Journal of Financial Economics 150 (2023) 139–165

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Active trading and (poor) performance: The social transmission channel☆

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ARTICLE INFO

Article history:
Received 30 September 2021
Revised 4 August 2023
Accepted 6 August 2023
Available online 24 August 2023

JEL classification:
G11
G41
D83

Keywords:
Stock market participation
Peer effects
Active trading
Lottery stocks
Social finance

ABSTRACT

We study the influence from social interactions on equity trading. Using unique data on stock transactions, we exploit the quasi-random assignment of students to classrooms in a financial training program to identify how peer experience affects investor behavior. We find that individuals react more to peer gains than to peer losses. Students enrolled in courses where peers have positive outcomes: (i) are more likely to start trading, (ii) purchase similar stocks as their classmates, and (iii) are disproportionally attracted to stocks with extreme returns. These stocks have low subsequent returns, and new investors reacting to peer gains underperform other investors.

1. Introduction

Social interactions play an important role in financial decision-making, including stock market participation and portfolio choice.[1] Peer influence, however, might be a conduit for the propagation of biases and investment mistakes.[2] As argued by Hirshleifer (2020), selective communication in social groups can lead to the distortion or amplification of certain ideas, the so-called *Social Transmission Bias*. Despite extensive research on the effects of social interactions on trading strategies, asset prices, and information acquisition, most existing studies rely on indirect measures to assess their relevance. For instance, using proxies such as geographical proximity (e.g., Hong et al., 2005; Kaustia & Knupfer, 2012) or church attendance (Hong et al., 2004) to capture the extent of social interactions. In this paper, we use data from a large-scale financial train-

☆ We are grateful to Dimitris Papanikolaou and two anonymous referees for detailed comments and suggestions. We benefited from in-depth discussions with Deniz Anginer and Sugata Ray on the role of peer effects in market participation (Section 3). We also thank Toan Do, Alfredo Garcia, Xavier Gine, David Hirshleifer, Aart Kraay, Pete Kyle, Claudia Ruiz, Giorgo Sertsios, Jinfei Sheng, and Robert Shiller, as well as from seminar participants at the 2021 ASSA Annual Meeting, University of Maryland, Texas A&M University, Universidad de los Andes-Chile, 27 Finance Forum, and DC Juniors Finance Conference for comments. We thank members of the Colombian Stock Exchange Research Committee for providing the data and for multiple discussions. We acknowledge financial support from the *Strategic Research Program*. The views expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

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[1] See for example, Duflo & Saez (2003), Hong et al. (2004), Bursztyn et al. (2014), and Li (2014). There is also evidence that peer effects improve financial literacy (Haliassos et al. 2020; Ouimet & Tate, 2020).

[2] People may tend to boast about good stock trades, favoring the transmission of appealing but inaccurate ideas about active trading (Shiller, 1995; Shiller, 2015).

https://doi.org/10.1016/j.jfineco.2023.103706
0304-405X/

ing program to present direct evidence on the impact of noisy word-of-mouth communication on equity trading. We show that individuals react more to peer gains than to peer losses when they decide whether to participate in the stock market and for stock selection.

Our analysis relies on a natural experiment involving quasi-random assigned peer groups. The setting is ideal to study the impact of social interactions on stock trading for at least three reasons: (i) participants interact directly and repeatedly in a small classroom setting; (ii) individuals trade substantial amounts of their own money – over six trades per year on average and close to 9,000 USD per trade– in contrast to typical laboratory experiments that offer small monetary rewards to participants using artificial trading accounts; and (iii) we observe their stock transactions both before and after social interactions take place.

Starting in 2008, the Colombian Stock Exchange (CSE) launched a series of professional courses on financial topics (discussed in detail in Section 2),[3] with the majority focusing on equity strategies. Registered individuals were assigned to small sections that studied stock trading in a classroom environment 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. We will show that 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.

The paper contains four main results. First, students enrolled in courses where peers have positive outcomes are more likely to start trading. Second, individuals reacting to peer gains buy the same stocks that their experienced classmates purchase after the course. Rather than selecting stocks that experienced investors bought before taking the course, investors tend to copy the new purchases of their successful classmates. Third, this herding in stock selection is mostly concentrated in lottery stocks (i.e., low-priced stocks with high idiosyncratic volatility and high positive skewness) and illiquid stocks. Fourth, since lottery stocks generate losses on average, new investors reacting to peer gains underperform other investors. We elaborate on each of these findings below.

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 24%. To examine if outcomes from experienced classmates influence the market participation decision, we decompose peer returns into negative and positive regions. We find that negative peer returns do not affect market participation and that the relation between peer outcomes and entry is exclusive to positive peer returns. We control/test for alternative mechanisms that do not involve social interactions in the classroom. 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 of the class instructor. Overall, our baseline results suggest a strong presence of peer effects in our classroom setting, with positive outcomes from experienced classmates further encouraging individuals to start trading.

We also track individuals and their classmates over time and examine their stock selection. We document a strong positive correlation between the stock purchases of new investors and purchases of experienced students after the course: a one standard deviation increase in the purchases by experienced investors in a stock, results in a 21% increase in the fraction of purchases allocated to that stock by new investors from the same classroom. The effect, however, is exclusive to courses where peers display positive outcomes. In courses where peer returns are negative, the correlation between stock purchases among new and experienced investors after the course is small and statistically indistinguishable from zero. To control for time-varying unobserved factors that might influence the demand for any given stock, we include time-stock fixed effects. The empirical strategy effectively compares the purchases in each stock from students enrolled in courses that started in the same month. The main variation that we exploit is whether an individual interacts with peers who recently obtained positive returns.

To complement our analysis, we study if peer effects in stock selection are stronger for certain types of stocks. To do so, we classify each stock according to its market beta, book-to-market value, size, momentum, liquidity, idiosyncratic volatility, and whether it has lottery-type attributes. We show that students registered in courses where peers experienced good outcomes are mostly attracted to lottery-type stocks and to stocks with low liquidity. When an experienced classmate with positive returns purchases a lottery (illiquid) stock, the share of total purchases from new investors from the same course and in the same stock increases by 295% (390%).

Stocks with ex-ante lottery-type features exhibit poor subsequent returns.[4] In turn, new investors enrolled in courses where peer outcomes are positive, and who disproportionally buy these stocks, underperform in their first year of trading. This underperformance is both in abso-

[3] 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.

