Active Trading and (Poor) Performance: The Social Transmission Channel

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Abstract

We study the influence from social interactions on stock market participation. Using unique data on stock transactions, we exploit the exogenous assignment of students to classrooms in a financial training program to identify how peer experience affect market entry. We show that students assigned to courses where peers experience positive returns on recent trades are more likely to start trading, but their trading profits are lower than other rookie investors. We examine possible explanations for this systematic underperformance. The evidence is consistent with social learning under selective communication: people share their most successful outcomes encouraging stock trading among uninformed individuals.

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1. INTRODUCTION

Social interactions allow for information dissemination about technologies, products, job opportunities, and beliefs (Jackson, 2010; Jackson, 2011). In finance, substantial evidence shows that information sharing with peers plays an important role for investment decision making, including stock market participation and portfolio choice (e.g., Duflo & Saez, 2003; Hong, et al., 2004; Bursztyn, et al., 2014; Li, 2015; Hvide & Ostberg, 2015). In social settings, however, individuals are selective about the information they want to share with others. For example, people may tend to boast about good stock trades, favoring the transmission of appealing but inaccurate ideas about active trading (Shiller, 1995; Shiller, 2015), or they may try to convince others that they are wealthier or more intelligent than what they really are.[3] Despite extensive research on the effects of social interactions on investment choices, the role of selective communication in the diffusion of trading strategies remains largely unexplored.[4] In this paper, we use data from a large-scale financial training program to study the effects of noisy word-of-mouth communication on stock market participation. We show that biased signals from peers disproportionally attract uninformed individuals to equity trading. These investors overestimate the value of active trading and generate inferior returns once they enter the stock market.

Canonical models of social learning assume that peer choices are perfectly observed by members of the social network (Banerjee, 1992; Bikhchandani, et al.,

[3] This behavior has long been recognized and studied in sociology and psychology. See for example, Schlenker (1980), Leary & Kowalski (1990), and Gonzales & Hancock (2011). Although people often avoid lying given their preference for being seen as honest (Abeler, et al., 2019), they might selectively omit information that is unfavorable, or that may give the impression that they are not successful. Bénabou & Tirole (2002) present a general economic model in which agents protect their self-esteem by engaging in self-deception through selective memory awareness.

[4] Two notable exceptions are Kaustia & Knupfer (2012) and Han, et al. (2020). Hirshleifer (2020) argues that *social transmission bias* – "the systematic directional modification of ideas as they pass from person to person" – is a key yet underexplored concept in social economics and finance.

1992). In practice, peer preferences and outcomes are not always observed directly, and such information is often transmitted via informal conversations. When negative outcomes (e.g., trades that generated low or negative returns) are filtered out to present a positive self-view to others, less information is available to those who are forming an opinion about the value of an activity. Our paper examines how investment choices are affected by biases in information transmission.

Our analysis relies on a natural experiment involving exogenously assigned peer groups. Starting in 2008, the Colombian Stock Exchange (CSE) launched a series of professional courses on financial topics (discussed in detail in Section 3),[5] with the majority focusing on equity strategies. Registered individuals were assigned to small sections that studied stock trading in a classroom setting with 16 students per class, on average. Each group was formed based on availability, and the CSE did not use nor it verified past trading experience as a prerequisite to enroll in the program. Hence, the setting resembles a random assignment. We combine class records with administrative microdata of stock transactions to distinguish students with trading experience from those with no such background. In other words, we observe the trades of students who were active in the stock market before participating in one of the CSE's financial courses. We also observe the trades and performance of students who began trading only after completing a course; that is, after interacting with experienced classmates in their artificially formed group. Overall, our novel data set combines the official class records and trading activity of 13,730 students from over 1,100 courses between 2008 and 2016.

While we accurately observe the stock trades of experienced students, we do not know the specific information that was shared among classmates. To formalize the role of selective communication in our setting, we introduce

[5] Most courses were scheduled on weeknights or Saturdays to accommodate working professionals. However, there was no educational background requirement or age restriction that constrained student participation.

information-transmission bias in a model of social learning. In the model, potential investors with different trading skills are uncertain about the expected payoffs from trading stocks. These individuals update their beliefs after observing public information in stock prices and signals from experienced investors in their classroom. The theoretical model allows us to identify a set of testable predictions that are unique to the story of selective communication, relative to predictions from alternative or complementary explanations about investment choices under social interactions. For example, we compare our predictions to multiple settings: (i) when information is transmitted accurately across peers; (ii) when investors are overconfident (Kyle & Wang, 1997; Odean, 1998; Benos, 1998); and (iii) when investors have relative wealth concerns, if people imitate their peers due to a "keeping up with the Joneses" effect (Abel, 1990; Gali, 1994; Bakshi & Chen, 1996; Campbell & Cochrane, 1999; DeMarzo & Kaniel, 2004).

The two unique predictions from the model under selective communication are the following: first, only positive peer outcomes influence investment decisions. Second, peer outcomes promote market participation, especially among uninformed individuals. In the model, unskilled investors have low precision in their private information. In turn, they put more weight on outside signals than other better-informed individuals; that is, the effect from the peer signal is higher if an individual is less informed a priori. Consequently, positive peer returns encourage more unskilled than skilled investors to trade stocks. If communication among classmates is accurate, uninformed individuals would be more likely to refrain from trading stocks after hearing about the bad experiences from peers. However, when negative information is not transmitted, low peer outcomes have no marginal effect on the entry decision. In turn, the probability of entering the market for both skilled and unskilled students is constant – independent from the magnitude of the peer underperformance. In other words, the model predicts that the proportion of skilled entrants is the same in courses where there are no experienced classmates and in courses where peers have experienced low trading returns.

In our empirical design, we exploit the fact that the representation of students with trading backgrounds, their trades, and past performance vary considerably across groups. We find that students assigned to groups with a high share of experienced classmates are more likely to start trading stocks after completing the course. A one-standard-deviation increase in the share of experienced students in a group increases the likelihood of market participation by three percentage points, a gain of 25%. Alternative mechanisms that do not involve social influence are ruled out. For example, time fixed effects control for market-wide news releases and other aggregate shocks that influence market participation. City fixed effects control for systematic regional differences and teacher fixed effects remove the influence from the class instructor. Overall, our baseline results suggest a strong presence of peer effects in our classroom setting.

To evaluate the empirical predictions from our learning model, we follow the methodology used by Kaustia & Knupfer (2012) and decompose peer performance into negative and positive regions to analyze how different outcomes from experienced classmates influence market entry. We find that negative peer returns do not affect market participation and that the relation between peer returns and entry is exclusive to recent positive peer returns–those within a 6-month window before the course start date. For positive peer returns measured over longer horizons, 12 or 36 months before the training, the effects on market entry are smaller or negligible. A crucial and novel empirical finding is that the effect of peer returns is not only originating from salient outcomes, but from interactions with classmates with high volatility portfolios; precisely those that produce the most extreme returns. We show that signals from peers with high volatility strategies and who happened to experience positive returns before the course disproportionally attract new investors to active trading.

Our second set of finding relates to the performance of investors after the training program. We show that experienced students underperform relative to new investors for a common investment horizon after the course. The finding highlights a key attribute of the social learning environment: students with trading background are not necessarily sophisticated investors, they are simply more active. Among these experienced students, individuals with positive returns before the course have the lowest performance in the 12 months following the training. Relatedly, classmates of these apparently successful investors also underperform once they begin trading. Other individuals that attend courses without experienced classmates, or where peers had negative returns prior to the course, have the highest returns in their first year of trading–they outperform new investors from other courses and experienced students from their own classroom. Overall, the results are consistent with the hypothesis that selective communication encourages more market entry among uninformed investors.

To directly test how communication in the classroom is related to market entry and performance, we asked former students if they had any discussions about stock trading with classmates during the course. Using the sample of survey respondents, we confirm our main findings. Students that report investment conversations with classmates in courses where peers had positive returns are more likely to start trading, but they underperform in their first year after the course.

A potential explanation for low returns among new investors might correspond to mean reversion in stock prices.[6] For example, if individuals systematically buy the best-performing stocks of their peers and large price increases precede reversals, new investors would display poor performance. To

[6] Mean reversion refers to the tendency of asset prices to return to a trend path. Although the existence of mean reversion in stock prices is subject to much controversy, there is some evidence of mean reversion in stock prices in US and international markets (Poterba & Summers, 1988; Chaudhuri & Wu, 2003; Fama & French, 1988). Campbell, et al. (1997) summarize the debate concisely.

examine this possibility, we use the sample of market entrants and study the relation between an individual's stock selection and the stock selection decision made by experienced classmates. We document a strong positive relation between the stock purchases of new investors and purchases of experienced students after the course. As new investors try to look for investment opportunities, we show that instead of following past trades from classmates or stocks with high returns in the peers' portfolio prior to the class, they seem to select stocks in which peers are making new purchases.

Peer effects in stock selection have been widely documented in multiple social environments and are not surprising in our setting, but our evidence sheds new light on the role of information transmission bias. The mechanism is summarized as follows. Recent positive returns from experienced classmates attract new investors. Such outcomes, however, are the result of portfolios with high idiosyncratic volatility. Due to direct spillovers in stock selection, new investors then select similar strategies to their experienced peers. In turn, social interactions promote the adoption of high volatility strategies even when new investors have no inherent preference for volatility.

Another alternative explanation for our findings is that individuals accurately observe peer outcomes but decide to ignore negative signals; we refer to this behavior as *selective information neglect*. For instance, individuals might overestimate their ability to replicate peers' successful trades while avoiding peers' mistakes. According to our survey, informal conversations about stock trading are more common in courses where peer outcomes are good; 93% of students report investment conversations with classmates when peer returns are positive, compared with 79% in courses with negative peer returns. While the survey evidence does not directly rule out selective information neglect, it suggests that the exchange of investment ideas is stronger when some students have experienced positive outcomes.

Our work is closely related to Han, et al. (2020). The authors are the first to model communication bias among individual investors to explain why active strategies (e.g., those with more personal involvement and with more variance) dominate passive investments. Using a classroom enviroment, we present novel empirical evidence consistent with the view that selective communication plays a key role in financial decisions.[7] Our evidence suggests that positively-selected information about the value of active trading leads to enhanced stock market entry among uninformed individuals.

Our analysis contributes to the empirical literature that studies the effects of social interactions on investment (e.g., Hong, et al., 2004; Hong, et al., 2005; Ivkovic & Weisbenner, 2007; Brown, et al., 2008; Li, 2015; Hvide & Ostberg, 2015; Ouimet & Tate; 2020). Most of this literature focuses on identifying peer effects—whether information or behavior is transmitted—and on the strength of social contagion. We add to the literature by examining one important aspect of peer effects; that is, the transmission of investment ideas and its impact on behavior when communication is biased. Closely related to our analysis, Kaustia & Knupfer (2012) document that only positive peer outcomes from neighbors, defined as investors living in the same zip code, encourage stock market participation. In our study, social interactions are well-defined by classmates and the time and location of each course. In addition to providing support to the findings in Kaustia & Knupfer (2012) under a small group setting with quasi-random assignment, we contribute to the literature by presenting new evidence on the role of information transmission bias. We show that new investors, and in particular naïve individuals, are attracted by recent positive returns from peers, although such outcomes are the

[7] Other papers have used classroom settings to identify peer effects. Shue (2013) and Lerner & Malmendier (2013) use the random assignment of students into sections of Harvard's Master of Business Administration program to study how professional networks affect managerial decisions and how the interactions of students with successful and unsuccessful entrepreneurs affect new entrepreneurial activity.

result of portfolios with high idiosyncratic volatility. Social interactions also lead to correlated stock purchases after the training. In turn, the information environment promotes the transmission and adoption of high volatility strategies. Overall, our findings suggest that in order to understand peer effects in social groups, it is important to identify the biases that affect information transmission.

Finally, our findings relate to the literature on the determinants of individual trading performance. Excessive investor trading is commonly linked to poor returns and is often explained by overconfidence (DeBondt & Thaler, 1995; Barber & Odean, 2000). Furthermore, active trading could be exacerbated by social interactions as favorable ideas about stock trades are easily disseminated across people (e.g., Barber, et al., 2003; Hong, et al., 2004). However, because of self-selection, it is difficult to identify whether peer effects are the key driver in the transmission of active trading strategies. If individuals choose where to work or the type of peers, it is difficult to separate selection from peer effects. Our work contributes to this literature by empirically estimating how trading ideas are transmitted across people. While individuals self-select into CSE courses because of their interest in stock trading, they differ in their exposure to classmates with diverse trading histories. More broadly, our findings have important policy implications. The education program aimed to provide information to improve financial decisions. Contrary to this objective, selective communication among peers seems to disseminate inaccurate signals and consequently promotes misguided ideas about personal investing.

The rest of the paper proceeds as follows: in Section 2, we introduce a model of stock market participation with social learning. In Section 3, we describe the financial education program and data. We present our empirical methodology in Section 4 and main results in Section 5, and we explore different channels of peer effects in Section 6. Section 7 concludes.

2. HYPOTHESES

In this section we discuss hypotheses derived from interactions among individuals that could explain stock market entry decisions as well as the investment performance of new investors. In the model, potential investors with different trading skills are uncertain about the expected payoffs from trading stocks, and they update their beliefs about that value by observing public information in stock prices and the signals from the performance of classmates with trading experience.

