Active trader and it has the potential to offset any movement in the population towards Active trading. Holding all else equal, since it is quadratic in D, the average change in the fraction is as follows:

$$E\left[\triangle f\right] \geq 0 \; if \; D \leq 0$$

$$E\left[\triangle f\right] < 0 \; if \; 0 < D < \frac{(ad + bc)}{ac} \tag{25}$$

$$E\left[\triangle f\right]\geq0\;if\;D\geq\frac{(ad+bc)}{ac}$$

The first line of above is straightforward to explain: if there is a return premium to being an Active trader then the fraction of that type grows. This region of the function has $\lim_{D\rightarrow-\infty}E\left[\triangle f\right]=\infty$. The second line defines a positive range for D in which the average fraction of A traders is trending downwards. It makes sense that if there is a penalty to trading there will be fewer A's, but when traveling along the function there is a point, $D=\frac{(ad+bc)}{2ac}$, at which the penalty works increasingly less against the trend towards A trading. Since this is the positive sloped region of the function, we consider an explanation that also includes the last line of 25. This range, $D>\frac{(ad+bc)}{2ac}$, suggests that when D grows larger, $E\left[\triangle f\right]$ does as well. The only appealing explanation is that as D grows larger it becomes prohibitively costly to enter the market in the first place. This is because an increase in D results in a downward shift in the specification for returns, $R_{A}=\beta_{A}*\bar{R}+\varepsilon_{A}-D$. Incorporating market entry and exit could be accomplished by defining some minimum threshold for t period returns above which A traders participate. It also requires a non-constant population, n, which is beyond the scope of the modeling efforts of this paper.

Regardless of the potential modeling issues surrounding D, we believe that the market in question empirically, retail foreign exchange, is one in which there is a relatively low penalty to being an Active trader and thus unlikely to confound our results. Unstated in Hirshleifer (2010) is that, since there are costs associated with being a trader of any type, D is a relative term which defines the penalty (or premium) associated with being a A rather than a P. The term could account for a difference in risk-bearing, total transaction costs (for instance, the spread paid per trade times the number of trades or the account start-up fee), or even opportunity cost. With regards to risk-bearing, since the traders in the dataset chose to enter the market for foreign exchange they are all likely to have preferences towards risk. Transaction costs are also extremely low since retail brokerages usually charge the half-spread which is rarely more than one or two pips per trade on the most frequently traded pairs.

Section 3

If we assume that realized returns are achieved as indicated in equation 13, then it is sufficient to show empirically that $Var\left[R_A\right] > Var\left[R_P\right]$, to demonstrate that $\left((\sigma_A^2 - \sigma_P^2) + (\beta_A^2 - \beta_P^2)\sigma_{\bar{R}}^2\right)$ in equation 14 is positive.

$$Var\left[R_A\right] > Var\left[R_P\right] \tag{26}$$

Substituting in the returns structure from equation 13 into the equation above yields:

$$Var\left[\beta_A * \bar{R} + \varepsilon_A\right] > Var\left[\beta_P * \bar{R} + \varepsilon_P\right] \tag{27}$$

$$\beta_A^2\sigma_{\bar{R}}^2 + \sigma_A^2 > \beta_P^2\sigma_{\bar{R}}^2 + \sigma_P^2 \tag{28}$$

$$(\sigma_A^2 - \sigma_P^2) + (\beta_A^2 - \beta_P^2)\sigma_{\bar{R}}^2 > 0 \tag{29}$$

which is what we wanted to show.

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Table 1: **Social Networking Summary Statistics**

	Logins per user			**Friends per user**		
	Total	Active	Passive	Total	Active	Passive
Mean	30.8	36.7	27.6	20.9	31.9	18.5
Median	11.0	14.0	10.0	8.0	13.0	8.0
Std. Dev.	75.7	70.5	78.4	63.3	93.6	46.3
Max	2,723	913	2,723	1,801	1,801	1,004
Min	1	1	1	1	1	1
N users	5,597	1,981	3,616	3,871	1,456	2,415

	Sent Messages per user			**Messages Received per user**		
	Total	Active	Passive	Total	Active	Passive
Mean	38.4	55.4	28.2	23.3	31.8	18.6
Std. Dev.	254.4	378.0	133.4	33.8	46.0	23.3
Median	6.0	7.0	6.0	15.0	21.0	13.0
Max	7,460	7,460	2,047	1,101	1,102	411
95%	95.0	107.8	87.2	66.0	90.4	53.0
5%	1.0	1.0	1.0	3.0	5.0	2.0
Min	1	1	1	1	1	1
N users	3,271	1,224	2,867	5,391	1,921	3,470

Note: These statistics are conditional on having made at least one login, friendship, sent message, or received one message in their respective panels.