[4] The underperformance of lottery stocks has been extensively documented in the literature (e.g., Kumar, 2009; Bali et al., 2011). Consistent with previous findings, we show that our proxy for a stock's ex-ante lottery features has a negative relation with the stock expected returns.

lute terms and relative to the performance of new investors who registered in courses where peer outcomes are negative: the difference in risk-adjusted returns from students attending courses where peers display positive returns and those from other courses is -3.00% in the 12 months following the training. Relatedly, we find that the poor performance of new investors is mostly related to their stock selection rather than to their trading intensity. For instance, negative returns among new investors are not explained by their trading frequency, holding period, or trading amount. In other words, poor performance results from lottery stocks and not from portfolio rebalancing as in Barber & Odean (2000). More generally, while negative performance among individual investors is not surprising (Barber et al., 2009), we provide novel evidence that directly links social interactions to enhanced purchases in lottery stocks, and consequently, to worse performance.

Motivated by these findings, we discuss existing theories that might explain our evidence. For instance, communication in our classrooms could be biased toward positive outcomes if individuals benefit from appearing successful.[5] *Selective Communication* would be consistent with the observation that there is no correlation in stock selection between experienced peers and new students in classrooms where peer returns are negative. Also, if negative outcomes are filtered out the present a positive self-view to others, students in courses where peers have experienced poor returns and in courses with no experienced peers should observe similar kinds of information. To test this idea, we compare new investors across these groups and do not find any substantial differences in the type of stocks they purchase or in their first-year returns.

An alternative explanation is that experienced investors accurately share their performance, but signal receivers ignore negative outcomes–*Negative Information Neglect*. This behavior might result from overconfidence, or if individuals overestimate their ability to reproduce good peer outcomes and avoid peer mistakes.[6] The absence of any measurable influence from negative outcomes could result from a combination between a strong bias to communicate positive experiences, and a bias to ignore negative outcomes when these are transmitted.

Regardless of the strength of each bias in communication, these mechanisms alone cannot explain the documented bias in stock selection. For lottery stocks, the leading explanation is that investors have non-traditional preferences for portfolio skewness and thus are naturally attracted to securities with lottery-like payoffs (Brunnermeier et al., 2007; Barberis & Huang, 2008).[7] However, such preference-based models do not address how social interactions impact investor demand. In our groups, investors seem to learn about lottery stocks when they interact with experienced peers, especially if peer outcomes are positive. Alternatively, they might perfectly know the return distribution of individual stocks, but only decide to buy (or expand their demand) after hearing about the positive stories from classmates. In both scenarios, social interactions are playing a major role in the trading behavior of new investors, strengthening the demand for specific stocks. A key lesson from our analysis is that preference-based theories might benefit from the inclusion of social frictions; for example, if communication biases induce people to react more strongly to peer gains than to peer losses, such mechanism might explain why asset bubbles form.

Our work is closely related to Han et al. (2022). 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 environment, we present empirical evidence consistent with the view that biases in communication play a key role in financial decisions.[8]

Our analysis contributes to the empirical literature that studies the effects of social interactions on investment (e.g., Hong et al., 2004, 2005; Ivkovic & Weisbenner, 2007; Brown et al., 2008; Li, 2014). Most of these papers use indirect measures for social interactions to identify peer effects and to measure the strength of social contagion. For example, Kaustia & Knupfer (2012) use geographical proximity to document that only positive returns from neighbors, defined as investors living in the same zip code, encourage stock market participation. We complement this literature by providing direct evidence on how peer outcomes influence the transmission of investment ideas and trading behavior. In addition, a key advantage of our setting is that we observe investors' stock trades both prior to and following social interactions, and in turn, we can examine which assets are subject to herding.

Overall, we present the first direct evidence that social interactions and investor attention enhances the attraction to stocks with extreme payoffs. Relatedly, Bali et al. (2021) finds that the demand for lottery stocks is amplified when investor attention is high and when social interactions are more intense. The authors examine the aggregate stock ownership of retail investors and use different proxies to capture investor attention (e.g., high profile in public discussions or news events) and to measure the strength of social interactions (e.g., Facebook social conect-

[5] 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.

[6] 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).

[7] Even illiquid stocks might be associated with the potential of extreme payoffs, since these stocks have large absolute price movements with little trading volume.

[8] 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.

edness at the county level). In our study, social interactions are well-defined by classmates and the time and location of each course. In our natural experiment, positive peer returns strengthen the intensity of social interactions if investors are more willing to talk about good trading experiences. Similarly, positive peer outcomes appear to grab the attention of members of the group, as individuals from these courses disproportionally increase their purchases in lottery-type and illiquid stocks.

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, communication among students seems to exacerbate the demand for lottery-type stocks, which results in worse portfolio performance.

The rest of the paper proceeds as follows: in Section 2, we describe the financial education program and data. Sections 3 and 4 present our evidence on peer effects in market participation and stock selection. We examine the trading intensity and performance of new investors in Section 5. In Section 6, we discuss existing theories that might explain our evidence and connect our results to other work in the literature. Section 7 concludes.

2. 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.

2.1. 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 (*How to Trade in Stocks 0, 1 and 2*) in total, with instruction ranging from the basics of stock trading to fundamental and technical analysis. There were no placement tests, and participants had to register in the first level before continuing the program regardless of their trading background. 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, "How to Trade in Stocks," 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 one brokerage company over another. Similarly, slides used in the classroom and documents shared with students avoid specific references to securities listed by Colombian companies.[9]

2.2. 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 stu-

[9] When presenting a trading strategy, course materials generally refer to securities as 'Stock A' or 'Corporate Bond B' to avoid explicit mentions of domestic companies. The course documentation only refers to particular securities for general information purposes, for example, to list the securities that belong to an index.

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

dents 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. It is worth noting that we only observe direct equity transactions. Thus, individuals' indirect equity holdings through mutual funds or ETFs are excluded. However, aggregate data suggest that most of the equity exposure of Colombian individuals is through direct stock holdings. Between 2006 and 2017, domestic individuals held 38% of the total shares outstanding and accounted for 33% of the trading volume. Conversely, domestic mutual funds held less than 4% of shares outstanding and were responsible for 5.2% of the trading volume (Escobar et al., 2021).[10]

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.[11] 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

[10] It is still possible that individuals registered for CSE courses hold a disproportionate share of their investments via mutual funds. While we cannot determine whether participation in one the *How to Trade in Stocks* courses affect mutual fund holdings, we should note that the course material in our subsample of classes deals specifically with stock trading, rather than indirect or delegated equity investments.