We first derive hypotheses assuming that information is perfectly shared between experienced and inexperienced students. We refer to this setup as our model under *accurate communication*, when students with trading background truthfully reveal their recent trading performance. We then derive hypotheses on the investment choice implied when communication is biased toward positive peer outcomes, or *selective communication*. Finally, we discuss testable implications when overconfidence, a psychological attribute that is commonly linked to investor overtrading and underperformance, is introduced into the benchmark model of market entry. Other explanations based on mean reversion in stock prices, herding due to relative wealth concerns, and selective information neglect are discussed (and tested) in Section 6.

2.1. A MODEL OF STOCK MARKET PARTICIPATION

There are N potential new investors, $i = 1, \dots, N$. These individuals participate in different stock trading courses but have no previous trading background. The value of entering the stock market is uncertain, $\tilde{v}$, and is distributed normally with mean $\bar{v}$ and variance σ_v^2. We use τ_v to denote $1/\sigma_v^2$. New investors must pay a fixed cost of entry c, so the net payoff from entry is $\tilde{v} - c$.

Each potential investor is endowed with two signals about $\tilde{v}$ at the beginning of her training. The first is a public signal (e.g., stock market prices) that is denoted by $\tilde{s}_p = \tilde{v} + \sigma_p \tilde{\varepsilon}_p$, where $\tilde{\varepsilon}_p$ is independently and normally distributed with mean zero, unit variance, and $\tau_p = 1/\sigma_p^2$. The other signal is privately observed by each investor i, $\tilde{s}_i = \tilde{v} + \sigma_i \tilde{\varepsilon}_i$, where $\tilde{\varepsilon}_i$ is independently normally distributed across investors with mean zero and unit variance. The precision of this signal is denoted by $\tau_i = 1/\sigma_i^2$.

Participation in a stock trading course not only allows students to access specialized material and instruction that might be useful in making investment decisions, but it also provides a setting where classmates with trading background can share their experiences. When experienced classmates reveal their trading outcomes, these could be valuable information that allows potential new entrants to update their beliefs about the value of stock market participation. We model such signals as $\tilde{s}_e = \tilde{v} + \sigma_e \tilde{\varepsilon}_e$, where $\tilde{\varepsilon}_e$ is independently and normally distributed across experienced students with mean zero and unit variance. The precision of this signal is denoted as $\tau_e = 1/\sigma_e^2$. In the baseline model of accurate communication, we assume that peer performance is perfectly observed by all students in the same classroom. Of course, peer outcomes only represent small data samples that come with various biases. For example, random components in returns are large and factors like skill or risk exposure are likely unobserved. Regardless, peer experiences are expected to carry some information that is used in the updating process of potential investors.

We assume that individuals are risk neutral.[8] In turn, a student without trading background decides to participate in the stock market as long as the net payoff calculated after observing all the signals—public, private, and peer experience—is positive. We also assume, without loss of generality, that $\bar{v} = c$.

[8] We also solve for a model of learning where potential investors maximize expected terminal utility with mean-variance preferences and risk-aversion coefficient ρ. In such a setting, the binary choice of entering the stock market or staying out changes to a continuous choice of relative wealth invested in the risky asset. The main channels described in the text to compare accurately with selective communication also hold in this case.

That is, in the absence of any additional information, individuals are indifferent about the entry choice.

Skilled and Unskilled Investors: The only *ex ante* difference between potential investors is that a fraction ξ of them have *skill*, meaning their private signals about the value of entering the stock market are more informative. More concretely, we assume that the precision of the private signals of skilled individuals is higher than the precision of signals from those who are unskilled, $\tau_S > \tau_U$. Since we are comparing individuals who self-selected into the training program, we do not model the explicit choice to acquire information. In our setting, all potential investors already decided to become more informed by paying a registration fee and participate in a stock trading course. Instead, we model the investment choice of skilled and unskilled individuals, subject to observing different peer outcomes.

Market participation: The expected payoff from stock market participation, given signals $\tilde{s}_p$, $\tilde{s}_i$, and $\tilde{s}_e$, for a student with skill level *K={S,U}* is $E[\tilde{v} \mid \tilde{s}_p, \tilde{s}_i, \tilde{s}_e] = \Sigma(\tau_v \bar{v} + \tau_p \tilde{s}_p + \tau_K \tilde{s}_i + \tau_e \tilde{s}_e)$, with $\Sigma^{-1} = \tau_v + \tau_p + \tau_K + \tau_e$. An investor decides to start trading ($y = 1$) if the expected value under the posterior is above the fixed cost of investment, $E[\tilde{v} \mid \tilde{s}_p, \tilde{s}_i, \tilde{s}_e] \geq c$. In terms of the private and market signals, an individual chooses to start trading actively if $\tau_p \tilde{s}_p + \tau_K \tilde{s}_i \geq -[\tau_e(\tilde{s}_e - c)]$. When we bring the model to the data, we observe peer outcomes from transaction records, but we do not observe the private information of potential investors. In turn, we calculate the probability of entry unconditional on the private and market signals by integrating over all possible $\tilde{s}_i$ and $\tilde{s}_p$. Consequently, the probability of market participation given the peer signal and the skill level is:

$$\Pr(y = 1 \mid \tilde{s}_e, K) = \Phi[\beta_K(\tilde{s}_e - c)] \tag{1}$$

where $\Phi()$ is the cumulative distribution of the standard normal, $\beta_K = \tau_e / T_K$ and $T_K = \sqrt{\frac{1}{\tau_v}\left(\tau_p^2 + \tau_K^2\right) + \tau_p + \tau_K}$. Since β_K is always positive, this implies the following: HYPOTHESIS 1: *Under accurate communication, stock market entry is monotonically increasing in peer outcomes* $\tilde{s}_e$*:* $\partial \mathrm{Pr}/\partial \tilde{s}_e > 0$*.*

A potential investor is more likely to start trading if she observes large positive outcomes from experienced classmates, since she expects higher profitability from stock market participation. Conversely, if the peer signal is negative, the value of active trading is lower under the posterior, which reduces the probability of market entry.

For similar peer signals, skilled and unskilled investors enter the market at different rates. Skilled individuals, for example, put more weight on their private information and less on other signals, since $\beta_S < \beta_U$. Conversely, unskilled individuals rely more strongly on outside signals—in this case, on the information from peers' outcomes. Panel A of Figure 1 presents the probability of market participation for skilled and unskilled investors as a function of peer outcomes. When peer returns are positive, unskilled investors are more likely to start trading stocks than their more skilled counterparts. Conversely, when peer outcomes are negative, the probability of market participation is lower for unskilled students.

We define the ratio of skilled entrants among new investors as a function of the peer signal as follows:

$$\Pi(\tilde{s}_e) = \frac{\xi\Phi[\beta_S(\tilde{s}_e - c)]}{\xi\Phi[\beta_S(\tilde{s}_e - c)] + (1-\xi)\Phi[\beta_U(\tilde{s}_e - c)]}\,. \tag{2}$$

Equation (2) captures the average ability of new investors; that is, the proportion of new entrants that are well-informed.

PROPOSITION 1: *The ratio of skilled entrants has the following properties:*

(i) $\Pi(\tilde{s}_e^+) < \Pi(\tilde{s}_e^-)$ *for any* $\tilde{s}_e^+ \in (c, \infty)$ *and* $\tilde{s}_e^- \in (-\infty, c)$, and

(ii) *is decreasing (*$\partial \Pi/\partial \tilde{s}_e < 0$*) in the interval* $\tilde{s}_e \in (-\infty, c]$.

The proof is in Appendix A. The result is intuitive. Since the marginal effect of the peer signal on the entry decision is stronger for unskilled individuals, there is a higher share of skilled entrants when the peer signal is negative (i.e., below the investment cost) than when the signal is positive. According to the learning model, we should expect, in relative terms, more unskilled entry among students that interact with good-performing peers than in other courses (literal i Proposition 1). Literal ii of Proposition 1 refers to the marginal effect of the peer signal. For negative peer outcomes, as the peer signal increases, there is proportionally more entry from unskilled investors and Π decreases (see Figure 1-Panel B).[9]

Overall, information from peers generate a composition effect among entrants, encouraging or preventing more skilled vs. unskilled individuals depending on the sign and strength of the signal. The model with accurate communication produces at least two related testable implications about the ratio of skilled entrants: (i) Π is always smaller when peer outcomes are positive than when peer outcomes are negative, and (i) Π decreases on the peer signal if peer outcomes are negative ($\partial\Pi/\partial\tilde{s}_e < 0$ if $\tilde{s}_e < c$).

In the data, we do not measure *ex ante* skill. For example, we do not have a test of financial knowledge or mathematical ability at the beginning of the course. Instead, we measure trading profits among those who decide to trade actively after completing the course. If trading profits, especially those obtained in the first few months of trading activity are a good proxy for investors' inherent skill, we can write our second hypothesis as follows:

HYPOTHESIS 2: *The average trading performance of new investors is lower for courses where peers have positive outcomes than for courses where peers had negative outcomes. Moreover, under accurate communication, if peer outcomes are*

[9] For positive peer outcomes, the proportion of skilled entrants Π can be represented by a U-shaped function. The proof is included in Appendix A. For low positive peer returns (i.e., $\tilde{s}_e \in (c, s^*)$ with $\Pi'(s^*) = 0$), as the signal increases, unskilled entry dominates, and Π falls. When the peer signal is large enough ($\tilde{s}_e \geq s^*$), most unskilled investors enter the stock market, and further increases on the peer signal disproportionally encourage market participation among informed investors–those who are less sensitive to the peer signal in the first place.

negative, the average trading performance of new investors is decreasing in the peer signal.

2.2. SELECTIVE COMMUNICATION

Above we assume that peer experiences (past market participation and trading performance) are perfectly revealed across classmates. In practice, people cannot directly observe peer outcomes and have to rely on indirect cues such as verbal accounts. Communication could be biased toward positive investment outcomes if individuals benefit from appearing successful. The tendency of people to report positively about themselves has been studied in the psychology and sociology literature and is explained by the need to satisfy presentational norms (Schlenker, 1980; Leary & Kowalski, 1990; Gonzales & Hancock, 2011). In financial settings, there is ample evidence that people tend to focus on good rather than bad outcomes. For example, Simon & Heimer (2015) report that the frequency with which investors contact other traders is increasing in the investor's short-term performance. Also, investors tend to examine their portfolios more frequently if the market has risen than after market declines (Karlsson, et al., 2009; Sicherman, et al., 2012).

We model selective communication by assuming that the revealed peer signal is a nonlinear function of the true peer outcome, $\tilde{s}_e^r = \max(0, \tilde{s}_e - c)$. We assume that signal receivers do not internalize the bias in communication similar to Han, et al. (2020), but we also relax this assumption by solving a model where potential investors understand that only positive peer outcomes are shared (see Appendix B). The testable implications of both models are similar, so we focus here on the case with naïve signal receivers.[10] Using a signal that is biased toward

[10] In the case where signal receivers internalize the fact that negative information is not shared when $\tilde{s}_e^r = 0$, individuals cannot distinguish between not having experienced peers in the classroom and having peers with negative trading outcomes who avoid discussing losses. Bayes'

positive outcomes implies an asymmetric relation between peer outcomes and market participation:

HYPOTHESIS 3: *Under selective communication, market participation is constant for negative peer outcomes (*$\partial \Pr / \partial \tilde{s}_p = 0$ *if* $\tilde{s}_e < c$*) and increases on positive peer outcomes (*$\partial \Pr / \partial \tilde{s}_p > 0$ *if* $\tilde{s}_e > c$*).*

The second implication of the model with selective communication is related to the ratio of skilled entrants, Π. Since potential investors always observe a signal equal to zero for negative realizations of trading returns among experienced classmates, the proportion of skilled entrants remains constant independent from the true peer outcome $\tilde{s}_e$. Moreover, the ratio of skilled entrants is the same for cases when students interact with underperforming peers and in cases when there are no experienced students in the classroom. For positive peer outcomes, the predictions from the model of selective communication are indistinguishable from those under accurate communication (dashed line in Figure 2). In terms of average performance among amateur investors, we can express the hypothesis as follows:

HYPOTHESIS 4: *The average trading performance of new investors is lower for courses where peers have positive outcomes than for courses where peers had negative outcomes. Under selective communication, the average trading performance of new investors is constant for* $\tilde{s}_e \leq c$.

In our model, each of the N students could enter the stock market after observing all the signals. Under selective communication, negative outcomes are not transmitted, so the magnitude from negative returns has no marginal effects, which under perfect communication would have discouraged proportionally more entry among unskilled individuals in the first place.

Law in this case implies that a zero-peer signal has some negative information on the value of trading. In such a case, all investors end up reducing their probability of entry relative to the case with naïve investors.

2.3. OVERCONFIDENCE

A psychological attribute among investors that is often linked to excessive stock trading and negative performance is overconfidence,[11] the tendency to place an irrationally excessive degree of confidence in one's abilities and beliefs. We introduce overconfident individuals in our model as an irrational shift in the perceived variance, when the confidence interval around the investor's private signal is tighter than what it is in reality. We assume that unskilled individuals wrongly assume that the precision of their private information is $\theta\tau_U$, with $\theta > 1$.[12]

Overconfident individuals put less weight on the peer signal, following more their biased prior. In other words, while overconfidence in this setting reduces the marginal effect of the peer signal, individuals still increase their participation rate monotonically on peer outcomes $\tilde{s}_e$. In this case, a miscalibration of the signal precision would make unskilled individuals less responsive to peer outcomes, but the overall effect of the peer signal is still symmetric around good and bad past peer outcomes (dash-dotted line in Figure 2). To summarize, while overconfidence dampens the effects from the peer signal, its effects on the entry choice are indistinguishable from Hypothesis 1 and 2 in the benchmark model.