Table 2: **Trading Volume per User**

	Number of Positions Opened per User		
	Total	pre-myForexBook	post-myForexBook
Mean	377.5	197.3	276.2
Median	128	65	70
Std. Dev.	1,541.7	478.2	1,526.1
Max	97,448	9,202	93,732
Min	1	1	1
N users	5,693	3,913	4,985

Note: This document presents summary statistics on the number of trades issued per user in the dataset. In columns two and three, we partition the data into trades made before and after the user joined myForexBook. All statistics are conditional on having made at least one trade.

Table 3: **Profitability**

	Profitability per Trade (US$)		
	Total	Active	Passive
Mean	-6.20	-5.49	-8.50
Std. Dev.	1,109.7	899.7	1,612.8
Median	0.22	0.24	0.13
Max	32,825	32,825	26,190
Min	-59,300	-59,300	-37,510
N trades	2,149,083	1,642,262	506,821

	Profitability per Week (US$)		
	Total	Active	Passive
Mean	-112.48	-143.48	-83.28
Std. Dev.	8,500.0	10,449.2	6,120.04
Median	-1.53	-3.07	-0.70
95%	697.76	1,033.23	439.05
5%	-948.53	-1,320.45	-640.90
N	80,828	39,208	41,620

Note: This table presents summary statistics on the profitability of individual trades in the dataset. In the top panel we assess profitability per trade. In the bottom panel we examine profitability when summing dollar gains made by each trader during a week. A week is sampled between consecutive Saturdays at 12 am GMT. In columns two and three, we partition the data into trades made by those classified as Active and Passive traders.

Table 4: **Initial Account Balances (US$)**

	Total	Active	Passive
Mean	2,773	8,512	1,101
Median	983	1,938	612
Std. Dev.	7,975	10,536	3,273
Max	185,650	185,650	95,458
Min	16	100	16
N users	5,361	1,885	3,476

Note: The number of users in this sample, 5,361, is less than the total number of traders we studied, 5,693, because the data was unavailable when coming from certain brokerages. In these instances we were unable to use the existing data to construct realistic estimates for their initial balance.

Table 5: **The Decision to Quit Trading**

	Total Deciles (deflated)			Within Group Deciles		
Decile	Baseline	Passive	Active	Baseline	Passive	Active
(Lowest) 1st	1.263***	1.545***	1.086	1.399***	1.481***	1.263***
	(0.069)	(0.114)	(0.088)	(0.070)	(0.091)	(0.113)
2nd	1.135**	1.213***	1.136	1.086	1.158**	0.963
	(0.058)	(0.081)	(0.090)	(0.056)	(0.072)	(0.087)
3rd	1.118**	1.202***	1.039	1.162***	1.225***	1.044
	(0.055)	(0.072)	(0.089)	(0.057)	(0.073)	(0.090)
4th	1.228***	1.196***	1.274***	1.265***	1.293***	1.216**
	(0.057	(0.067)	(0.106)	(0.059)	(0.074)	(0.097)
5th	1.505***	1.355***	1.734***	1.391***	1.286***	1.607***
	(0.065)	(0.070)	(0.134)	(0.062)	(0.073)	(0.116)
6th	1.257***	1.157***	1.316***	1.197***	1.134**	1.331***
	(0.057)	(0.062)	(0.115)	(0.056)	(0.067)	(0.103)
7th	0.816***	0.719***	1.003	0.805***	0.779***	0.871
	(0.044)	(0.047)	(0.095)	(0.044)	(0.054)	(0.078)
8th	0.581***	0.587***	0.569***	0.617***	0.647***	0.566***
	(0.037)	(0.045)	(0.065)	(0.038)	(0.049)	(0.062)
9th	0.529***	0.541***	0.549***	0.547***	0.542***	0.547***
	(0.036)	(0.048)	(0.060)	(0.037)	(0.045)	(0.063)
(Greatest) 10th	0.598***	0.598***	0.625***	0.591***	0.556***	0.630***
	(0.045)	(0.067)	(0.063)	(0.043)	(0.050)	(0.076)
Subjects	5,358	3,430	1,928			
Observations	77,307	39,354	37,953			
Quitters	4,135	2,693	1,442			

Robust standard errors in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%.