[11] 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.

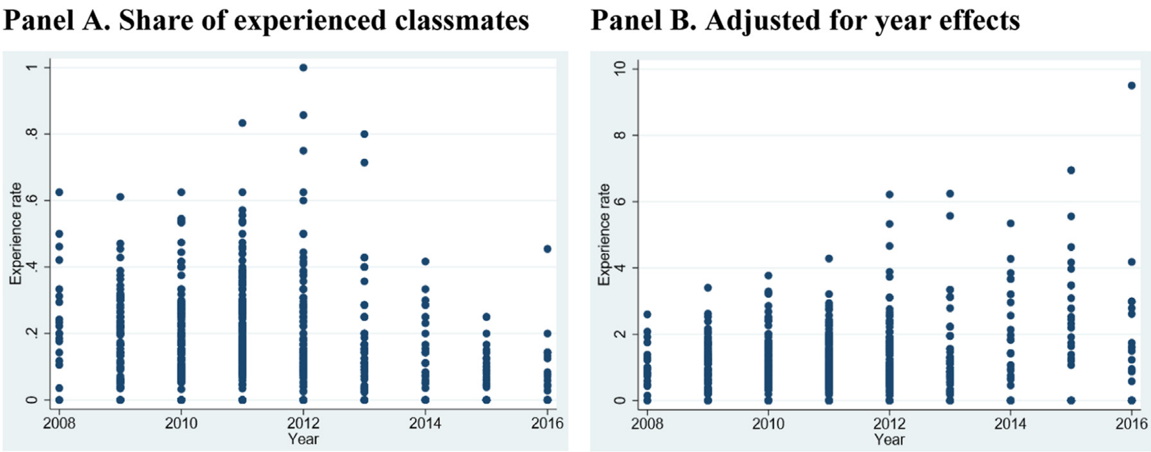

Fig. 1. Variation in experienced students.
The graph plots each course-year observation of the rate of students with pre-course trading background: the share (Panel A) and adjusted for year effects, that is, the share divided by the average share in that year (Panel B).

respondents had graduate education, 17% had some type of foreign portfolio investment, and many (86%) reported having conversations about stock trading with classmates.

2.3. 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.[12] 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 10^{th}–90^{th} 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 (Fig. 1). 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 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%.[13]

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 at that time, -0.86%.

2.4. 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

[12] 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.

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

Table 2
Stratification checks: comparing courses by peer experience.

	Q1	Q2	Q3	Q4	Q1-Q4 (t-stat)
Panel A. Sorted by share of experienced students					
Female	0.34	0.33	0.31	0.28	(2.99)***
	(0.17)	(0.14)	(0.15)	(0.18)	
Age > 30y	0.50	0.52	0.51	0.53	(-1.40)
	(0.27)	(0.20)	(0.23)	(0.27)	
Earnings > 5MM COP	0.33	0.47	0.38	0.35	(-1.01)
	(0.35)	(0.43)	(0.41)	(0.38)	
Graduate Schooling	0.47	0.44	0.48	0.46	(0.36)
	(0.37)	(0.43)	(0.41)	(0.41)	
Teacher Experience (log hours)	5.19	5.22	5.26	5.33	(-1.08)
	(1.64)	(1.52)	(1.53)	(1.62)	
Teacher returns (%)	-0.19	0.07	0.33	0.26	(-1.58)
	(1.68)	(2.84)	(3.41)	(2.93)	
Panel B. Sorted by average returns of experienced students					
Female	0.32	0.32	0.30	0.32	(-0.56)
	(0.16)	(0.17)	(0.16)	(0.17)	
Age > 30y	0.48	0.49	0.58	0.48	(-0.15)
	(0.26)	(0.25)	(0.22)	(0.25)	
Earnings > 5MM COP	0.35	0.38	0.38	0.39	(-0.59)
	(0.38)	(0.42)	(0.44)	(0.39)	
Graduate Schooling	0.43	0.54	0.50	0.46	(-0.46)
	(0.39)	(0.42)	(0.46)	(0.40)	
Teacher Experience (log hours)	5.41	5.15	5.03	5.32	(0.59)
	(1.77)	(1.51)	(1.55)	(1.40)	
Teacher returns (%)	0.17	-0.19	0.68	-0.14	(1.02)
	(2.43)	(2.35)	(3.75)	(2.61)	

The table shows mean and standard deviation in parentheses of variables of interest stratifying the courses by quartiles of peer experience (Panel A) and performance (Panel B). 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 first and last quartile. The shares of female students, students older than 30, with earnings above 5 million COP and with graduate schooling are calculated among students in the classroom without trading experience. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

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 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 a larger proportion of peers with pre-course trading experience display significant differences in any of their observable characteristics. We also sort the sample in quartiles of peer returns. The raw results of all six characteristic variables in our data set are presented in Table 2 where the proportions for female students, those older than 30, participants with earning above 5 million COP and with graduate schooling are calculated from the pool of inexperienced students in each classroom.

According to Panel A of Table 2, courses with less experienced peers seem to have a larger share of female students – when sorting by classmates' experience, the difference between the share of female students in the first and last quartile is 6% (significant at the 1% level).[14] Other characteristics do not appear to be correlated with peer experience. Furthermore, according to Panel B, none of the observable characteristics, including the student's gender, seem to be related to the past returns of experienced classmates. Overall, we do not find evidence supporting the view that courses where experienced students had the highest pre-course trading returns attract more sophisticated participants (proxied by gender, age, income, and education) or that they attract more experienced teachers.

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

[14] The negative relation between peer experience and the share of inexperience female students in the CSE courses may result from the fact that women are more likely to sign up with friends than men; 27% indicate that they register for a class with a friend, relative to 16% of men.