3. DATA AND INSTITUTIONAL SETTING

This section describes the data and the construction of key variables. We begin by discussing the Colombian Stock Exchange's education program.

[11]Kyle & Wang (1997) use overconfidence as a commitment device for trading intensity. Odean (1998) and Benos (1998) develop a model in which overconfidence leads to trading. Empirical evidence on the relation between overconfidence and trading frequency includes Glaser & Weber (2007) and Deaves, et al. (2008). Experimental work also relates overconfidence to underperformance (Biais, et al., 2005).

[12]We introduce overconfidence only among unskilled investors as an extreme case to try to generate asymmetries between the proportion of skilled to unskilled individuals as a function of the peer signal. As it turns out, the irrational shift in the precision, only changes the total proportion of skilled to unskilled entrants, even if the cognitive bias was present among both types of investors. In turn, the asymmetric effects from the peer signal in Hypothesis 3 and 4 are exclusive to the model of communication bias.

3.1. THE CSE FINANCIAL EDUCATION PROGRAM

In 2008, the Colombian Stock Exchange (CSE) launched a nationwide financial education program to promote financial literacy and stock market participation among individual investors. Among the strategies was the promotion of "Puntos de Bolsa" ("CSE Spots"). Located at universities, chambers of commerce, and business centers throughout the country, these information centers opened to the public in order to provide information and training. In particular, the CSE introduced specialized courses covering a range of topics, from basic ones such as *Introductory Excel for Finance* to more complex curricula that included fixed-income and derivatives trading. From the 1,136 courses taught between 2008 and 2016, 876 concerned stock trading. Since we want to examine the determinants of stock market participation and the transmission of trading strategies, and given their popularity, we focus exclusively on these.

During the program's first few years, each stock trading course lasted two weeks and totaled 10 hours. Students had to complete each level before registering for the next course. There were three levels (0–2) in total, with instruction ranging from the basics of stock trading to fundamental and technical analysis. Students had to register separately for each course; depending on their interest, they would choose to continue to the next level or not. Starting in 2013, the CSE adopted a new strategy that implemented courses of longer duration with more developed curricula and modules for different topics. In this new system, a student registered for a single course of about 24 hours that covered the entire stock trading program. It is important to note that since the inception of the education initiative in 2008, students in any given course met in the same classroom with the same instructor for the entire duration of that course. As a result, the social interactions in our setting are well-defined by classmates and by the time of the course.

For each course, the syllabus and supporting training materials were designed directly by the CSE. The rigidity of the program protects the CSE from conflict of interest issues. For instance, since brokerage companies are members of the exchange, when an instructor covers topics such as trading costs, buying on margin, or short sales, the training material is designed to avoid references or examples that could encourage investors to use of one brokerage company over another.

3.2. DATA

Our analysis draws on three primary sets of data. First, we obtained data from the CSE on courses and participants. Each record includes detailed information on the beginning and end date of the course, matriculated students, cost of tuition, total number of hours, location, and name and curriculum vitae of the instructor. Table 1, panel A shows summary statistics on these courses for each year in the sample. In accordance with CSE directives, courses between 2008 and 2012 were shorter and less expensive (averaging 10.8 hours and 110 USD) than courses in the last four years of the sample (averaging 22 hours and 276 USD). Classes had 16 students on average, with few classes of over 30 students, and some with as few as 10 students. One limitation is that the CSE did not collect demographic or socioeconomic information on students. We classify students by gender using their first and middle names. We also determine the age range of each student at the time of each course using the national identification number. On average, female students represent 31% of the sample, and 55% of all students were over 30 years old at the time of the course.

Second, we use the CSE's official record of equity trades and stock portfolio holdings for all investors in Colombia between 2006 and 2017. The CSE records every single transaction for listed equities, and the data disclose the date and time of each transaction, a stock identifier, order type (buy or sell), transaction price, number of shares, broker, and investor type (i.e., individuals or institutions). Transaction costs such as broker fees are not captured by the CSE. During our sample period, trades by individual investors accounted for over seven million transactions. Importantly for our analysis, the data include the national identification number for each individual, which can be used to merge the information with the financial education initiative. Overall, 36% of the students in the CSE's education program had at least one stock trade throughout our sample period, either before or after taking the course. These 3,960 students with some trading history are more active in the stock market than the average Colombian individual investor. For example, while the average investor in Colombia owns 2.2 different stocks, makes 1.3 stock transactions per year, and averages 7,200 USD per trade, the program students who actively trade hold 6.2 stocks, make 6.6 trades per year, and average 8,781 USD per trade.

Third, we collect additional information about students via an electronic survey. The survey had three parts: (i) socioeconomic information (i.e., age, education, academic history, and earnings); (ii) experience in financial assets (e.g., whether the individual had any foreign investments or mutual funds, which are not captured in the CSE data); and (iii) self-reported social interaction (i.e., whether they took the course with a friend or a relative and whether they talked to classmates about investment strategies during the course). The survey was sent electronically in March 2018 to 4,600 students with emails reported in the CSE data set.[13] To encourage participation, students who completed the questionnaire before May 30, 2018 were automatically registered for a lottery with a total payoff of 5,000,000 COP (around 1,600 USD). The response rate was 18% (842 students). According to the survey, 44% of respondents had graduate education, 17% had some type of foreign portfolio investment, and many (86%) reported having conversations about stock trading with classmates.

[13] We tested a pilot of the survey with an ongoing class in February 2018. Follow-up interviews were carried out to confirm the interpretation of the questionnaire.

3.3. TRADING EXPERIENCE

The key variables of interest are the share of students in a class c who have stock trading experience ($Experience\ Rate_c$) and their trading performance ($Peer\ Returns_c$). To be precise, we define experienced students as those with at least one stock purchase in a 12-month window prior to the beginning of the course.[14] The average share of experienced students in a class is around 13.3%, with significant variation across courses (Table 1, panel B). For instance, the 10th–90th percentile range is between 0% and 30.7%. To distinguish time-series from cross-sectional variation, we graph the full distribution of experienced classmates, both the share and adjusted-for-year effects; that is, the share divided by the average share in that year (Figure 3). While some courses have no students with prior trading background, others have up to 60% of registered students and, year adjusted, a rate nearly seven times the rate of other courses in that year.

For each investor i, we calculate holding period returns as the percentage change in the value of the stock portfolio, VS, between t and $t+1$ adjusting for net flows and dividends, NF and D respectively: $r_{i,t+1} = (VS_{i,t+1} - NF_{i,t+1} + D_{i,t+1})/VS_{i,t}$. The portfolio value is calculated adding the market value of all known open positions in domestic stocks at the end of each month. Net flows include stock purchases and sells during the period. Since we do not observe broker fees, we are effectively measuring gross returns in domestic stocks. Our measure also excludes potential gains from indirect equity holdings through mutual funds or exchange-traded funds.

For each experienced student, we compute excess portfolio returns 6, 12, and 36 months before the course as the difference between the holding period returns and the short-term interest rate (i.e., the Colombian deposit rate reported by

[14] Throughout the paper, we also present results for an alternative definition of experienced students. That is, students with at least one stock purchase during a 36-month window prior to the start of the course.

the Central Bank). We then calculate $Peer\ Returns_c$ for each horizon as the average of excess returns among students with trading background who registered in the same class. As a measure of portfolio riskiness, we calculate $Peer\ Volatility_c$ as the standard deviation of monthly returns for each experienced student during a 36-month window prior to the start of the course and average across experienced peers in a class.

According to Table 1, panel B, in the 12 months before the start of a course, classmates with experience made 10 stock transactions an obtain excess returns of 1.84%. Importantly for our identification, there is significant variation in Peer Returns across courses, with the 10^{th}–90^{th} percentile ranging from -9.70% to 15.77%. In the 12 months following the course, experienced students increased their activity, making on average 30 stock transactions, but their excess returns during this period was negative at -3.35%.[15]

Finally, we define new investors as students without trading experience who made at least one stock purchase in the year following the course. We have a total of 1,373 market entrants in the sample. These amateur investors made on average 29 stock transactions in their first year of trading, with average returns below the deposit rate in that time, -0.86%.

3.4. RANDOM ASSIGNMENT

As we are studying peer effects on market entry, it is important to elucidate the obvious self-selection that may affect our results. Students of CSE courses are interested in stocks and consequently take a class, but among them, some inexperienced students are exposed to peers with trading histories and differences in performance. Since courses were formed based on availability and not on trading experience or past returns, the setting resembles a random assignment. However, it

[15] Enhanced trading activity after the training course is expected since individuals self-select into the program precisely because of their interest in stock trading.

is possible that as the courses were formed, a group of individuals with distinctive characteristics might have matriculated at the same time. For example, if the decision of individuals with trading background to register for a course coincides with the choice of high-income men to sign up for these classes (characteristics known to correlate with market participation), market entry might be driven by the attributes of individuals rather than by their interaction with peers inside the classroom.

To deal with this concern, we test whether students without trading background in courses with more (above-median) and less (below-median) precourse trading experience display significant differences in any characteristics. We also run the same stratification test, splitting the sample in courses where experienced students have returns above and below the median. The raw results of all six characteristic variables in our data set are presented in Table 2. Only gender is significant, although the difference is small in magnitude; courses with below-median experienced classmates have 3.3% more women than men. Other characteristics, such as age, students' earnings, and education are similar for the two groups. Also, both groups have instructors with similar teaching experience and trading returns.

Another potential concern with our class setting is that friends or acquaintances might register together for a CSE course. If an inexperienced student enrolls in a course with a friend who has a trading background, interactions about trading strategies and past performance might occur outside the classroom before the start of the course. According to our electronic survey, while 22% of students reported registering for a stock trading class with a friend, among experienced students, only 5% said they had taken the course with an acquaintance. In other words, most experienced students did not know their classmates before the program began.

4. EMPIRICAL METHODOLOGY

To analyze peer effects and the role of selective communication in stock market participation, we estimate several variations of the following baseline empirical model:

$$y_{i,c,t} = \alpha + \beta Experience\ Rate_c + \gamma Peer\ Returns_c + \boldsymbol{Q}'\Omega_t + \boldsymbol{M}'\Psi_c + \boldsymbol{Z}'\Gamma_i + \mu_t + \delta_p + \gamma_l + \varepsilon_{i,c} \quad (3)$$

The subscript *i* refers to an individual, *c* indexes each course, *l* indexes the location (city), *t* is the month when the course started, and p indexes courses with the same syllabus. In our first set of empirical exercises, the dependent variable $y_{i,c,t}$ is a binary variable that represents market entry. The variable is equal to one if a student without a trading background made her first stock purchase within 12 months of taking a course and is zero otherwise.

Common time-varying shocks might affect market entry and at the same time be correlated with peers' communication, thus biasing our estimates. For example, market volatility is likely associated with increased visibility of stocks in the media. Salient information about the stock market might promote market entry while encouraging individuals to exchange ideas about potential investments. To control for this possibility, we include Ω_t, a set of market characteristics at the start date of each course—namely, stock market returns and volatility.[16] Furthermore, we control for any other market-wide time-varying influences by including year-month fixed effects in the analysis (μ_t).

We include course-level controls Ψ_c, such as the value of tuition and total hours of instruction. Students who register for courses with more advanced curricula are likely more sophisticated or might be more inclined to trade stocks in

[16] Both are measured at the same horizon as *Peer Returns*. For example, our baseline specification which uses a 6-month windows include market returns and market variance calculated during the same time frame. Similar to *Peer Returns*, market returns are adjusted for the deposit rate during the period.

the first place. In turn, we include program fixed effects δ_p; that is, courses with identical syllabi. Another important set of controls, Γ_i, captures student-specific characteristics. These include gender, age range, and whether the student took trading courses previously, which is a proxy for her interest in the stock market. Finally, common time-invariant unobservables might also generate a positive relation between experienced peers and participation. For example, if residents in a city are financially more sophisticated, stock market participation might be more common. We eliminate this type of influence from our analysis by including city fixed effects γ_l.

In summary, our empirical strategy compares the entry decision of students who took the same type of course in the same city and during the same month, but who differ in their exposure to experienced peers. To be precise, after controlling for all these factors, we ask whether the market participation decision is affected by the presence of experienced peers in the classroom ($Experience\ Rate_c$) and by the past performance of those with a trading background ($Peer\ Returns_c$). Furthermore, to test if peer outcomes have a stronger influence on investment decisions when these outcomes have been positive (Hypothesis 1 vs. Hypothesis 3), we estimate a piecewise linear model in which we break down $Peer\ Returns_c$ into two variables that separately capture the slope estimates for positive and negative peer performance.

Next, we modify our baseline empirical specification to evaluate the performance of new investors. We use the returns of each new investor in the first 12 months of trading as the dependent variable in equation (3). This specification allows us to explore whether the performance of new investors is driven by interactions with a particular subgroup of experienced classmates—peers with good or bad outcomes (Hypothesis 2 vs. Hypothesis 4).