Description: This table displays hazard rates from estimating a Cox-proportional hazard model. The event in question is whether or not a trader quit in a given week. We generate independent variables by sorting the entire sample space of weekly returns and giving the observation a "1" if it is part of a given decile, "0" otherwise. In some specifications we deflate returns by the individual's median trade size in an attempt to capture individual wealth. We also try sorting the entire sample of weekly returns into deciles and in other specifications just the subset belonging to a trader's type. In all estimations we include controls for trader experience and age as well as the number of trades issued by the trader in each week. All three controls are associated with a decreased probability of quitting trading. Furthermore, we examine but do not report the prior week's and monthly performance and found similar results. Both cases yield similar coefficients, but the results are of lower significance. We also computed, but do not report standard errors when clustering by trader and by week using the method outline in Froot (1989). This did not change the statistical significance of the results.

Table 6: **The Sending Function**

	I		II		III	
	logit (odds-ratios)		OLS		zero-truncated Poisson	
	message indicator$_{i,t}$		*message count*$_{i,t}$		*message count*$_{i,t}$	
log sender returns$_{i,t}$	1.207***	1.214***	12.31*	18.90***	0.332***	0.477***
	(0.0390)	(0.0547)	(7.329)	(6.670)	(0.111)	(0.00757)
controls	yes	no	yes	no	yes	no
time trend	yes	yes	yes	yes	yes	yes
individual FE	no	yes	no	yes	no	yes
constant	-0.550**		-10.04		0.594	
	(0.219)		(12.49)		(0.787)	
N	44,618	42,744	4,798	3,756	4,798	3,756
R^2			0.012	0.003		
pseudo R^2	0.037	0.003			0.113	0.087

Standard errors in parentheses

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

Description: This table describes results from estimating the relationship between the returns of the sender and the number of trades issued by the receiver. The dependent variables in each specification and the estimation method are listed below. The independent variable in all regressions is log weekly returns. Regressions include controls for receiver age, experience, and an indicator variable for whether or not a trader is a Active or Passive according to our definition. In other regressions we include brokerage fixed effects, as well as standard errors clustered by trader and by time, all of which had no effect on our results.

I: Logit, the dependent variable is an indicator for having sent a message (we present the coefficient).
II: OLS, the dependent variable is the number of trades issued, conditional on having sent at least one message.
III: Zero-Truncated Poisson Regression, the dependent variable is the number of trades issued, conditional on having sent at least one message.

Table 7: **The Sending Function by Trader Experience**

	Trading Experience (years)				
	none specified	0 - 1	1 - 3	4 - 5	5 - up
log sender returns$_{i,t}$	-1.062**	-0.035	0.113*	0.280***	0.187**
	(0.026)	(0.073)	(0.618)	(0.109)	(0.074)
N	481	14,642	22,719	4,578	5,682

Coefficients from logistic regression

Robust standard errors in parentheses

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

Description: This table presents the coefficients from estimating a logit model, as in Table 6, column I, in which the dependent variable is an indicator variable for having sent a user message in a given week and the dependent variable is log weekly returns. We estimate each model separately for users binned into different experience levels. New myForexBook users are asked to specify their level of trading experience when registering and setting up their profile. They are allowed to choose one of the four options listed above, 0 - 1, 1 - 3, 4 - 5, or 5 - above years, or can bypass the question (none specified).

Table 8: **The Sending Function Robustness**

	I	II	III
	logit (odds-ratios)	OLS	zero-truncated Poisson
	$message\ indicator_{i,t}$	$message\ count_{i,t}$	$message\ count_{i,t}$
$log\ sender\ returns_{i,t}$	1.187***	12.27*	0.341***
	(0.0385)	(7.298)	(0.116)
$average\ chatter_t$	1.117***	9.078***	0.408***
	(0.0150)	(3.382)	(0.0920)
$community\ performance_t$	0.998	0.133	0.00325
	(0.00132)	(0.145)	(0.00704)
$USD\ index_t$	0.392**	-46.05	-2.433
	(1.300)	(113.7)	(5.919)
controls	yes	yes	yes
time trend	yes	yes	yes
constant	2.473*	14.96	2.093
	(1.326)	(120.7)	(6.212)
N	44616	4796	4796
R^2		0.017	
pseudo R^2	0.039		0.161

Standard errors in parentheses

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Description: This table is identical to Table 6, but includes additional control variables that account for aggregrate activity of the community. *"average chatter"* is equal to the total number of messages sent in the network over the total number of active users in the network at time t. *"community performance"* is the average dollar gains per trade for all trades made within the week at time t. *"USD index",* is the trade-weighted US dollar index, a measure of the value of the US dollar relative to other world currencies in time t obtained from Thomson Reuters.