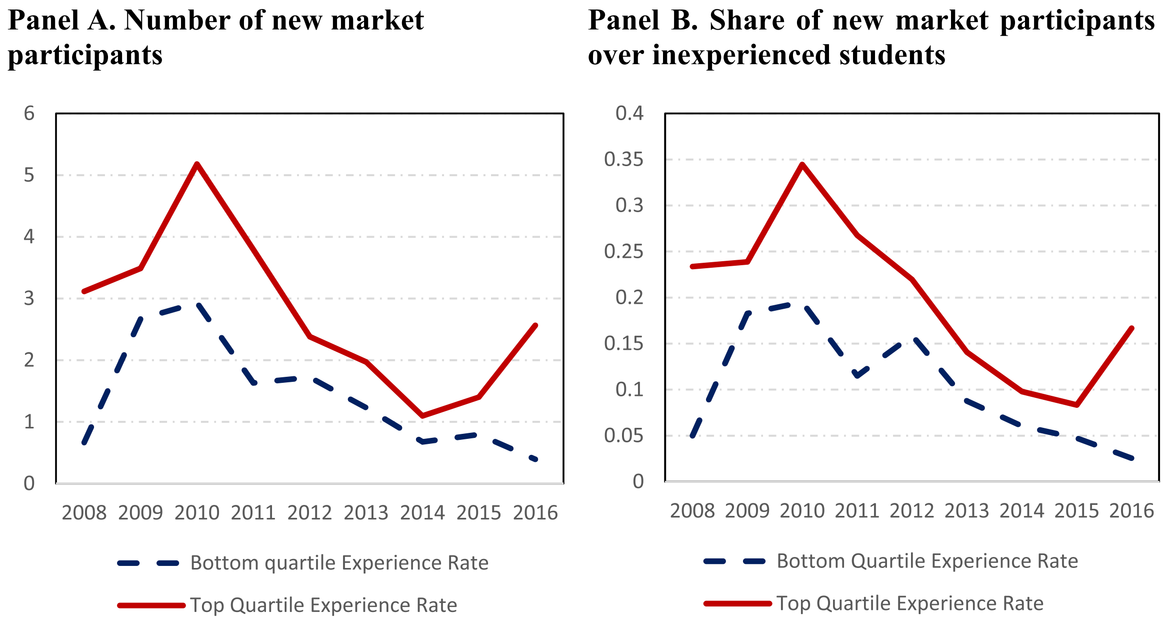

Fig. 2. Market participation.
The graphs plot the average number of new market participants per course (Panel A) and the corresponding percentage, normalized by the number of inexperienced students in each group (Panel B). Solid and dashed lines compare market participation across courses in the top and bottom quartile sorted by Experience Rate (i.e., share of students with trading background in the course).

the course with an acquaintance. In other words, most experienced students did not know their classmates before the program began.

3. Peer Effects in Stock Market Participation

We begin the analysis of peer effects by plotting the average participation rate per classroom—number (Fig. 2A) and share (Fig. 2B) 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.

To analyze peer effects in the stock market participation decision, we estimate the following baseline empirical model:

$$\begin{aligned} y_{i,c,t} = {} & \alpha + \beta \textit{Experience Rate}_c + \gamma \textit{Peer Returns}_c \\ & + \boldsymbol{Q}'\Omega_t + \boldsymbol{M}'\Psi_c \\ & + \boldsymbol{Z}'\Gamma_i + \mu_t + \rho_n + \delta_p + \gamma_l + \varepsilon_{i,c} \end{aligned} \quad (1)$$

The subscript i refers to an individual, c indexes each course, l indexes the location (city), t is the month when the course started, n is the number of registered students in each class, and p indexes courses with the same syllabus. The dependent variable, $y_{i,c,t}$, represents market entry; it 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 starting day of each course—namely, stock market returns and volatility.[15] 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 the first place. In turn, we include program fixed effects δ_p; that is, courses with identical syllabi. To the extent that both the *Experience Rate* and *Peer Returns* will converge to their respective population average as class size increases, smaller courses are more likely to have unusually high or low participation rate or peer returns. To account for the non-linear relation between size and course characteristics we include class size fixed effects ρ_n.

Another important set of controls, Γ_i, captures student-specific characteristics. These include gender, age range, and whether the student took trading courses previously,

[15] 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.

Table 3
Determinants of market participation.

Experience Student Definition =	1 Year			3 Years		
Returns horizon =	6	12	36	6	12	36
Experience Rate	0.029***	0.029***	0.028***	0.027***	0.028***	0.027***
	(6.320)	(6.327)	(6.009)	(5.631)	(5.756)	(5.399)
Peer Returns	0.015**	0.011**	0.009	0.013*	0.007	0.007
	(2.326)	(2.004)	(1.604)	(1.780)	(1.141)	(1.275)
Market Returns	-0.001	-0.052	-0.025	0.005	-0.039	-0.013
	(-0.035)	(-1.009)	(-0.620)	(0.256)	(-1.234)	(-0.463)
Market Variance	0.040**	-0.058**	-0.143	0.033*	-0.044*	-0.080
	(2.077)	(-2.518)	(-1.022)	(1.687)	(-1.791)	(-0.551)
Female	-0.132***	-0.134***	-0.130***	-0.131***	-0.127***	-0.126***
	(-5.599)	(-5.705)	(-5.501)	(-5.344)	(-5.250)	(-5.211)
Age > 30y	0.107***	0.107***	0.107***	0.093***	0.093***	0.093***
	(14.149)	(14.139)	(14.125)	(12.276)	(12.185)	(12.211)
Tuition	0.000	-0.002	0.002	-0.001	-0.002	0.000
	(0.008)	(-0.204)	(0.288)	(-0.157)	(-0.302)	(0.014)
Hours	-0.001	-0.003	-0.002	-0.000	-0.001	-0.000
	(-0.290)	(-0.612)	(-0.455)	(-0.089)	(-0.264)	(-0.026)
Previous Course	0.053***	0.051***	0.053***	0.055***	0.056***	0.053***
	(6.148)	(5.834)	(6.193)	(6.173)	(6.449)	(6.095)
Constant	0.130***	0.132***	0.129***	0.122***	0.121***	0.121***
	(13.160)	(13.363)	(13.011)	(12.257)	(12.191)	(12.152)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
R-squared	0.114	0.113	0.114	0.109	0.109	0.108
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes
Size 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 Re turns 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, class size, 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%.

which is a proxy for her interest in the stock market. Other 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 a course during the same month, but who differ in their exposure to experienced peers (while also controlling for class size, course curriculum, city, etc.). 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*$_c$).