5. MAIN RESULTS

5.1. DETERMINANTS OF STOCK MARKET PARTICIPATION

We begin the analysis of peer effects by plotting the average participation rate per classroom—number (Figure 4A) and share (Figure 4B) of inexperienced students—sorted by the share of students with a trading background (top and bottom quartile). In the nine years of our sample, more students consistently enter the stock market from courses with a larger share of experienced classmates, both in absolute and relative terms. That is, the participation rate is 20% (around three students per classroom) in courses with more experienced classmates, and 10% for courses where peers have less trading experience.

We present the results of our baseline specification (equation 3) in Table 3 for two separate definitions of students with experience (i.e., students with at least one stock purchase in a 1 year and 3 years window prior to the course). We adjust standard errors for heteroskedasticity and course-level clusters. Independent variables are scaled by their standard deviation so that the estimated coefficients are directly informative about the economic significance of the effects.

According to the table, the coefficient of *Experience Rate* is positive and economically meaningful. We find that a one-standard-deviation increase in the share of experienced students in a course translates into an increase of 25% in the predicted stock market participation rate. That is, the share of inexperienced students that begins to trade stocks after the course rises by 3.0 percentage points from an average of 12.1%.

The coefficient of *Peer Returns* measured in a six-month window before the course is positive and statistically significant. On the contrary, the magnitude of the coefficients for peer returns measured at longer horizons, 12 and 36 months, appear smaller and indistinguishable from zero. Recent outcomes from classmates are more salient, leading to increased attention to the stock market, and in turn, these seem to promote market entry. We further explore this idea in the next subsection.

Overall, peer effects seem to have a strong impact on the market participation decision among students of the CSE education program. [17]

5.2. POSITIVE VERSUS NEGATIVE PEER OUTCOMES

According to our learning model in Section 2, public information should encourage market participation when signals are good (e.g., positive market returns) and deter market entry amid bad signals (e.g., negative market returns). Conversely, under selective communication, peer signals only affect market entry when students with trading history have experienced favorable outcomes. To test these ideas, we estimate a variant of equation (3) where we break down $Peer\ Returns_c$ into two variables that separately capture the slope estimates for positive and negative outcomes. Following Kaustia & Knupfer (2012), we use $Max(0, Peer\ Returns_c)$ to estimate the effect of positive outcomes and $Min(0, Peer\ Returns_c)$ for negative outcomes.

We present our findings in Table 4. We find that negative peer returns do not affect entry; the coefficient of $Min(0, Peer\ Returns_c)$ is indistinguishable from zero in all specifications. In fact, the relation between peer outcomes and market participation comes solely from the most recent positive returns. The coefficient of $Max(0, Peer\ Returns_c)$ measured in a 6-month window is positive and statistically significant. The marginal effect from positive peer outcomes can be read as follows: an increase of one standard deviation in the 6-month average return of experienced students in a group raises the likelihood of market entry by 12%. Positive peer returns measured over longer time windows before the course – 12 and 36 months– have a smaller effect on the entry decision or the estimated

[17] The set of controls in Table 3 has the expected signs. For example, market entry is higher for men, older students, and individuals who take multiple courses. Lower stock market participation among women has been widely documented in the literature and is often related to risk aversion and lower financial literacy (Haliassos & Bertaut, 1995; Rooij, et al., 2011; Almenberg & Dreber, 2015).

coefficient is indistinguishable from zero. The evidence that peer effects are stronger only when outcomes are positive is consistent with Hypothesis 3.

While recent positive outcomes from classmates seems to attract individuals to equity trading, the theoretical model in Han, et al. (2020) suggests that extreme returns should be incrementally more persuasive to the receiver. Since high volatility portfolios generate extreme returns more often, it is possible that students from our classrooms are inadvertently attracted to high volatility strategies from peers who happened to report recent returns that are positive. Moreover, individuals that select portfolios with large volatilities might be more inclined to talk about their trading experience than other experienced classmates. To evaluate higher order effects in the participation decision we include *Peer Volatility* and the interaction with peer returns, *Peer Volatility x Peer Returns*, as covariates in equation (3). We focus on the 6-month window to measure peer returns.

The coefficient of *Peer Volatility* is indistinguishable from zero (Table 5). The result is not surprising since individual risk exposure is likely unobserved. While students could be selective about the outcomes they want to share with others, it is less likely that details such as portfolio risk would be transmitted in informal conversations. When we include the interaction terms, we find that the direct effect from peer returns is no longer positive nor statistically significant. Peer returns, and in particular those that are positive, have large effects on market participation when portfolio volatility is high. Using the estimates from column 3, we find that an increase in one standard deviation of positive peer returns for portfolios with volatility of 1 standard deviation above the mean, the participation rates increase by 28% (3.4% from an average of 12%).

In unreported results, we add quadratic terms of peer returns to evaluate the impact from extreme outcomes (e.g., $Max(0, Peer\ Returns)^2$) and do not find any effects from these higher order terms. Overall, the evidence is consistent with the view that signals from peers with high volatility portfolios, who experience positive returns before the course, disproportionally attract new investors to active trading.

5.3. PERFORMANCE OF NEW INVESTORS

So far, we have documented peer effects in the market participation decision and a strong bias for classmates' positive outcomes to stimulate active trading. We now examine performance among rookie investors. In particular, we use the sample of students who entered the stock market after the completion of a course, and we calculate their returns during the 12 months following the training program.

Both social learning models, accurate and selective communication, predict that the share of skilled entrants is lower in courses where peers have experienced positive outcomes relative to courses where peers had negative returns. If low-skilled (or less-informed) individuals are trading actively, we should expect lower trading profits from this group; that is, investors' performance should be lower in courses where *Peer Returns* are positive. The learning models differ in the predictions about the marginal effect from negative peer outcomes. Under accurate communication, the share of skilled entrants is decreasing on the peer signal (Hypothesis 2). On the contrary, selective communication implies that there are no marginal effects on the composition of skilled entrants when peer returns are negative. In our empirical setting, any relation between *Peer Returns* and investors' first-year performance should be only observable when peer outcomes are positive (Hypothesis 4).

To study whether there are systematic differences in performance among amateur investors, we sort new entrants by *Peer Returns*. There were 739 students that started trading actively after interacting with classmates who experienced positive returns (*Peer Returns*>0). During the first year of active trading, these rookie investors made 29 trades on average and their average returns in excess of the deposit rate were -1.45%.[18] Among new entrants, 466 students interacted with peers with negative experience (*Peer Returns<0)*. The first-year rate of return for these rookie investors was 1.10% and they made 27 trades on average. The difference in returns between the two groups of amateur investors is 2.55% and is statistically significant at the 1% confident level. Consistent with our social learning models, rookie investors who attend courses with high-performing peers seem to underperform other new entrants.

We also sort courses by quintiles of *Peer Returns* (measured during the 6-month window before the class) and calculate the average returns among new investors in each group. According to Figure 5, students who participate in courses with high *Peer Returns* display the lowest performance during their first year of trading. In the figure, we also compare the performance of new investors to that of their experienced classmates for the same horizon after the class. Notably, for courses where *Peer Returns* are high, both the returns of new investors and those from classmates with trading background are low in the 12 months following the course. In other words, experienced peers with high returns prior to the class also underperform following the training program, and their returns are similar to those of new investors. Conversely, for courses with low *Peer Returns*, new investors overperform relative to their experienced classmates after the class.

Figure 5 also highlights an important feature about our setting and the learning environment: experienced students do not seem to obtain higher returns than new investors under a common investment horizon after the course. These experienced students are not necessarily sophisticated investors; they are simply more active and have some recent trading history relative to their classmates.

[18] First-year returns of new investors were calculated similar to *Peer Returns*. These are based on the change in the investor's portfolio, adjusting for net flows and dividend payments, but excluding transaction costs. The returns are calculated in excess of the deposit rate during the measurement period.

Regardless of investor sophistication, their experience does seem to generate strong peer effects. It appears that positive outcomes from investors with high volatility portfolios are attracting naïve investors to stock trading. The performance of new investors motivated by such positive accounts is low once they start trading, and they underperform just as their experienced peers do following the course (in section 6.1 we explore spillovers in stock selection). On the contrary, in courses where peer outcomes have been negative, those entering the stock market overperform, even relative to classmates with recent trading background.

It is possible that the performance of new investors is driven by market conditions at time of entry or by individual characteristics such as age or gender. To control for factors that affect investor performance, we estimate equation (3) using the returns of new investors in excess of the deposit rate during their first year of active trading as the dependent variable. Columns 1-4 of Table 6 present our findings. As documented above, there appears to be a negative relation between *Peer Returns* and first-year performance, although this relation comes exclusively from the positive region of peer returns. We do not find differences in first year returns among new investors who registered in courses where peers had negative outcomes. On the contrary, individuals who attend courses where peer outcomes are positive obtain lower returns once they start trading. In fact, the performance of new investors is lower as *Peer Returns* are higher: a one-standard-deviation increase in *Peer Returns* is associated with 1.44% lower first-year returns among new investors. In columns 2 and 4 we further confirm our results after controlling for the contemporaneous market returns (i.e., during the same period when the new investor was active) and for the number of executed trades by each new investor.

To compare the performance of new investors and experienced classmates for a common investment horizon, we calculate the difference between the returns of an investor *i* and the returns of her experienced classmates in the 12 months following course *c*, $r_{i,c,t+12} - PeerReturns_{c,t+12}$. We use this difference as the dependent variable in equation (3) and present our findings in columns 5-8 of Table 6. New investors outperform their more experienced classmates after the training– the difference in 12-month returns between these two groups is 3.10% (constant term in column 5). However, excess returns relative to experienced classmates are smaller precisely for students who attend courses in which peer returns prior to the course were high. Overall, the documented relation between peer outcomes and investors' performance is consistent with Hypothesis 4.

To summarize, students who are exposed to classmates with precourse trading experience, and in particular to peers with high volatility portfolios and recent positive returns, are more likely to trade stocks, but these individuals generate lower returns once they start trading. In our model of social learning, the underperformance of new investors is explained by their innate ability since biased signals encourage participation among less-informed individuals. However, it is possible that low performance among new investors is also related to herding strategies in stock selection. In the next section, we examine alternative explanations for our findings.

6. ALTERNATIVE EXPLANATIONS

This section presents analysis that addresses various alternative explanations and discusses results from further robustness checks.

6.1. TRADING STRATEGIES ON INDIVIDUAL STOCKS

Informal conversations with experienced classmates might encourage individuals to hold similar portfolios as their peers. An extensive body of evidence suggests that individuals and even professional asset managers living in the same region hold similar portfolios (Ivkovic & Weisbenner, 2005; Hong, et al., 2005). In addition to the information that is conveyed when peers hold a particular stock (*social learning* channel), the possession of an asset might affect investors' utility via relative wealth concerns ("keeping up with the Joneses" as in Abel, 1990) or through utility gains from joint consumption (Bursztyn, et al., 2014).

A simple explanation for the underperformance of rookie investors might be related to a combination of herding in individual stocks and mean reversion in stock prices. If investors systematically buy the best-performing stocks of their peers, and large stock returns are followed by reversals, new investors would mechanically display poor performance. To evaluate this possibility, we use the sample of market entrants and study the relation between an individual's stock selection and the stock selection decision made by her experienced classmates. The regression methodology follows the one applied by Hvide & Ostberg (2015) who study social interactions and stock selection at the workplace.

We create a variable $f_{i,c,t+\Delta,s}$ that represents the fraction of total purchases in stock s by a new investor i during Δ months after the course start date. The dependent variable, $f_{i,c,t+\Delta,s}$, is defined for all stocks traded by individuals during the measurement period, and $\sum_s f_{i,c,t+\Delta,s} = 1$ by construction. The main explanatory variables are the fraction of purchases made by the experienced classmates in Δ months prior to the course, $F_{c,t-\Delta,s}$, and Δ months after the course start date, $F_{c,t+\Delta,s}$. We consider stock purchases separately for pre and post training to examine whether direct spillover effects in stock selection are related to past and/or future trades by peers. Since groups are formed exogenously and most courses last less than a month, the correlation between classmates' stock selection decision might be more pronounced in the short term. Alternatively, some classmates could develop long-lasting friendships and they might continue to discuss their trading activity well beyond the course end date. To account for these possibilities, we evaluate stock selection in different time windows (i.e., Δ is three or 12 months). There was a total of 70 different stocks traded by individuals in the CSE courses during the sample period and the mean fraction of total purchases invested in a stock by new investors in their first year of trading was 0.92% (Table 7).

To relate an individual's stock selection to that of her experienced classmates, we estimate the following regression:

$$f_{i,c,t+\Delta,s} = \alpha + \beta F_{c,T,s} + \gamma Peer\ Returns_{c,t-\Delta,s} + \boldsymbol{Q}'\Omega_{t,s} + \boldsymbol{M}'\Psi_{c} + \boldsymbol{Z}'\Gamma_{i,s} + \mu_{s,t} + \delta_{p} + \gamma_{l,t} + \varepsilon_{i,c,t+12,s} \quad (4)$$

In equation (4), T is either t-Δ or t+Δ and $Peer\ Returns_{c,t-\Delta,s}$ are the average trading returns among experienced students calculated for each stock during Δ months before the course start date. We control for time-varying stock characteristics ($\Omega_{t,s}$) by including stock returns and variance in addition to our previous controls for market conditions (i.e., market returns and market variance). Following our previous exercises, we control for course curriculum (δ_{p}). We include year-month dummies and city dummies for each stock to control for time-varying aggregate patterns and location patterns in the demand for individual stocks. As an additional control, we include stock selection by investors from other CSE courses that started on the same month as course c, $F_{c^{-},T,s}$. Table 8 presents the results.