Table 9: **Sending Function, IV with Lagged Dependent Variable**

	message indicator$_{i,t}$			
$log\ \widehat{sender}\ returns_{i,t}$	0.276***	0.260***	0.286***	0.294***
	(0.0943)	(0.0944)	(0.0967)	(0.0969)
$community\ performance_t$		0.00105		-0.000221
		(0.000768)		(0.000770)
$USD\ index_t$		-0.266		-2.459***
		(0.759)		(0.764)
individual controls	no	no	yes	yes
time trend	yes	yes	yes	yes
constant	-1.249***	-0.977	-0.292***	2.175***
	(0.00918)	(0.759)	(0.0501)	(0.768)
N	35,833	35,833	35,833	35,833
chi2	8.581	10.47	814.1	825.2

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description: This table presents the results of employing a two-stage estimation on panel I of Table 6 in which we instrument using the lagged dependent variable, $log\ sender\ returns_{i,t-1}$.

Table 10: **The Receiving Function (OLS)**

	I	II	III	IV
	receiver trades$_{j,t+1}$	*receiver trades*$_{j,t}$	*receiver trades*$_{j,t+1}$	*receiver trades*$_{j,t+1}$
log sender returns$_{i,t}$ *(sum)*	0.746***	0.753***		
	(0.202)	(0.205)		
log sender returns$_{i,t}$ *(max)*			0.600**	
			(0.267)	
log sender returns$_{i,t}$ *(mean)*				0.168
				(0.190)
controls	yes	yes	yes	yes
time trend	yes	yes	yes	yes
constant	-7.977**	-12.57***	-9.640**	-9.643***
	(3.310)	(3.312)	(3.943)	(3.272)
N	4,632	5,027	5,879	4,632
R^2	0.014	0.011	0.012	0.012
$Prob > F$	0.000	0.000	0.000	0.000

Robust standard errors in parentheses

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

Description: This table describes results from using OLS to estimate the relationship between the log weekly returns of the sender and the log number of trades issued by the receiver. Regressions include controls for receiver age, experience, an indicator variable for whether or not a trader is an Active or Passive trader according to our definition, and a time trend. In other regressions we include brokerage fixed effects, as well as standard errors clustered by trader and by time, all of which had no effect on our results.

I: The lagged one week forward number of receiver trades on the sum of sender returns.
II: The same week receiver trades on the sum of sender returns.
III: The lagged one week forward number of receiver trades on the max of sender returns.
IV: The lagged one week forward number of receiver trades on the mean of sender returns.

Table 11: **The Receiving Function (zero-truncated Poisson)**

	I	II	III	IV
	receiver trades$_{j,t+1}$	*receiver trades*$_{j,t}$	*receiver trades*$_{j,t+1}$	*receiver trades*$_{j,t+1}$
log sender returns$_{i,t}$ *(sum)*	0.0425^{***}	0.0448^{***}		
	(0.00979)	(0.0113)		
log sender returns$_{i,t}$ *(max)*			0.0313^{**}	
			(0.0137)	
log sender returns$_{i,t}$ *(mean)*				0.0220^{**}
				(0.0110)
controls	yes	yes	yes	yes
time trend	yes	yes	yes	yes
constant	1.806^{***}	1.584^{***}	1.893^{***}	1.721^{***}
	(0.162)	(0.178)	(0.205)	(0.177)
N	4890	4504	5779	4504
pseudo-R^2	0.213	0.220	0.197	0.215

Robust standard errors in parentheses

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

Description: This table is identical to Table 10, but uses a zero-truncated Poission regression.

Table 12: **User Messages and Quitting Trading**

	Total	Active	Passive
sent message	2.128***	1.765***	2.626***
	(0.103)	(0.109)	(0.207)
received message	0.675***	0.766***	0.569***
	(0.040)	(0.055)	(0.059)
Subjects	5,693	3,681	2,012
Observations	126,212	73,730	52,482
Quitters	4,587	3,051	1,536

Robust standard errors in parentheses

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

Description: This table displays hazard rates from estimating a Cox-proportional hazard model. The event in question is whether or not a trader quit in a given week. The independent variables are indicators for whether or not a trader sent a message to another individual or received and read a message. We also computed, but do not report standard errors when clustering by trader using the method outline in Froot (1989). This did not change the statistical significance of our results.