We present the results of our estimating Eq. (1) 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-year 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 24% in the predicted stock market participation rate. That is, the share of inexperienced students that begins to trade stocks after the course rises by 2.9 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. For peer returns measured at longer horizons, 12 and 36 months, the magnitude of the estimated coefficients appears smaller and, in some cases, indistinguishable from zero. As recent outcomes from classmates are more salient, these might lead to increased attention to the stock market, and in turn, promote market entry.

Averaging returns across experienced students might mask some of the relation with market participation. For instance, while the average returns among experienced students in a classroom might be small (or even negative), it is possible that a single experienced classmate obtained large trading profits. If communication is skewed towards positive outcomes, that single individual might promote market participation among her classmates. As an alternative measure of *Peer Returns*, we take the maximum rate of return among the experienced students in a class for each time horizon and estimate Eq. (1). The results, presented in Table B.1-Panel A in the Appendix, confirm the idea that large returns from classmates and particularly those that are more recent tend to increase market participation. We further explore this idea in the next subsection. Overall, peer effects seem to have a strong impact on the market

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	0.030***	0.030***	0.029***	0.029***	0.030***	0.028***
	(6.468)	(6.445)	(5.992)	(5.998)	(6.006)	(5.524)
Max (0, Peer Returns)	0.015**	0.010*	0.010*	0.017**	0.012*	0.012*
	(2.189)	(1.690)	(1.680)	(2.254)	(1.757)	(1.833)
Min (0, Peer Returns)	0.003	0.004	0.001	-0.003	-0.003	-0.002
	(0.686)	(1.284)	(0.374)	(-0.809)	(-0.939)	(-0.585)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
R-squared	0.095	0.094	0.095	0.094	0.093	0.093
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
Size 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, class size, 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%.

participation decision among students of the CSE education program.[16]

To test if peer outcomes have a stronger influence on investment decisions when these outcomes have been positive, we estimate a variant of Eq. (1) in which we break down *Peer Returns*$_c$ into two variables that separately capture the slope estimates for positive and negative peer performance. 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 exclusively from 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– appear to have a smaller effect on the entry decision. We further confirm these findings using the returns of the best performing peer in each class instead of the average returns among experienced classmates (Table B.1-Panel B).

[16] 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).

4. Peer effects in stock selection

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 less studied but important aspect about the role of social interactions on portfolio choice is the extent to which peer outcomes affect the stock selection among members of the group. In this section, we examine if new investors purchase similar stocks as their experienced classmates and study whether such choices differ when individuals interact with classmates with positive vs. negative outcomes.

4.1. Baseline results

Following 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 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. We examine if stock purchases by a new investor are correlated with 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

Table 5
Descriptive statistics on stock selection.

	Mean (%)	Std. Dev (%)	Min (%)	Max (%)	N
3-month window					
Individual stock selection					
f_{t+3}	1.46	9.10	0	100	35,889
Peer stock selection					
F_{t-3}	3.28	12.39	0	100	31,203
F_{t+3}	2.64	9.24	0	100	31,203
6-month window					
Individual stock selection					
f_{t+6}	1.93	9.38	0	100	35,889
Peer stock selection					
F_{t-6}	3.71	12.43	0	100	31,203
F_{t+6}	2.62	8.25	0	100	31,203
12-month window					
Individual stock selection					
f_{t+12}	2.31	9.39	0	100	35,889
Peer stock selection					
F_{t-12}	4.12	12.55	0	100	31,203
F_{t+12}	2.58	7.68	0	100	31,203

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, 6 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.

to examine whether direct spillover effects in stock selection are related to past and/or future trades by peers. Since 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, six 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 three months of trading was 1.46% (Table 5).[17]

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

$$
\begin{aligned}
f_{i,c,t+\Delta,s} = \alpha &+ \beta_0 F_{c,T,s} + \gamma\, Peer\ Returns_{c,t-\Delta,s} \\
&+ \boldsymbol{Q}'\Omega_{t,s} + \boldsymbol{M}'\Psi_c \\
&+ \boldsymbol{Z}'\Gamma_{i,s} + \mu_{s,t} + \rho_n + \delta_p + \gamma_{l,t} + \varepsilon_{i,c,t+\Delta,s} \qquad (2)
\end{aligned}
$$

In Eq. (2), 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.[18] 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 the stock selection by investors from other CSE courses that started on the same month as course c, $F_{c^-,T,s}$. Table 6-Panel A 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 1-3. On the contrary, contemporaneous stock selection between new investors and experienced peers is highly correlated, particularly in the three months following the course. The estimated β_0 is positive and significant in column 4 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 15% increase in the fraction of purchases allocated to that stock by the new investor (i.e., the point estimate in column 4 [0.218] divided by the mean of f [1.46]). Correlated trading between new investors and experienced students seems to decline over time, with a smaller estimated coefficient of peer purchases during the six- and 12-month window following the course.

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.

4.2. Positive versus negative peer outcomes

In Section 3, we document that peer outcomes have an asymmetric effect on market participation, attracting more

[17] For an individual that is purchasing only one stock in this period, the share of stock purchases would be zero for all stocks, except for the one that she buys. Hence, the average share of stock purchases (f) for that individual would be 1.43% (1/70).

[18] Since the returns include roundtrip trades and the exact timing in which a stock was traded, two individuals that hold stock s at any moment in t-Δ might experience different returns during the period.

Table 6
Peer effects in stock selection.