We do not find evidence that new investors purchase the same stocks that their experienced classmates were buying prior to the beginning of the training course. The coefficient β is small and indistinguishable from zero in columns 1-4. On the contrary, contemporaneous stock selection between new investors and experienced peers is highly correlated. The estimated β is positive and highly significant in columns 5-8 and large in terms of economic magnitude; a one standard deviation increase in the fraction of experienced classmates' purchases to a particular stock 3 months after the course results in a 24% increase in the fraction of purchases allocated to that stock by the new investor (i.e., the point estimate in column 6 [0.133] divided by the mean of f [0.56]).[19]

Importantly, there is no evidence that new investors disproportionally buy stocks with the highest performance in their peers' portfolio. As new investors try to look for investment opportunities, instead of following past stocks where peers have performed well, they seem to select stocks in which peers are making new purchases. While peer effects in stock selection in social settings is not surprising, the combination with selective communication does seems to produce a novel empirical finding which can be summarized as follows. High returns from experienced classmates positively attract new investors. Such extreme returns, however, are the result of high volatility portfolios. Due to spillovers in stock selection, new investors then select similar strategies to their experienced peers. In turn, social interactions lead to high volatility portfolios even when new investors have no inherent demand for volatility.

6.2. SELECTIVE INFORMATION NEGLECT

A potential explanation for our results is that experienced individuals accurately share their performance, but signal receivers ignore negative outcomes. Specifically, if inexperienced students believe they can replicate peers' successful trades and avoid peers' losses, only positive outcomes would impact market entry. In psychology, there is evidence of self-enhancing thought processes, such as the tendency of people to attribute wins to their own virtues but losses to external circumstances (Bem, 1972; Langer & Roth, 1975). Similarly, people might

[19] While we argue that peer stock selection has a strong effect on new investors, the magnitude of our estimated coefficient is smaller than the effects documented by Hvide & Ostberg (2015), who also consider a small group setting. In our case, groups are formed artificially, and courses only last a few weeks. Consequently, channels such as utility from joint consumption or relative wealth concerns that might enhance herding behavior might be weaker than when groups are formed endogenously or when the interaction between individuals last longer, for example, in the workplace.

disregard negative peer outcomes, assuming that these result from lack of skill or from other unique circumstances that do not apply to them. At the same time, people might be encouraged to trade actively if they overestimate their ability to reproduce good peer outcomes.

To shed more light on this issue, we use the answers from the social interaction section of the electronic survey. We ask former students if they engaged in informal discussions about stock trading with classmates.[20] Among the respondents of our electronic survey, 760 students had no trading history prior to the course start date. Within this group, 80% of people reported engaging in investment conversations with others in the class. We classify our respondents in three groups based on their classmates' experience: (i) those who attended courses with no experienced classmates (330 students), (ii) those in courses where peer returns were positive (252 students), and (iii) those registered in courses with negative peer returns (178 students).

Among students in courses where the *Experience Rate* was zero, 72% indicated having investment conversations with peers. This number was significantly higher at 93% among students in courses with positive peer returns. Even in courses where peer returns were negative, students report more investment conversations—79% of individuals in this group—than those with no experienced classmates. In other words, the presence of peers with trading experience in a classroom seems to positively correlate with the exchange of investment ideas, albeit communication about investments seems to stronger when peer outcomes are positive.

We test our hypothesis of social learning with the sample of survey respondents. In particular, we augment our baseline model by interacting our main

[20] A question to directly test information transmission bias would inquire about the type of the personal experience that was shared among classmates (e.g., positive vs. negative outcomes). Unfortunately, at the time of the survey design, the objective was to test direct spillover effects.

covariates with a dummy variable that captures if the student had investment conversations with classmates ($talks_i$) as follows:

$$y_{ict} = \alpha + \theta talks_i + \beta_2 talks_i \cdot Experience\ Rate_c + \gamma_1 talks_i \cdot Peer\ Returns_c + \beta_2 ExperienceRate_c + \gamma_2 PeerReturns_c + \boldsymbol{Q}'\Omega_t + \boldsymbol{M}'\Psi_c + \boldsymbol{Z}'\Gamma_i + \mu_t + \delta_p + \gamma_l + \varepsilon_{i,c} \quad (5)$$

We use a 6-month window to measure *Peer Returns* and estimate equation (5) using as dependent variable our definition of market entry as well as first-year returns of new investors. Table 9 presents our findings.

Students that report having investment conversations with classmates and share a classroom with high-performing peers are more likely to start trading after the course–coefficient γ_1 is positive and highly significant in column (1). More precisely, the relationship between peer outcomes and entry for those who report investment conversations is exclusive to students who interact with classmates with positive returns (column 2). Interactions with negative performing peers, on the contrary, do not appear to have any effect on market entry. Also consistent with previous findings, first-year returns of new investors appear to be lower if these students interact with classmates whose recent returns are positive. The coefficient of *Max(0, Peer Returns) x Talks* is negative although not statistically significant. In this case, the low power in the estimation is a direct consequence from the small sample size; only 63 students that answered the survey started trading actively after their training.

We should note that the evidence from the survey does not directly rule out selective information neglect, nor does it show that negative information is completely absent. For instance, according to the survey, students recall having informal conversations about investments even in classrooms where peers had negative outcomes (although we do not know the type of information that was shared). If information about negative returns is shared through the social network, the extent to which such information is discounted by signal receivers remains an open question. The two key related findings from the survey are as follows: (i) information transmission is more intense when individuals experience good outcomes and (ii) individuals are attracted to active trading when they interact with classmates who have experience recent positive returns.

6.3. TEACHER EFFECTS

Informal communication might be present among students and also between teachers and students. If teachers share their own trading history with students, it might impact stock market participation.

We test for teacher effects in two ways. First, we check whether our results of market entry hold once we control for teacher fixed effects in our baseline empirical model (equation 3). Second, we augment the empirical specification by including the instructor's teaching experience (number of hours teaching previous courses) as well as the instructor's most recent trading experience prior to the beginning of a course.[21] Table C.1 presents our findings. The documented peer effects are robust to the inclusion of variables that control for teacher influence. Also, we find no evidence that the instructor's teaching or trading experience had any influence on stock market entry. For example, we do not find evidence consistent with the idea that teachers with good trading returns promote more active trading (column 3).

The absence of teacher effects could be explained as follows: teachers might avoid discussing personal investment stories with students in order to focus exclusively on the course material. Alternatively, students might disregard information about teachers' outcomes. For example, since teachers are experts in

[21] During the nine years of our sample, 113 different instructors taught the stock trading courses. Among them, 33 made stock transactions on their individual brokerage accounts (we cannot observe the stock transactions of instructors who are trading for an institutional portfolio), accounting for over 58% of all stock trading courses.

the subject matter, their successful trades might be heavily discounted by amateur investors. An individual might believe that replicating her teacher's winning strategy is too difficult because she does not have the same background or training. Notwithstanding the explanation for the lack of teacher effects, our key finding is that peer effects are robust to the inclusion of variables that control for teacher influence.

An alternative mechanism that might be related to our findings is that the nature of instruction in the course might differ depending on the background of the students who are enrolled. For instance, even with a rigid syllabus and random assignment, in a class where some students have positive returns, the teacher could be more affirming of the virtues of active trading. If investors with trading background dominate the class discussion, inexperienced students might get less instruction that is tailored to their needs. In turn, there would more participation after the course, but less success among new investors. Under such conditions, we should expect to find complementarities between the teacher and the students' trading outcomes. For example, an instructor with high portfolio returns teaching in a class where experienced students also have positive returns could be more encouraging of stock trading. In column 4 of Table C.1, we include interaction terms between teacher returns and peer returns, but we do not find any evidence of complementarities between teachers' and students' outcomes. Our evidence, including our results using the survey sample, is most consistent with the idea that direct communication between classmates are driving the market participation decision.

6.4. External validity

A final important concern regards the external validity of the findings. There are several important qualifications to the generality of the impact from selective communication on financial decision making. First, the type of social learning on which we focus differs from classic models such as Banerjee (1992) and Bikhchandani, Hirshleifer, & Welch (1992), in that peer choices and outcomes are revealed imperfectly. Many individual choices are accurately observed by members of a social group; for example, peer effects have been documented in automobile purchases (Grinblatt, et al., 2008); choice of workplace (Bayer, et al., 2008); and health plan (Sorensen, 2006). But several other choices are only transmitted via informal channels and could suffer from self-enhancement and selectivity. In social media, people take time when posting information about themselves, carefully choosing the aspects they want to emphasize. This might lead other group members to similar choices—for example, where to travel, what product to buy, and whether to undertake a business venture. Under selective communication, signal receivers base their decisions on biased information, limiting their ability to correctly measure risks and expected payoffs. Our evidence suggests that low-skilled or less-sophisticated people are more susceptible to influence from positively selected outcomes; these individuals generate worse trading profits. In similar settings, members of a social network might spend more money than they would otherwise, take on excessive debt, or underestimate the costs of a business investment.

Second, our effects from positive outcomes on active trading are estimated using a particular sample of peers. The groups we study are exogenously formed because most classmates do not know each other before taking the course. Selective communication is likely more pronounced in our setting than among groups with close connections, since self-presentation concerns are more pervasive when people interact with strangers. For example, people often try to avoid excessive bragging about personal achievements with family members or with close friends who already know their qualities (Tice, et al., 1995). The peers we study are in an environment where selective self-presentation strategies might be used to gain admiration and respect. While we expect information transmission bias to be attenuated in groups with strong social ties, in several social settings (e.g., among coworkers or on digital media), people might still benefit from self-enhancement strategies. In such cases, talking about one's successes can have large effects on risk-taking activity by other group members.

7. CONCLUSIONS

This paper examines how social interactions—in particular, informal word-of-mouth communication among peers—affect an individual's decision to participate in the stock market. We examine the decision to trade stocks among students in a financial education program. The setting is empirically attractive due to the exogenous assignment of students to groups where peers have experienced different outcomes. We find that a higher share of students with trading history in a given course increases the likelihood that other students will start trading actively, an effect that strengthens when peers have experienced large returns.

We introduce a parsimonious model of social learning to distinguish predictions that are unique to a setting where information transmission is biased toward positive outcomes. We show that only positive peer returns affect market entry. Furthermore, we find that students registered in courses where peers had large returns underperform during the first year of active trading relative to other amateur investors. We rule out competing explanations for investor underperformance and show that the evidence is mostly consistent with the idea that selective communication encourages active trading among low-skilled individuals. These investors appear drawn to the stock market by successful classmate accounts but obtain lower returns once they start trading.

While self-enhancement is common in many social settings and has been widely studied among social psychologists, the extent of its influence on the decision making of others is less understood. In finance, most of the empirical literature on social interactions focuses on identifying peer effects in investment choices or on estimating the strength of social contagion. Our findings suggest that it is also valuable to understand the sources of communication bias within a social group. According to our evidence, selective communication seems to play a key role in the transmission of ideas, and—most importantly—in the behavior of people exposed to such information.

Our analysis of peer effects in investment decisions is relevant to policy makers, finance scholars, and asset managers. Our findings highlight the limits and potential negative side of social learning; namely, that portfolios with salient outcomes – those with high idiosyncratic volatility – are easily transmitted and adopted by members of the social group. The attraction to such strategies is an emergent behavior that results from biases in communication and does not require explicit preferences for volatility. Although positive peer outcomes seem to attract more people to the stock market, perhaps would-be investors need transparent unbiased signals in order to critically evaluate investment ideas and correctly assess the likelihood of success.