Table 13: **Receiver Function Robustness (OLS)**

	I	II	III	IV
	receiver trades$_{j,t+1}$	*receiver trades*$_{j,t}$	*receiver trades*$_{j,t+1}$	*receiver trades*$_{j,t+1}$
log sender returns$_{i,t}$ *(sum)*	0.0150	0.00384		
	(0.0102)	(0.00899)		
log sender returns$_{i,t}$ *(max)*			-0.00146	
			(0.00763)	
log sender returns$_{i,t}$ *(mean)*				-0.00334
				(0.00919)
community performance$_t$	-0.00174	-0.00347*	-0.00189	-0.00332
	(0.00229)	(0.00202)	(0.00175)	(0.00202)
USD index$_t$	0.1000***	0.158***	0.149***	0.158***
	(0.0134)	(0.0137)	(0.0109)	(0.0137)
log receiver returns$_{j,t}$	-4.640**	-4.016**	-3.081*	-4.060**
	(2.115)	(1.851)	(1.600)	(1.852)
receiver trade count$_{j,t-1}$	0.00334*	0.00498***	0.00468***	0.00499***
	(0.00203)	(0.00147)	(0.000893)	(0.00147)
controls	yes	yes	yes	yes
time trend	yes	yes	yes	yes
constant	5.857***	4.936***	4.057**	5.019***
	(2.132)	(1.867)	(1.616)	(1.868)
N	1769	1992	2604	1992
R^2	0.331	0.433	0.447	0.433

Robust standard errors in parentheses

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

Description: This table is identical to Table 10, but includes additional control variables that account for aggregrate activity of the community. *"average chatter"* is equal to the total number of messages sent in the network over the total number of active users in the network at time t. *"community performance"* is the average dollar gains per trade for all trades made within the week at time t. *"USD index",* is the trade-weighted US dollar index, a measure of the value of the US dollar relative to other world currencies in time t obtained from Thomson Reuters. It also includes

Table 14: **Receiver Function Robustness (zero-truncated Poisson)**

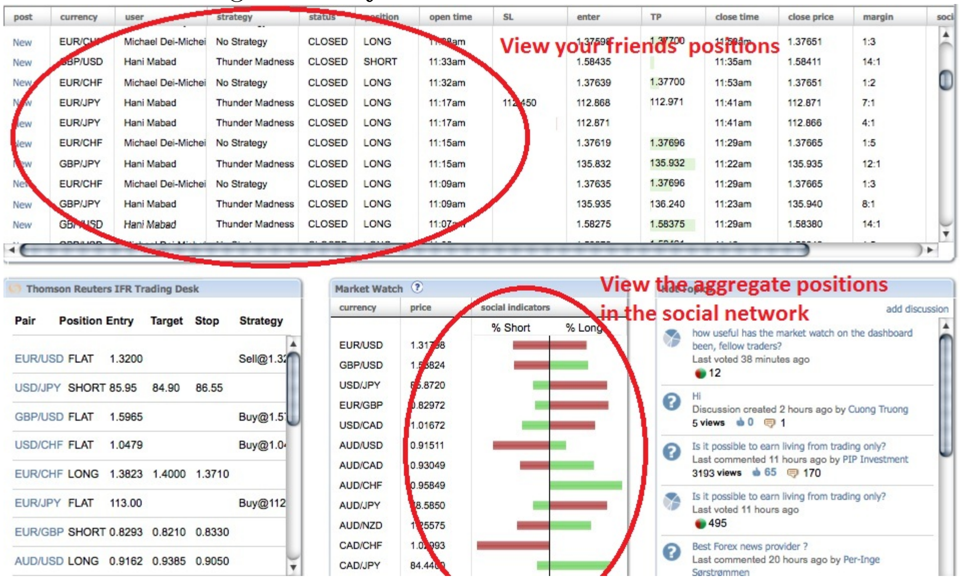
	I	II	III	IV
	receiver trades$_{j,t+1}$	*receiver trades*$_{j,t}$	*receiver trades*$_{j,t+1}$	*receiver trades*$_{j,t+1}$
log sender returns$_{i,t}$ *(sum)*	0.0452***	0.0437***		
	(0.0107)	(0.0120)		
log sender returns$_{i,t}$ *(max)*			0.0311**	
			(0.0131)	
log sender returns$_{i,t}$ *(mean)*				0.0196*
				(0.0117)
community performance$_t$	-0.00630**	-0.00239	-0.00292	-0.00169
	(0.00302)	(0.00245)	(0.00501)	(0.00243)
USD index$_t$	-0.199	-1.700	1.809	-1.659
	(2.166)	(2.085)	(1.964)	(2.075)
log receiver returns$_{j,t}$	-0.0000107***	-0.00000880**	-0.00000394*	-0.00000900**
	(0.00000392)	(0.00000387)	(0.00000235)	(0.00000388)
controls	yes	yes	yes	yes
time trend	yes	yes	yes	yes
constant	1.915	3.353	0.113	3.464*
	(2.188)	(2.107)	(1.938)	(2.101)
N	4890	4122	5323	4122
pseudo-R^2	0.222	0.212	0.187	0.207