Period (T) =	t-3 (1)	t-6 (2)	t-12 (3)	t+3 (4)	t+6 (5)	t+12 (6)
Panel A. New investors in all courses						
Peer Purchases F_T	0.121	-0.008	-0.031	0.218**	0.124*	0.137
	(1.141)	(-0.069)	(-0.277)	(2.447)	(1.680)	(1.615)
Peer Returns by Stock	-1.064***	-1.253***	-0.936***	-1.065***	-1.253***	-0.929***
	(-6.666)	(-8.169)	(-4.212)	(-6.683)	(-8.170)	(-4.179)
Peer Purchases other Courses F_{T,c^-}	0.358	0.013	0.195	0.342	-0.038	0.016
	(0.834)	(0.025)	(0.371)	(0.939)	(-0.169)	(0.062)
Observations	30,712	30,712	30,712	30,712	30,712	30,712
R-squared	0.147	0.185	0.209	0.148	0.185	0.209
Panel B. New investors from courses with positive vs. negative peer returns						
Peer Purchases F_T [β_0]	0.006	-0.142	-0.139	0.083	-0.024	0.096
	(0.053)	(-1.143)	(-1.025)	(1.064)	(-0.262)	(0.833)
Peer Returns by Stock	-1.064***	-1.254***	-0.937***	-1.063***	-1.252***	-0.929***
	(-6.666)	(-8.177)	(-4.214)	(-6.673)	(-8.164)	(-4.177)
Peer Purchases other Courses F_{T,c^-}	0.322	-0.038	0.169	0.299	-0.088	0.006
	(0.746)	(-0.074)	(0.320)	(1.005)	(-0.382)	(0.022)
Peer Purchases x Peer Returns$^+$ [β_1]	0.151	0.169	0.137	0.217**	0.215**	0.067
	(1.299)	(1.439)	(1.147)	(1.967)	(2.069)	(0.525)
Peer Returns$^+$	-0.364**	-0.008	-0.019	-0.397***	-0.060	-0.038
	(-2.308)	(-0.052)	(-0.159)	(-2.598)	(-0.380)	(-0.316)
Observations	30,712	30,712	30,712	30,712	30,712	30,712
R-squared	0.147	0.185	0.209	0.148	0.185	0.209
$\boldsymbol{\beta_0 + \beta_1}$ **=**	0.157	0.027	-0.002	0.300**	0.192**	0.163*
	(1.335)	(0.214)	(-0.016)	(2.585)	(2.163)	(1.667)

This table shows the estimation of the fraction of purchases in a particular stock by a new investor as a function of peer purchases (Panel A) and comparing courses with positive and negative peer returns (Panel B). The dependent variable $f_{i,c,t+\Delta,s}$ is the fraction of purchases by investor i in stock s during 3-, 6-, 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. Control variables are described in the text. The OLS regressions include time-stock, city-stock, course curriculum and class size fixed effects. 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%.

investors to stock trading when peer returns are positive. To examine the role of peer outcomes on stock selection, we augment Eq. (2) by including a dummy variable that captures when peer outcomes in the classroom have been positive (i.e., *Peer Returns*$_c^+$ is one if peer returns are above the short term rate and is zero otherwise) and its interaction with peer purchases: $\beta_1 F_{c,T,s} \times \textit{Peer Returns}_c^+$.[19]

Results are presented in Table 6-Panel B. Our major finding is that the high contemporaneous correlation in stock selection between new students and their experienced classmates is exclusive to courses where peers have performed well in the past. For courses where peer returns are negative, there is no correlation between new investors' purchases and the trades of experienced peers. The coefficient β_0 is small and indistinguishable from zero in all specifications. On the contrary, new investors that join courses where peers' most recent outcomes have been positive are more likely to copy the stock purchases of their experienced classmates. A one standard deviation increase in the fraction of experienced classmates' purchases to a particular stock 3 months after the course results in a 21% increase in the fraction of purchases allocated to that stock by the new investor (i.e., $\beta_0 + \beta_1$ [0.30] divided by the mean of f [1.46]).

The impact of positive peer outcomes on correlated trading, however, appears to decline over time. A similar one standard deviation increase in stock purchases in the 6- and 12-month windows following the course, results in a 10 and 7% increase, respectively in the fraction of purchases by new investors in the same stock and period. In unreported results, we exclude the trades during the first six months after the course and examine stock transactions between six and 12 months following the classroom interaction. We do not find any correlation in stock purchases within this period. In other words, the correlation in stock selection in classrooms where peer outcomes are positive last for about six months and is more pronounced in the first few months after the course starts.

4.3. Stock characteristics

We now focus on how the presence of experience classmates influence the types of stocks that new investors purchase. To do so, we classify each stock according to seven different characteristics for every month in the sample period: small firms (SMALL), high market beta (BETA), growth (GROWTH), high momentum (MOM), low liquidity (ILLIQ), high idiosyncratic volatility (IVOL), and whether the stock

[19] We use a 6-month window to calculate Peer Returns since earlier evidence suggests that peer outcomes closer to the course start date have the strongest effect on market participation.

exhibits lottery-type payoffs (LOTT).[20] Each category is represented by a dummy variable equal to one if the stock is in the group and is zero otherwise. Appendix A provides a detailed description of the variables that were used to classify each stock.

We estimate the fraction of total purchases in stock s by a new investor ($f_{i,c,t+3,s}$) as a function of the stock characteristic in the month before the beginning of the training (e.g., $BETA_{s,t-1}$). Following the results from the previous subsection, we focus on stock purchases in a three-month window after the course start date, when the correlation in stock selection among classmates is the strongest. We estimate the following regression model:

$$f_{i,c,t+3,s} = \alpha + \sum_{g} \lambda_g TYPE^{g}_{s,t-1} \times Peer\ Returns^{+}_{c} + \boldsymbol{Q}'\Omega_{t,s} + \boldsymbol{M}'\Psi_c + \boldsymbol{Z}'\Gamma_{i,s} + \mu_{s,t} + \rho_n + \delta_p + \gamma_{l,t} + \varepsilon_{i,c,t+3,s} \quad (3)$$

where g represents each of the seven stock attributes. Since we include time-stock fixed effects $\mu_{s,t}$, the interaction $TYPE^{g}_{s,t-1} \times Peer\ Returns^{+}_{c}$ effectively compares the purchases for a particular stock across courses that started in the same month; the key variation that we explore is whether or not individuals interact in the classroom with peers who recently obtained positive returns.

In Table 7-Panel A, we present the estimation of Eq. (3) for all stock purchases of new investors in a three-month window after the course start date –unconditional from the trades of experienced classmates in the same time window. According to the table, new investors that interact with peers displaying positive returns are more likely to buy lottery-type and illiquid stocks than investors from other courses. When a student enrolls in a classroom where peers experienced positive returns, once she begins trading, her fraction of purchases of lottery-type stocks is 70% higher than those from students in courses where peer returns are negative ([1.024] divided by the mean of f [1.46]).