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Table 1
Course characteristics

	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
Panel A. Stock Trading Courses										
N. of Courses	21	78	141	200	178	83	56	71	48	876
Average students	17.14	17.81	18.02	17.61	12.92	16.08	12.14	17.45	16.17	16.14
Average hours	10.00	10.00	10.00	11.20	12.57	15.53	25.34	24.34	23.23	14.19
Tuition (USD)	82.72	94.28	92.16	113.86	169.26	174.07	240.98	286.66	400.99	162.70
Age > 30 years (%)	61.04	70.32	72.40	59.49	53.86	44.60	40.80	31.55	23.36	54.58
Females (%)	43.93	29.51	27.94	31.32	31.20	32.13	31.95	34.74	28.90	31.15
Panel B. Experienced Students										
% per class	20.61	16.16	14.92	17.51	14.48	11.54	7.02	3.24	4.3	13.31
10th percentile	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
90th percentile	46.15	34.48	31.82	37.27	33.33	28.57	25.0	12.5	14.29	30.68
Before the course										
Peer Returns (12 months %)	8.57	-1.36	14.36	7.89	-2.8	-4.81	-5.8	-7.51	-6.47	1.84
10th percentile	-8.83	-14.24	-3.85	-5.69	-10.74	-12.49	-14.63	-15.96	-12.82	-9.7
90th percentile	22.53	18.21	33.63	26.36	10.92	3.28	.41	-4.07	-.89	15.77
Number of Trades	19.92	19.02	12.6	12.27	6.88	10.38	4.18	3.1	8.35	10.36
Peer Volatility (%)	6.66	5.87	5.26	4.38	3.56	2.6	1.8	1.52	1.82	3.84
After the course										
Average number of trades	26.84	53.35	42.34	27.17	17.06	28.59	21.64	9.9	18.82	29.64
Average 12-month Returns (%)	-1.98	6.94	0.16	-6.51	-5.53	-6.41	-7.77	-7.69	-5.28	-3.35
Panel C. Inexperienced Students										
% of market participants	7.2	13.4	20.5	16.	12.6	6.	3.4	3.	2.2	12.05
Average number of trades	22.4	38.5	29.5	27.2	25.1	19.5	29.2	42.1	7.3	28.58
Average 12-month returns (%)	2.12	10.1	4.12	-4.92	-6.19	-11.53	-7.77	-10.31	-6.77	-0.86

Table 2
Stratification checks: Comparing courses by peer experience

	Full Sample	Below Median	Above Median	t-stat
Panel A. Sorted by share of experienced students				
Female	0.31	0.32	0.29	(2.12)**
	(0.16)	(0.15)	(0.16)	
Age > 30y	0.51	0.50	0.52	(-1.62)
	(0.25)	(0.25)	(0.25)	
Earnings > 5MM COP	0.36	0.36	0.36	(-0.04)
	(0.39)	(0.39)	(0.39)	
Graduate schooling	0.46	0.45	0.47	(-1.51)
	(0.40)	(0.40)	(0.41)	
Teacher experience (log hours)	5.26	5.21	5.30	(-1.05)
	(1.59)	(1.60)	(1.57)	
Teacher returns (%)	0.06	-0.10	0.25	(-1.49)
	(2.62)	(2.19)	(3.01)	
Panel B. Sorted by average returns of experienced students				
Female	0.31	0.31	0.31	(0.37)
	(0.16)	(0.16)	(0.16)	
Age > 30y	0.51	0.49	0.52	(-1.48)
	(0.25)	(0.25)	(0.23)	
Earnings > 5MM COP	0.36	0.36	0.38	(-0.50)
	(0.39)	(0.39)	(0.40)	
Graduate schooling	0.46	0.46	0.47	(-0.09)
	(0.40)	(0.40)	(0.42)	
Teacher experience (log hours)	5.26	5.31	5.18	(1.10)
	(1.59)	(1.67)	(1.47)	
Teacher returns (%)	0.07	-0.01	0.19	(-0.85)
	(2.62)	(2.30)	(3.05)	

The table shows mean (and standard deviation in parentheses) of different course characteristics. The sample consists of the 876 courses on stock trading. The last column shows t-statistics for the test of difference in means between the subsamples. The courses are sorted by the share of experienced students (Panel A) and by the average returns (Panel B). All comparisons exclude students with trading experience, except teacher experience and teacher returns. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 3
Determinants of market participation

Experience Student Definition =	1 Year			3 Years		
Returns horizon =	6	12	36	6	12	36
Experience Rate	0.030***	0.030***	0.030***	0.040***	0.040***	0.040***
	(6.733)	(6.839)	(6.545)	(8.847)	(8.861)	(8.592)
Peer Returns	0.014**	0.008	0.006	0.013*	0.006	0.006
	(2.175)	(1.456)	(1.120)	(1.889)	(1.037)	(1.131)
Market Returns	-0.007	-0.036	-0.018	-0.005	-0.028	-0.0105
	(-0.411)	(-1.095)	(-0.628)	(-0.301)	(-0.882)	(-0.983)
Market Variance	0.037**	-0.058**	-0.158	0.033*	-0.056**	-0.142
	(2.066)	(-2.513)	(-1.221)	(1.861)	(-2.360)	(-1.094)
Female	-0.127***	-0.124***	-0.125***	-0.122***	-0.120***	-0.118***
	(-5.482)	(-5.335)	(-5.422)	(-5.271)	(-5.223)	(-5.131)
Age > 30y	0.106***	0.106***	0.106***	0.104***	0.104***	0.104***
	(14.036)	(13.990)	(14.014)	(13.796)	(13.767)	(13.743)
Tuition	-0.004	-0.004	-0.002	-0.004	-0.005	-0.002
	(-0.581)	(-0.626)	(-0.288)	(-0.608)	(-0.701)	(-0.300)
Size	0.002	0.002	0.001	0.004	0.003	0.003
	(0.606)	(0.489)	(0.273)	(1.052)	(0.913)	(0.856)
Hours	0.000	-0.001	-0.000	-0.000	-0.002	-0.001
	(0.066)	(-0.321)	(-0.116)	(-0.039)	(-0.394)	(-0.209)
Previous Course	0.056***	0.059***	0.057***	0.058***	0.055***	0.053***
	(6.646)	(6.808)	(6.937)	(6.906)	(6.817)	(5.943)
Constant	-0.172***	-0.008	0.509	-0.159***	-0.001	0.452
	(-3.716)	(-0.254)	(1.268)	(-3.412)	(-0.030)	(1.129)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
R-squared	0.110	0.110	0.110	0.114	0.113	0.113
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the results of regressions on market participation. The dependent variable is set to one for inexperienced students who made at least one stock purchase in a 12-month window after the start of a course and is zero otherwise. Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase either 1 year or 3 years prior to the begin of the course). Peer Returns are average returns, calculated in a 6, 12, and 36-month window, among students with trading background in a given course. Other control variables are described in the text. The OLS regressions include time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 4
Good versus bad returns: Effects on market participation

Experience Student Definition =	1 Year			3 Years		
Returns horizon =	6	12	36	6	12	36
Experience Rate	0.031***	0.031***	0.031***	0.043***	0.043***	0.042***
	(6.874)	(6.921)	(6.566)	(9.420)	(9.271)	(8.970)
Max(0, Peer Returns)	0.014**	0.008	0.007	0.018**	0.012*	0.010
	(2.039)	(1.278)	(1.239)	(2.427)	(1.851)	(1.599)
Min(0, Peer Returns)	0.003	0.002	0.000	-0.003	-0.004	-0.002
	(0.734)	(0.646)	(0.007)	(-0.956)	(-1.417)	(-0.674)
Constant	-0.104**	0.060*	0.626	-0.098**	0.061*	0.521
	(-2.267)	(1.740)	(1.405)	(-2.161)	(1.778)	(1.189)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
R-squared	0.091	0.091	0.091	0.096	0.095	0.095
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the results of regressions on market participation. The dependent variable is set to one for inexperienced students who made at least one stock purchase in a 12-month window after the start of a course and is zero otherwise. Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase either 1 year or 3 years prior to the begin of the course). Peer Returns are average returns, calculated in a 6, 12, and 36-month window, among students with trading background in a given course. The estimation is performed with a piecewise linear model that employs a single change in the slope of peer returns at zero. Control variables are described in the text. The OLS regressions include time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 5
Peer volatility and market participation

Experience Student Definition =		1 Year			3 Years	
	(1)	(2)	(3)	(4)	(5)	(6)
Experience Rate	0.030***	0.032***	0.037***	0.040***	0.042***	0.048***
	(6.212)	(6.663)	(7.041)	(8.575)	(8.872)	(9.837)
Peer Returns	0.014**	-0.009		0.013**	0.004	
	(2.241)	(-1.034)		(1.989)	(0.599)	
Peer Volatility	-0.000	0.006	0.009	-0.002	-0.000	-0.007
	(-0.049)	(1.137)	(1.434)	(-0.473)	(-0.057)	(-1.269)
Peer Volatility x Peer Returns		0.025***			0.014***	
		(3.363)			(2.681)	
Max(0, Peer Returns)			-0.015			0.013
			(-1.573)			(1.469)
Peer Volatility x Max(0, Peer Returns)			0.034***			0.015**
			(3.931)			(2.341)
Min(0, Peer Returns)			0.004			-0.007*
			(0.590)			(-1.708)
Peer Volatility x Min(0, Peer Returns)			-0.002			0.001
			(-0.433)			(0.417)
Constant	-0.172***	-0.225***	-0.190***	-0.156***	-0.185***	-0.136***
	(-3.671)	(-4.516)	(-3.653)	(-3.286)	(-3.714)	(-2.669)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
R-squared	0.110	0.111	0.093	0.114	0.115	0.097
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the results of regressions on market participation. The dependent variable is set to one for inexperienced students who made at least one stock purchase in a 12-month window after the start of a course and is zero otherwise. Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase either 1 year or 3 years prior to the begin of the course). Peer Returns is the average returns calculated in a 6-month window among students with trading background in a given course. Peer Volatility is the standard deviation of monthly returns of an experienced student measured over 36 months and average across those attending the same course. Control variables are described in the text. The OLS regressions include time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 6
Peer effects and investor performance

Experienced Student Definition =	1 Year		3 Years		1 Year		3 Years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience Rate	-0.315	-0.284	-0.246	-0.272	-0.685	-0.638	-0.528	-0.512
	(-0.658)	(-0.600)	(-0.559)	(-0.627)	(-1.160)	(-1.081)	(-0.990)	(-0.975)
Peer Volatility	0.947*	0.721	0.722	0.529	0.724	0.496	0.514	0.313
	(1.809)	(1.393)	(1.424)	(1.054)	(1.063)	(0.741)	(0.791)	(0.490)
Max(0, Peer Returns)	-1.439***	-1.255**	-1.160**	-0.958*	-1.202**	-1.153**	-0.841	-0.792
	(-2.940)	(-2.505)	(-2.121)	(-1.725)	(-2.064)	(-1.989)	(-1.477)	(-1.376)
Min(0, Peer Returns)	0.422	0.557	0.610	0.785*	0.575	0.533	0.703	0.677
	(0.959)	(1.248)	(1.370)	(1.749)	(1.024)	(0.961)	(1.293)	(1.252)
Number of Trades		-1.720***		-1.714***		-1.946***		-1.933***
		(-3.983)		(-3.956)		(-4.352)		(-4.318)
Market Returns t+1		4.921		5.108		4.249		4.370
		(1.482)		(1.563)		(1.171)		(1.188)
Constant	-0.191	-0.289	0.169	0.094	3.100**	2.798**	3.359***	3.097**
	(-0.182)	(-0.284)	(0.159)	(0.091)	(2.490)	(2.303)	(2.713)	(2.558)
Observations	1,362	1,362	1,362	1,362	1,362	1,362	1,362	1,362
R-squared	0.402	0.413	0.400	0.412	0.187	0.203	0.185	0.202

This table estimates the first-year performance of new investors. The dependent variables are the excess returns of new investors during the 12 months following the course start date relative to the deposit rate (columns 1-4) and relative to the returns of experienced classmates from the same course (columns 5-8). Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase either 1 year or 3 years prior to the begin of the course). Peer Returns are average returns calculated in a 6-month window among students with trading background in a given course. The set of controls is described in the text. The OLS regressions include time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 7
Descriptive statistics on stock selection

	Mean (%)	Std. Dev	Min	Max	N
3-month window					
Individual stock selection					
f_{t+3}	0.56	5.67	0	1	97,838
Peer stock selection					
F_{t-3}	1.14	7.47	0	1	97,838
F_{t+3}	0.94	5.74	0	1	97,838
12-month window					
Individual stock selection					
f_{t+12}	0.92	5.96	0	1	97,838
Peer stock selection					
F_{t-12}	1.47	7.74	0	1	97,838
F_{t+12}	0.92	4.72	0	1	97,838

The table presents descriptive statistics of individual and peers stock selection. $f_{i,c,t+\Delta,s}$ is the fraction invested in stock *s* by investor *i* in Δ months (3 and 12) after the start of course c. $F_{c,t-\Delta,s}$ and $F_{c,t+\Delta,s}$ are the average fraction invested in stock *s* by experienced students in course *c* before and after the training.