Standard errors in parentheses

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

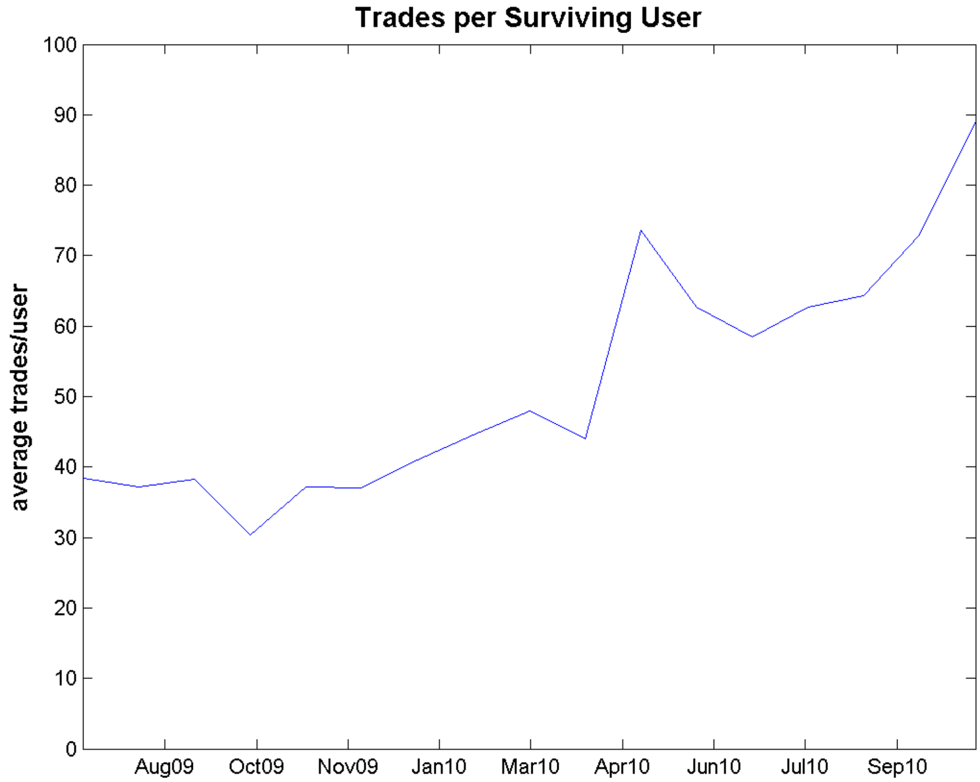
Description: This table is identical to Table 13, but uses a zero-truncated Poisson regression.

Figure 1: **myForexBook "Dashboard"**



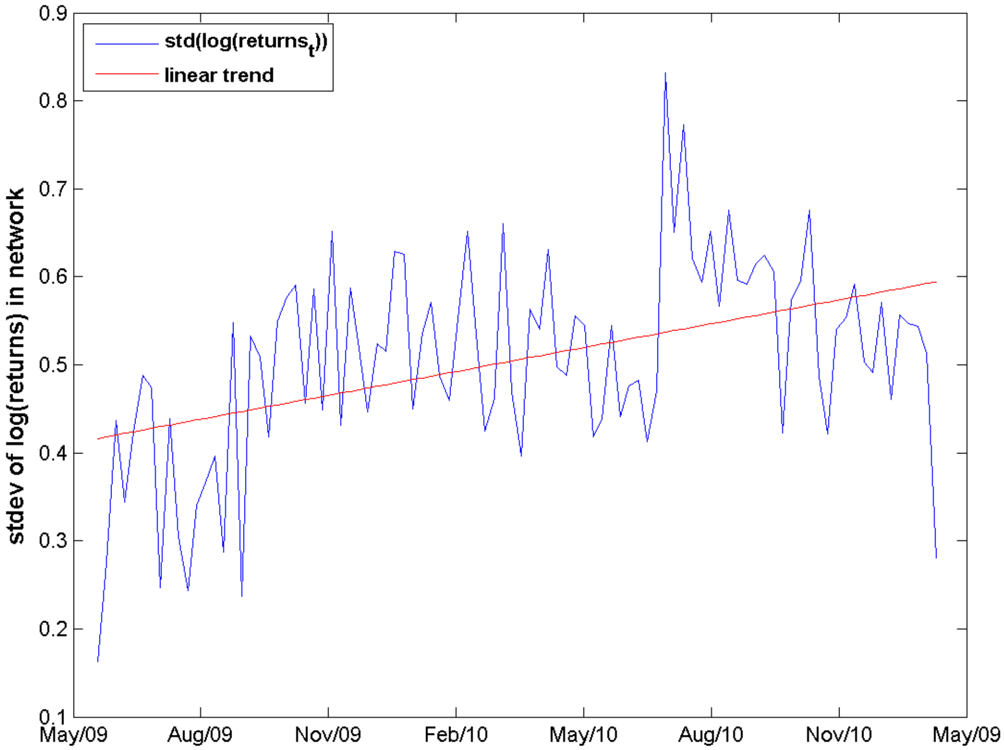
Note: This image displays the contents of a web browser that would be viewed by a myForexBook trader.