We further restrict the sample to the set of stocks purchased by experienced students from the same classroom in the three-month window (Table 7-Panel B). The results provide strong support for the role of social interactions in the classroom, and especially, on the asymmetric effect of peer outcomes on investors' choices. We show that when an experienced classmate purchases a lottery (illiquid) stock, the share of total purchases from new investors from the same course and in the same stock is 295% (390%) greater if peer returns are positive.

To classify lottery stocks, we use the average of the largest five daily returns within a month for each stock. One limitation with this measure, however, is that we cannot distinguish between stocks with high positive skewness and those with high kurtosis. To address this concern, we use the average of the lowest five daily returns in a month for each stock. Notably, when we estimate Eq. (3) with this measure, we do not find any evidence that new investors buy stocks with extreme negative returns.[21] In other words, it appears that positive skewness in returns rather than kurtosis matters more when investors copy the trades of their experienced classmates.

It is possible that experienced peers with positive outcomes are simply more likely to purchase illiquid and lottery-type stocks than other individuals; for example, as they obtain good trading outcomes, they might gain a preference for stocks with extreme returns. If new investors copy the strategies of experienced classmates, they will end up overweighting stocks with similar attributes in their portfolios. To explore this possibility, we study the stock purchases of experienced students after the course. In Table 8, we estimate a variant of Eq. (3) using as dependent variable the share of stock purchases of experienced investors, $f_{e,c,t+3,s}$, where e are students with trading background. In Panel A, we use month and stocks fixed effects, instead of month-stock dummies, to capture the demand of experienced investors for stocks with different features. We find that after the course, the average investor with pre-course trading experience tends to purchase lottery-type stocks, small stocks, and stocks with higher liquidity. Importantly, there are few differences in stock selection between experienced students with positive vs. negative outcomes. For example, according to Panel B of Table 8, experienced peers with recent positive returns buy the same proportion of lottery stocks, high beta, high momentum, and illiquid stocks after the course relative to experienced peers with negative returns.[22] Table 9

The key implication from these findings is that the propensity of new investors to purchase lottery and illiquid stock is not a mechanical result from the kind of stocks that experienced peers buy in the first place. In other words, after hearing about the positive outcomes from peers in the classroom, new investors are attracted to assets with specific attributes, apparently to stocks with extreme returns. The case of illiquid stocks illustrates this idea. While the average investor with experience seems to purchase more liquid stocks, when an experienced peer with good outcomes purchases an illiquid stock, other students from the same classroom are overwhelmingly attracted to this trade.

In summary, peer gains rather than losses seem to affect the stock selection of new investors. Positive outcomes from peers generate a strong correlation between the stock transactions of new and experienced investors from the same classroom. Interestingly, new investors are more likely to copy the trades of their experienced classmates in stocks with extreme outcomes, highlighting a potential bias in stock selection towards lottery-type and illiquid stocks.

5. Peer effects in other outcomes

In this section, we examine peer effects in other dimensions of investor behavior. For example, we study if the

[20] Lottery-type stocks are often defined as low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness.

[21] Results not shown in Table 7 and can be provided upon request.

[22] The only exception is growth stocks. It seems that experienced peers with good returns are more likely to purchase growth stocks after the course than other experienced investors with negative returns.

Table 7
Peer effects and stock characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Purchases by new investors								
LOTT x Peer Returns$^+$	0.806***							1.024***
	(3.022)							(2.758)
IVOL x Peer Returns$^+$		0.464						-0.279
		(1.591)						(-0.720)
BETA x Peer Returns$^+$			0.423					0.395
			(1.115)					(0.835)
SMALL x Peer Returns$^+$				0.524				0.749
				(1.083)				(1.241)
MOM x Peer Returns$^+$					-0.221			-0.278
					(-0.459)			(-0.532)
ILLIQ x Peer Returns$^+$						0.501**		0.718**
						(2.149)		(2.413)
GROWTH x Peer Returns$^+$							0.406	0.612
							(0.916)	(1.299)
Observations	30,447	30,385	30,447	30,447	30,447	30,447	30,447	30,385
R-squared	0.144	0.144	0.144	0.144	0.144	0.144	0.144	0.145
Panel B. Purchases by new investors conditional on peer purchase								
LOTT x Peer Returns$^+$	5.836***							4.312**
	(3.693)							(2.018)
IVOL x Peer Returns$^+$		5.803***						2.716
		(3.661)						(1.343)
BETA x Peer Returns$^+$			0.420					-0.823
			(0.364)					(-0.509)
SMALL x Peer Returns$^+$				0.807				2.584
				(0.473)				(1.156)
MOM x Peer Returns$^+$					0.014			0.415
					(0.008)			(0.241)
ILLIQ x Peer Returns$^+$						7.602***		5.079**
						(3.035)		(2.134)
GROWTH x Peer Returns$^+$							-0.779	0.138
							(-0.492)	(0.092)
Observations	4,649	4,649	4,649	4,649	4,649	4,649	4,649	4,649
R-squared	0.213	0.212	0.211	0.211	0.211	0.212	0.211	0.213

This table shows the estimation of the fraction of purchases in a particular stock by a new investor as a function of stock characteristics and whether experienced students in the class had positive or negative returns. The dependent variable $f_{i,c,t+3,s}$ is the fraction of purchases by investor i in stock s for 3 months following course c. Panel A presents the estimation with the universe of all stocks purchased by new investors. Panel B conditions the sample on the set of stocks purchased by experienced peers in the same class. Control variables are described in the text. The OLS regressions include time-stock, city-stock, course curriculum and class size fixed effects. 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%.

presence of experienced peers in a classroom, as well as differences in the exposure to peer outcomes, impact the trading frequency of new investors, their holding period, or the number stocks that they trade. The empirical exercise follows the strategy in Section 3. We condition the sample to students who entered the stock market after the competition of a course and estimate how different aspects of their behavior in their first 12 months of trading are related to the *Experience Rate* and to *Peer Returns*.

We estimate Eq. (1) using as dependent variables the following measures: the average dollar amount among stock purchases (*Amount*); the average number of days between the first purchase and the first sell of the same stock (*Holding period*); the number of days making stock transactions (*Frequency*); and the number of different stocks purchased in the year (*Stocks*). In addition, for each new investor, we calculate a measure of the disposition effect.[23] The reported coefficient (*Disposition*) represents the difference in the likelihood to sell a stock whose price is above the purchase price than a stock that has fallen in value.