Table 8
Peer effects in stock selection

Period (T) =	t-3	t-3	t-12	t-12	t+3	t+3	t+12	t+12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Purchases F_T	0.063	0.062	0.001	-0.000	0.130**	0.133***	0.135**	0.136**
	(1.231)	(1.189)	(0.015)	(-0.004)	(2.575)	(2.616)	(2.480)	(2.475)
Peer Returns by Stock	-0.931***	-0.932***	-1.049***	-1.049***	-0.934***	-0.934***	-1.046***	-1.046***
	(-6.420)	(-6.422)	(-5.257)	(-5.258)	(-6.441)	(-6.440)	(-5.235)	(-5.235)
Peer Purchases other courses F_{T,c^-}		-0.111		-0.062		0.101		0.014
		(-1.248)		(-1.005)		(1.276)		(0.314)
Observations	96,341	96,341	96,310	96,310	96,341	96,341	96,310	96,310
R-squared	0.159	0.159	0.246	0.246	0.159	0.160	0.247	0.247
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time x Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City x Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the estimation of the fraction of purchases in a particular stock by a new investor as a function of peer purchases. The dependent variable $f_{i,c,t+\Delta,s}$ is the fraction of purchases by investor *i* in stock *s* during 3 or 12 months following course *c*. $F_{c,T,s}$ are the fraction of purchases in stock s by experienced classmates during a T month window (before and after the class). $F_{c^-,T,s}$ are the fraction of purchases in stock *s* by experienced students in other courses that started during the same month as course *c*. T-statistics in parentheses are based on robust two-way (course and year-month) clustered standard errors. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Table 9
Tests of selective communication

	Market Participation		First Year Returns	
	(1)	(2)	(3)	(4)
Experience Rate	0.284	0.281	-0.314	-0.316
	(0.619)	(0.612)	(-0.467)	(-0.478)
Talks	-0.012	-0.007	0.090	0.058
	(-0.435)	(-0.248)	(0.905)	(0.592)
Peer Returns	-0.069**		0.503	
	(-2.409)		(0.375)	
Experience Rate x Talks	-0.401	-0.436	0.227	0.220
	(-0.863)	(-0.941)	(0.346)	(0.300)
Peer Returns x Talks	0.084***		-0.417	
	(2.763)		(-0.345)	
Max(0, Peer Returns)		-0.022*		3.649
		(-1.763)		(1.072)
Max(0, Peer Returns) x Talks		0.050**		-2.737
		(2.357)		(-0.899)
Min(0, Peer Returns)		-0.062		-1.118
		(-1.051)		(-0.574)
Min(0, Peer Returns) x Talks		0.015		-0.416
		(1.060)		(-0.353)
Constant	-0.267	-0.280	-0.843	-1.017
	(-0.587)	(-0.602)	(-0.570)	(-0.718)
Observations	760	760	63	63
R-squared	0.281	0.284	0.879	0.901
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes

This table shows the results of regressions on market participation (columns 1 and 2) and first year returns of new investors (columns 3 and 4) from a sample of students who completed an electronic survey. For market participation, the dependent variable is set to one for inexperienced students who made at least one stock purchase in a 12-month window after the start of a course and is zero otherwise. Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase either 1 year prior to the begin of the course). Peer Returns is the average returns calculated in a 6-month window among students with trading background in a given course. *Talks* is a dummy variable equal to one for students that reported having investment conversations with classmates. Control variables are described in the text. The OLS regressions include time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

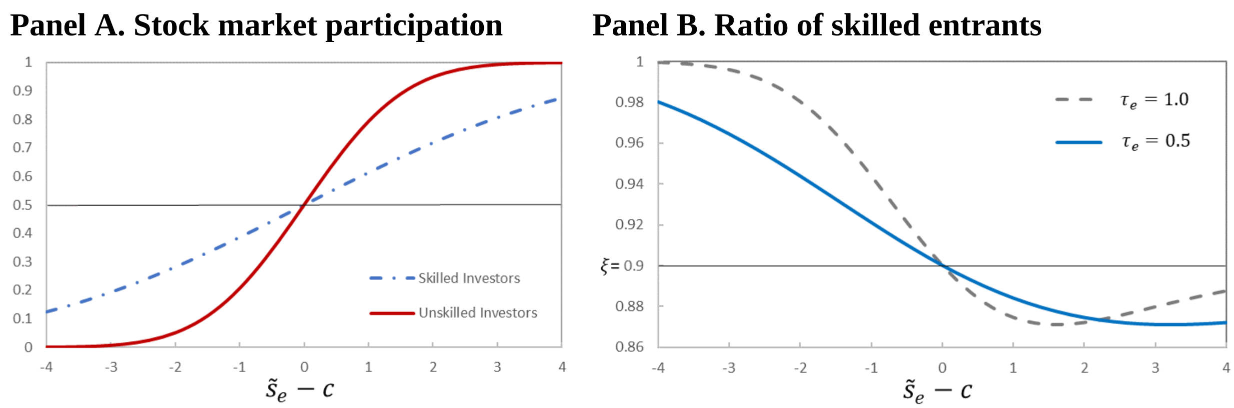


Figure 1

Probability of stock market participation and ratio of skilled entrants

Panel A plots the probability of stock market participation conditional on the peer signal $\tilde{s}_e$ (equation 1 in the text). The figure compares the entry rates between skilled individuals $\tau_S = 4$ (dashed dotted line) and unskilled individuals $\tau_U = 1$ (solid line). Panel B presents the ratio of skilled entrants for different values of the peer signal (equation 2 in the text). The figure compares the predicted rates from two different precisions of the peer signal, $\tau_e = 1$ (solid line) and $\tau_e = 0.5$ (dashed line). Other model parameters are: $\bar{v} = c$, $\tau_v = 2$, and $\xi = 0.9$.

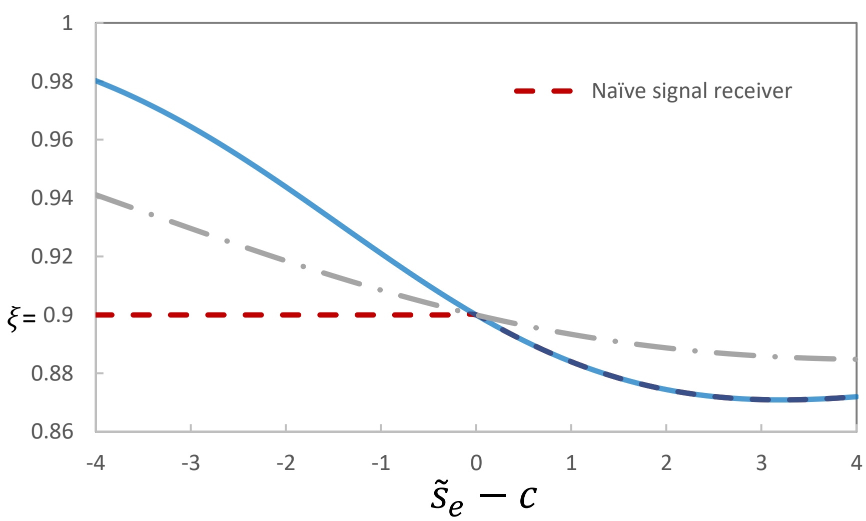
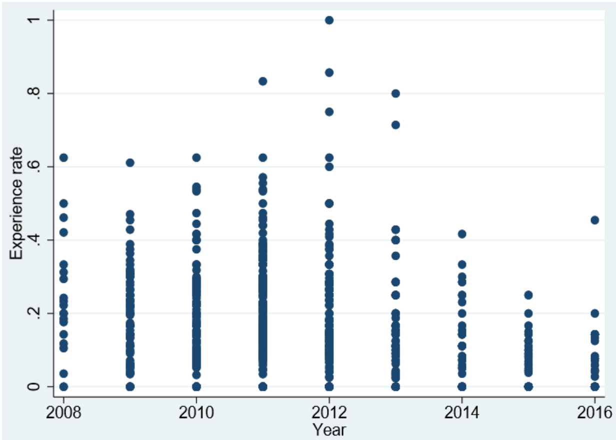


Figure 2

Ratio of skilled entrants: Accurate, selective communication, and overconfidence

The graph plots the expected rate of skilled entrants for different values of the peer signal (equation 2 in the text). The figure compares the predicted rates from three different models: (i) a model where information is accurately shared among individuals (solid line), (ii) when only positive peer outcomes are shared (dashed line), and (iii) when potential entrants overestimate the precision of their private signal (dashed dotted line). The parameters are $\bar{v} = c$, $\tau_e = 0.5$, $\tau_v = 2$, $\tau_S = 4$, $\tau_U = 1$, and $\xi = 0.9$. The overconfidence parameter is $\theta = 1.2$.

Panel A. Share of experienced classmates



Panel B. Adjusted for year effects

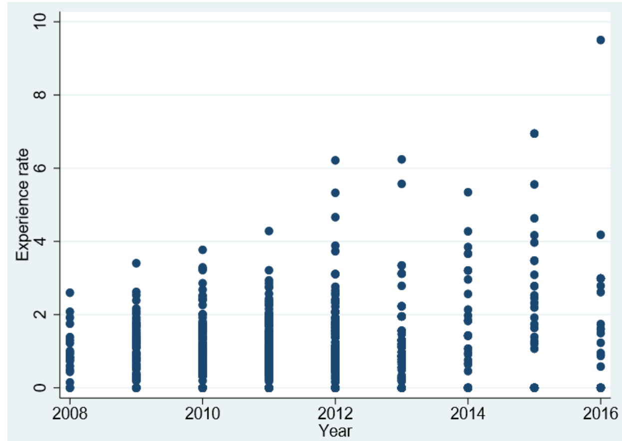
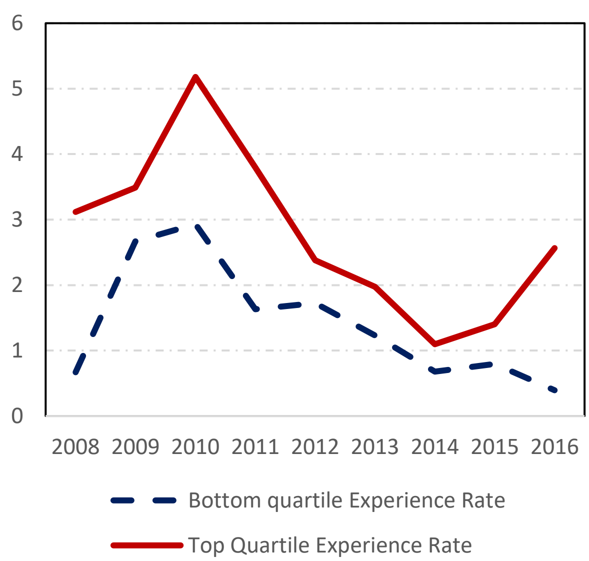


Figure 3

Variation in experienced students

The graph plots each course-year observation of the rate of students with precourse trading background: the share (Panel A) and adjusted for year effects, that is, the share divided by the average share in that year (Panel B).

Panel A. Number of new market participants



Panel B. Share of new market participants over inexperienced students

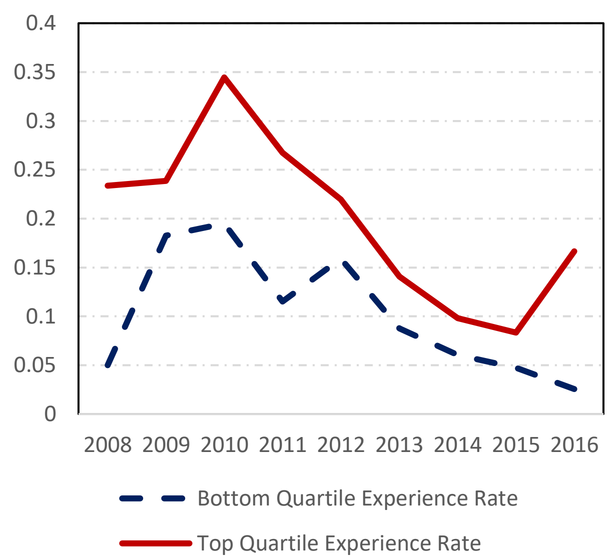


Figure 4

Market participation

The graphs plot the average number of new market participants per course (Panel A) and the corresponding percentage, normalized by the number of inexperienced students in each group (Panel B). Solid and dashed lines compare market participation across courses in the top and bottom quartile sorted by Experience Rate (i.e., share of students with trading background in the course).

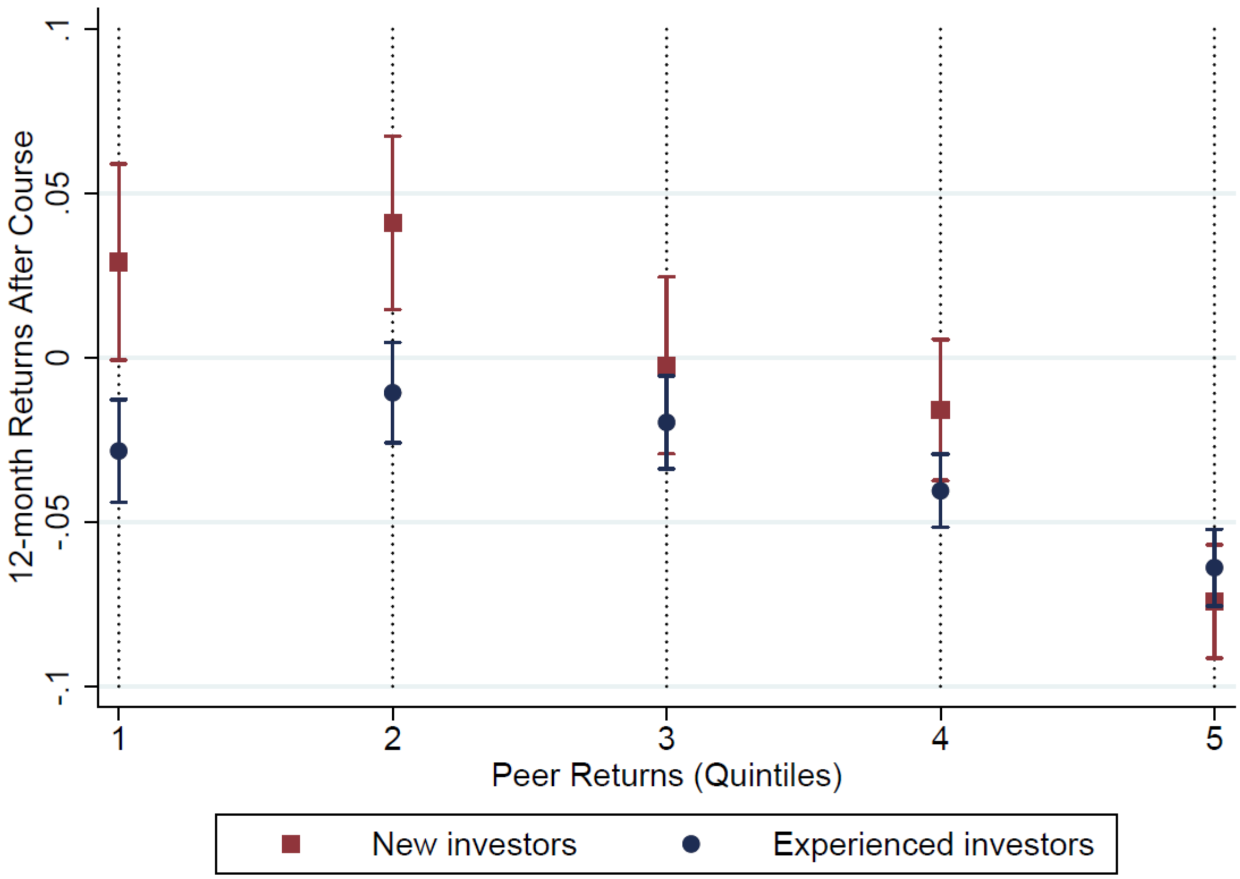


Figure 5
12-month portfolio returns after course
The figure plots the average excess returns of new investors (squares) and experienced investors (circles) calculated during a 12-month window after the start of a course. The groups are sorted for quintiles of peer returns, calculated during six-month window prior to the start date of the course. The solid lines represent the upper and lower bounds of 99% confidence intervals.