Figure 2: **Average Trades per Surviving User**



Note: This figure plots the number of trades made in a given month divided by the number of surviving users present in said month. A surviving user is defined as one who has had activity in the final month of the dataset. If the user did not survive, then they are said to have quit trading at the time of their last observable activity.

Figure 3: **Average Standard Deviation of Returns per User**



Note: This figure plots against time the standard deviation, $\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$, in time t per individual i where $x_i = R_{i,t} = \log\left(\frac{V_i^e}{V_i^b}\right)$ (as defined in Equation 5), conditional on the individual having made at least one trade.

Figure 4: **Friendships Made in myForexBook**

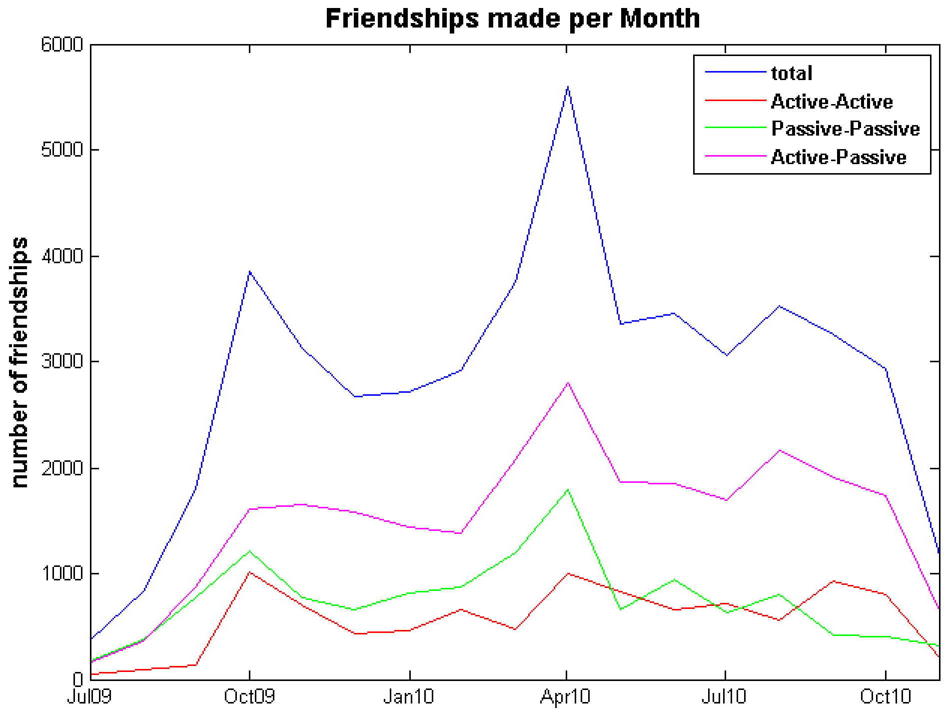
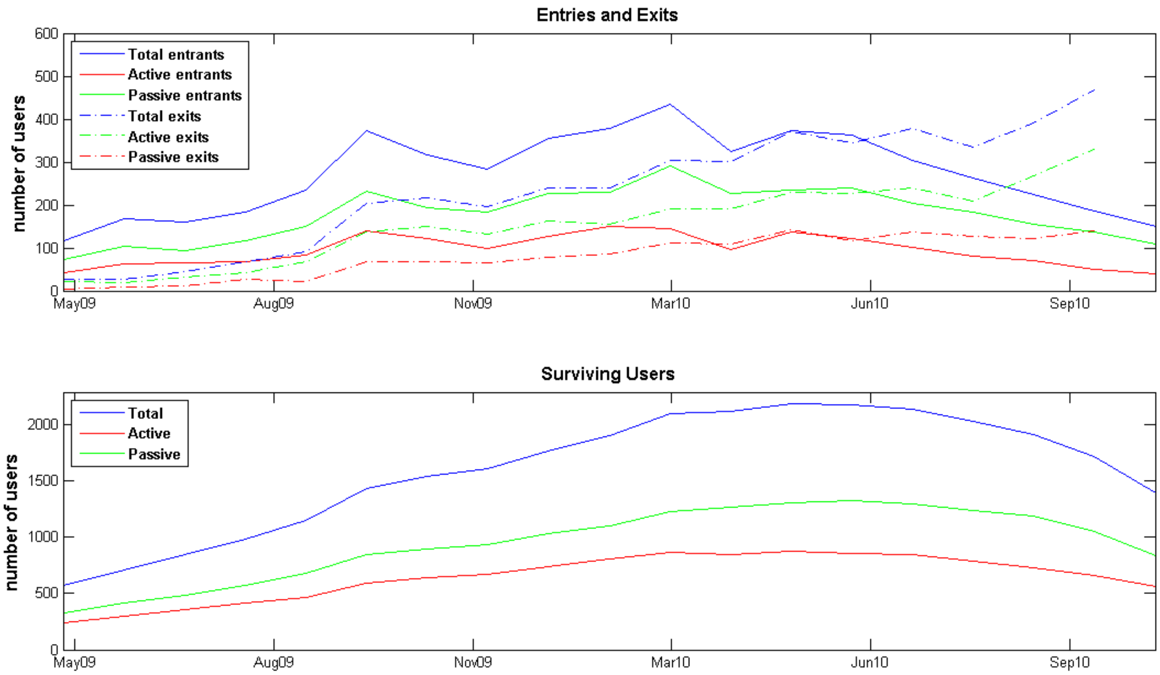
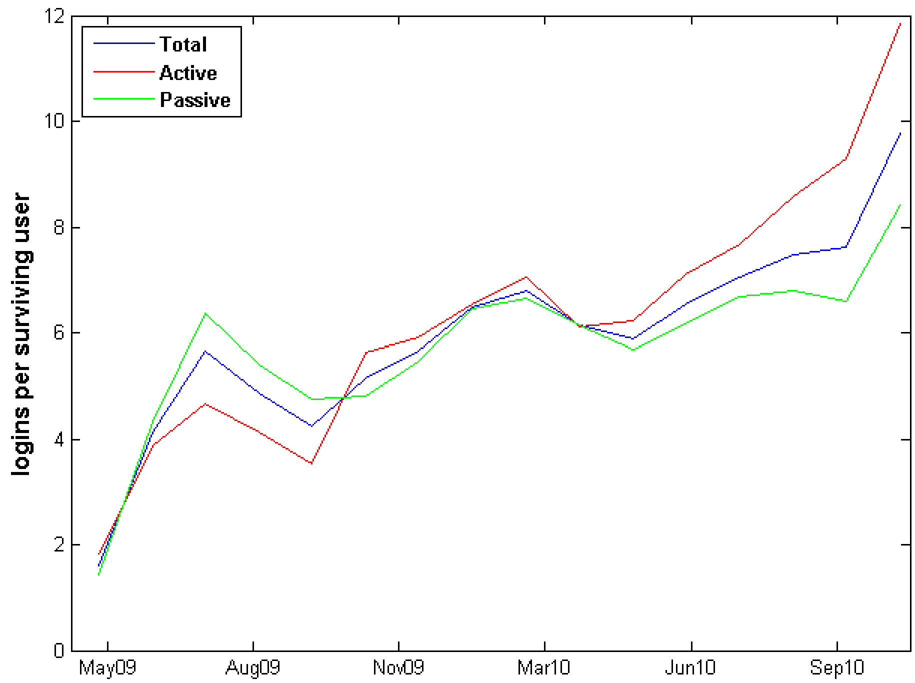


Figure 5: **Entries, Exits, and Survivors**



Note: A surviving user is defined as one who has had activity in the final month of the dataset. If the user did not survive, then they are said to have quit trading at the time of their last observable activity.

Figure 6: **Logins per Surviving User**



Note: This figure plots the number of logins made in a given month divided by the number of surviving users present in said month. A surviving user is defined as one who has had activity in the final month of the dataset. If the user did not survive, then they are said to have quit trading at the time of their last observable activity.