FOR ONLINE PUBLICATION

APPENDIX A. PROOF OF PROPOSITION 1

From direct substitution, it follows that $\Pi(c) = \xi$. The difference between the ratio of skilled entrants and ξ (the proportion of skilled students) can be written as follows:

$$\Pi(\tilde{s}_e) - \xi = \frac{\xi(1-\xi)\{\Phi[\beta_S(\tilde{s}_e - c)] - \Phi[\beta_U(\tilde{s}_e - c)]\}}{\xi\Phi[\beta_S(\tilde{s}_e - c)] + (1-\xi)\Phi[\beta_U(\tilde{s}_e - c)]}. \qquad A.1$$

It is straightforward to show that equation A.1 is always positive if $\tilde{s}_e < c$ and is always negative when $\tilde{s}_e > c$. Hence, the fraction of skilled entrants is lower when the peer signal is negative than when the signal is positive (literal i in Proposition 1).

To prove literal ii in the Proposition, let $\Pi(\tilde{s}_e) \equiv f(\tilde{s}_e)/g(\tilde{s}_e)$. Both f and g are cero when $a \to -\infty$. Also, since $\beta_U > \beta_S$, the function

$$\frac{f'(\tilde{s}_e)}{g'(\tilde{s}_e)} = \frac{\xi\beta_S}{\xi\beta_S + (1-\xi)\beta_U e^{-\frac{1}{2}(\beta_U^2 - \beta_S^2)(\tilde{s}_e - c)^2}}, \qquad A.2$$

is decreasing in the interval $(-\infty, c]$. By the Monotone L'Hopital Theorem, the function $\Pi(\tilde{s}_e)$ is also decreasing in the interval of $(-\infty, c]$.

From direct substitution, $\Pi(c) = \lim_{\tilde{s}_e \to \infty} \Pi(\tilde{s}_e) = \xi$. Since Π is a continuous function, differentiable on (c, ∞), with $\Pi(c) = \lim_{\tilde{s}_e \to \infty} \Pi(\tilde{s}_e)$, then by Rolle's theorem there is a point $\tilde{s}^* \in (c, \infty)$, such that $\Pi'(\tilde{s}^*) = 0$. Also, since $\Pi'(c) < 0$, $\tilde{s}^*$ must lie to the right of c (i.e., $\tilde{s}^* > c$) and it represents a minimum of the function Π. More generally, Π is a decreasing function in the interval $\tilde{s}_e \in (-\infty, s^*)$.

APPENDIX B. SELECTIVE COMMUNICATION WITH RATIONAL SIGNAL RECEIVERS

In the main text, we model the tendency to share positive outcomes by assuming that the transmitted peer signal from individuals with trading background to potential entrants is biased, $\tilde{s}_e^r = \max(0, \tilde{s}_e - c)$. In Section 2.2, signal receivers did not account for this bias in communication, updating their priors assuming that the peer signal follows a normal distribution—naïve signal receivers. In this section, we extend the model by assuming that individuals internalize that a peer signal equal to zero might result either from experienced traders unwilling to share their negative performance or from the absence of classmates with trading background in a group. We assume that the probability of having at least one student with trading experience in a classroom is p. When potential entrants observe $\tilde{s}_e^r = 0$, they update their expected payoffs from active trading as follows:

$$E\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p, \tilde{s}_e^r = 0\right] = (1-p)E\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p\right] + pE\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p,\ \tilde{s}_e < c\right]. \qquad B.1$$

The rest of the model assumptions are the same (i.e., public and private signals that are normally distributed and both skilled and unskilled potential investors). We define the updated mean and variance of the payoff from stock market participation when only public and private signals are present as follows:

$$\mu \equiv E\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p\right] = \frac{1}{\tau_v + \tau_i + \tau_p}\left(\tau_v \bar{v} + \tau_i \tilde{s}_i + \tau_p \tilde{s}_p\right) \qquad B.2$$

$$\sigma^2 \equiv Var\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p\right] = \left(\frac{1}{\tau_v + \tau_i + \tau_p}\right) \qquad B.3$$

If individuals assume that a zero signal corresponds to a negative peer outcome, Bayes' Law implies that the posterior probability distribution is:

$$f(\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p,\ \tilde{s}_e < \mathrm{c}) = \frac{Pr(\tilde{v} + \sigma_e \tilde{\varepsilon}_e < \mathrm{c}) f(\tilde{v}\,; \mu, \sigma^2)}{\int_{-\infty}^{\infty} Pr(\tilde{v} + \sigma_e \tilde{\varepsilon}_e < \mathrm{c}) f(\tilde{v}\,; \mu, \sigma^2) d\tilde{v}} \qquad B.4$$

where $f(\tilde{v}\,; \mu, \sigma^2)$ is a normal density function with mean μ and variance σ^2, and $Pr(\tilde{v} + \sigma_e \tilde{\varepsilon}_e < 0) = \Phi[-\tilde{v}/\sigma_e]$. In turn, the second term on the right-hand side of equation (B.1), which represents the expected value of active trading when the signal is zero because of selective communication, becomes:

$$E\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p,\ \tilde{s}_e < \mathrm{c}\right] = \frac{\int_{-\infty}^{\infty} \tilde{v}\, \Phi[-\tilde{v}/\sigma_e] f(\tilde{v}\,; \mu, \sigma^2) d\tilde{v}}{\int_{-\infty}^{\infty} \Phi[-\tilde{v}/\sigma_e]\, f(\tilde{v}\,; \mu, \sigma^2) d\tilde{v}} \qquad B.5$$

The expected value in B.5 can be calculated using integration by parts and yields $E\left[\tilde{v} \mid \tilde{s}_i,\ \tilde{s}_p,\ \tilde{s}_e < \mathrm{c}\right] = \mu\Phi\left(\sqrt{2}\mu\right) - K$, where the constant K is greater than zero and is given by $K = \sqrt{\frac{\tau_e}{2\pi(\tau_v+\tau_i+\tau_p)}} \frac{1}{\tau_v+\tau_i+\tau_p+\tau_e}$. Note that in the case when $\mu = 0$, the expected payoffs from trading are negative under the posterior, since no signal in a class where peers are present is equivalent to assuming that peer outcomes are negative. Overall, the expected payoff under the posterior when there is no peer signal transmitted is:

$$E\left[\tilde{v} \mid \tilde{s}_i, \tilde{s}_p, \tilde{s}_e^r = 0\right] = (1-p)\mu + p\mu\Phi\left(\sqrt{2}\mu\right) - pK \qquad B.6$$

and students enter the stock market whenever this payoff is above the fixed cost of investment. Although we don't have a closed-form solution for this model, we can characterize the solution and infer the effect from different levels of private information on the entry probability. We do this as follows. First, since equation B.6 is monotonic with infinite range, there exists a cutoff μ^* for which the equation is exactly equal to c. Using the implicit function theorem, it is straightforward to show that μ^* is decreasing in τ_i; that is, $\partial\mu^*/\partial\tau_i < 0$. Since the cutoff decreases on τ_i, there are more signal outcomes that lead to entry when investors have better private information. In other words, when the observed peer signal is zero, more skilled than unskilled individuals enter the market. Intuitively, a zero signal is associated with lack of communication, which is interpreted by potential entrants as negative peer outcomes. While signal receivers cannot distinguish the magnitude of the underperformance, they imply that there might be some potential negative peer returns and thus are more reluctant to enter. This dissuasion effect is higher among unskilled individuals, who have less private information and are more sensitive to outside information. In turn, the ratio of well-informed to less-informed individuals when the true peer outcome is negative is constant on the peer performance, but we should expect more well-informed entrants when individuals rationally anticipate that the signal is biased.

When the true peer outcome is positive, we assume that the signal is accurately shared across classmates, and the entry choice depends on $\tilde{s}_e$ following equation (1). Figure B1 presents the proportion of skilled investors in the market as a function, $\tilde{s}_e$, and compares this with the prediction of the model with naïve signal receivers. When signal receivers perfectly internalize the bias in communication, there is a discontinuity at $\tilde{s}_e - c = 0^+$. This happens because for any positive signal, the uncertainty about having an experienced classmate is resolved. Overall, the profile of skilled to unskilled entrants follows the same asymmetry as in the naïve case, which gives rise to Hypothesis 4 in the main text.

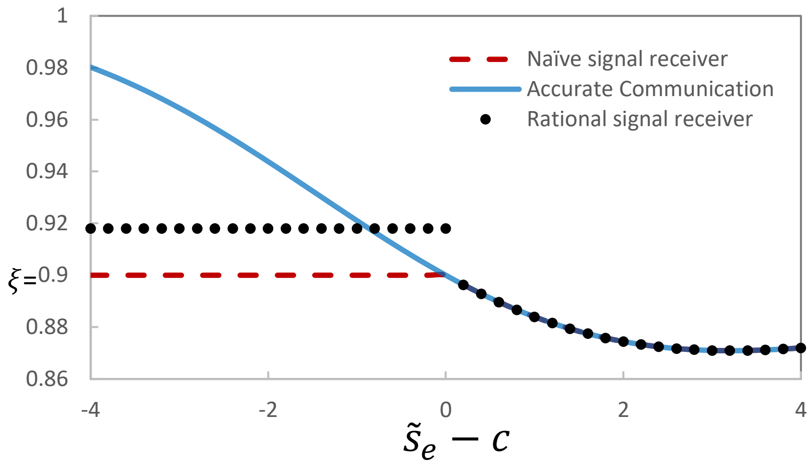


Figure B.1
Ratio of skilled to unskilled entrants
The graph plots the expected ratio of skilled entrants for different peer signals. The figure compares the predicted rates from different models: (i) accurate communication (solid line), (ii) selective communication with naïve signal receivers (dashed line), and (iii) selective communication with rational signal receivers (dotted line). The parameters are $\bar{v} = c$, $\tau_e = 0.5$, $\tau_v = 2$, $\tau_S = 4$, $\tau_U = 1$, and $\xi = 0.9$. The probability of having an experienced student in a classroom is set to $p = 0.2$.

APPENDIX C. OTHER TABLES

Table C.1
Teacher Effects

	(1)	(2)	(3)	(4)
Experience Rate	0.022***	0.026***	0.024***	0.024***
	(4.184)	(4.755)	(3.572)	(3.562)
Max(0, Peer Returns)	0.014**	-0.016*	0.027***	0.026**
	(1.963)	(-1.776)	(2.772)	(2.542)
Min(0, Peer Returns)	0.001	0.001	0.006	0.006
	(0.322)	(0.175)	(1.027)	(1.086)
Peer Volatility	-0.002	0.010	-0.002	-0.002
	(-0.388)	(1.544)	(-0.229)	(-0.203)
Peer Volatility x Max(0, Peer Returns)		0.034***		
		(4.084)		
Peer Volatility x Min(0, Peer Returns)		-0.000		
		(-0.008)		
Teacher Experience (hours)	0.019	0.016	0.019	0.020
	(1.417)	(1.231)	(0.914)	(0.948)
Max(0, Teacher Returns)			-0.011	-0.017
			(-1.372)	(-1.609)
Min(0, Teacher Returns)			-0.003	-0.002
			(-0.359)	(-0.238)
Max(0, Peer Returns) x Max(0, Teacher Returns)				-0.012
				(-0.518)
Min(0, Peer Returns) x Min(0, Teacher Returns)				-0.001
				(-0.190)
Observations	12,113	12,113	6,822	6,822
R-squared	0.101	0.102	0.096	0.096
Teacher FE	Yes	Yes	Yes	Yes

This table shows the results of regressions on market participation. For market participation, the dependent variable is set to one for inexperienced students who made at least one stock purchase in the following 12 months after the completion of a course and is zero otherwise. Experience Rate is defined as the percentage of students in a class with trading background (i.e. students with at least one stock purchase 1 year prior to the begin of the course). Peer Returns is the average returns calculated in a 6-month window among students with trading background in a given course. Teacher returns are the portfolio returns of the class instructor in a 6-month window prior to the beginning of the training. Control variables are described in the text. The OLS regressions include instructor, time (year-month), city, and course curriculum fixed effects. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.