During the first year of trading, the median new investor in our sample spends 5,847 USD per stock purchase, has an average holding period of 62 days, trades 9 different days, buys 5 stocks, and is $e^{0.54} = 1.7$ times more likely to sell stocks when the price is above the purchase price than when is below (Table 8-Panel A).[24] In Table 8-Panel C, we show our estimation results on trading intensity. New investors that attend courses with a greater share of ex-

[23] We follow the methodology in Seru et al. (2009) and estimate a hazard model using daily trades and returns. The hazard model is of the form $h_{i,\ s}(t) = \phi_i(t) exp\{\beta_i^d \text{PriceDummy}_{s,t} + \text{controls}\}$, where $h_{i,\ s}(t)$ is investor i's probability of selling a position s on date t, conditional on not having sold prior to that day. PriceDummy takes a value of one when the stock price on date t is above the purchase price, and zero otherwise. The set of controls are the same as those in Seru et al. (2009), which include the five-day moving averages of the market returns, squared market returns, and market volume. We use β_i^d as our measure of disposition coefficient. We perform the estimation via maximum-likelihood for each individual i who places at least seven round-trip trades in the first year after the course.

[24] In Panel B, we report the same statistics for experienced students trading after the course.

Table 8
Stock purchases by students with trading experience.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Purchases by investors with trading experience								
LOTT	0.289***							0.346**
	(2.770)							(2.512)
IVOL		0.086						-0.089
		(0.843)						(-0.651)
BETA			-0.285					-0.226
			(-1.145)					(-0.878)
SMALL				0.216*				0.226*
				(1.675)				(1.713)
MOM					-0.044			-0.092
					(-0.468)			(-0.953)
ILLIQ						-0.226***		-0.229***
						(-2.790)		(-2.630)
GROWTH							0.268*	0.237
							(1.753)	(1.490)
Observations	52,661	52,518	52,661	52,661	52,661	52,661	52,661	52,518
R-squared	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.055
Panel B. Purchases by investors with trading experience conditional on their returns prior to the course								
LOTT x Peer Returns+	0.019							0.051
	(0.099)							(0.167)
IVOL x Peer Returns+		-0.008						0.097
		(-0.044)						(0.321)
BETA x Peer Returns+			0.070					0.037
			(0.329)					(0.153)
SMALL x Peer Returns+				0.150				0.105
				(0.636)				(0.397)
MOM x Peer Returns+					0.072			-0.013
					(0.289)			(-0.052)
ILLIQ x Peer Returns+						-0.215		-0.175
						(-1.410)		(-0.962)
GROWTH x Peer Returns+							0.444*	0.437*
							(1.810)	(1.770)
Observations	52,438	52,297	52,438	52,438	52,438	52,438	52,438	52,297
R-squared	0.131	0.131	0.131	0.131	0.131	0.131	0.131	0.131

This table shows the estimation of the fraction of purchases in a particular stock by experienced students as a function of stock characteristics (Panel A) and whether these investors display positive returns before the start of the course (Panel B). The dependent variable $f_{e,c,t+3,s}$ is the fraction of purchases by an experienced investor e in stock s for 3 months following course c. Control variables are described in the text. All regressions include city-stock, course curriculum and class size fixed effects. Panel A includes time and stock fixed effects. Panel B includes time-stock fixed effects. 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%.

perienced students tend to invest larger amounts, trade more frequently, purchase more stocks, hold the stocks for fewer days, and display a larger disposition coefficient.[25] Our results for quasi-random formed groups are broadly in line with the literature that links social interactions to increased trading (e.g., Hong et al., 2004; Ivkovich & Weisbenner, 2007; Kaustia & Knupfer, 2012) and to the disposition effect (Heimer, 2016). The novel aspect of our analysis is whether peer outcomes, and in particular positive returns from classmates, have any effects on the trading activity of individual investors.

As it turns out, we do not find any evidence that positive peer returns encourage new investors to spend more on stock purchases, trade more often or in more stocks, nor do they seem to display significant differences in their holding period (the coefficient for *Peer Returns*+ is indistinguishable from zero in all specifications). Similarly, there is no evidence that investors from courses where peers had positive returns display a greater disposition effect than new investors from other courses. Overall, in our classroom setting, positive peer outcomes seem to have a strong influence on market participation and on the type of stocks that new investors purchase, but not on trading intensity.

We complement our analysis by studying the trading performance of new investors. To do so, we calculate the risk-adjusted returns during their first-year trading.[26] Overall, these investors have poor performance in the 12 months following the course: the median investor obtains

[25] A one-standard deviation increase in the Experience Rate is associated with an increase relative to the median investor in 11.7% of the trading amount (684 USD), 9.2% in the number of trading days (0.83 days), 6.7% in the number of stocks (0.34 stocks), and a reduction of the average holding period by 7.3% (4.5 days).

[26] For each investor-month, we calculate the portfolio alpha as $\alpha_{i,t} = (R_{i,t} - r_{f,t}) - \beta^W_{i,t}(R_{m,t} - R_{f,t})$, where $R_{i,t}$, $R_{m,t}$, $r_{f,t}$ are investor i's monthly returns, the market returns, and the risk-free rate. $\beta^W_{i,t}$ is the portfolio beta –the value weighted average of the beta ($\beta_{s,t}$) among all stocks s in investor i's portfolio (see Appendix A for individual stock characteristics). The yearly risk-adjusted returns are the accumulated alphas for each investor over the first 12 months trading. As an alternative measure of investor performance, we calculate the mean yearly market-adjusted return by subtracting the investor return on the market return. The findings are similar for the two definitions, so we omit the latter for brevity.

Table 9
Peer effects and investor behavior.

	Amount (USD)	Holding Period (days)	Days Trading	Stocks	Disposition Effect	Adj. Returns
			Panel A. New Investors			
Mean	9,808	120.65	15.07	5.74	1.31	-2.06
Standard deviation	16,526	152.18	17.95	4.32	5.25	15.19
10^{th} Percentile	1,597	13.43	2.00	1.00	-0.82	-19.64
Median	5,847	61.67	9.00	5.00	0.54	-3.21
90^{th} Percentile	20,292	304.00	36.00	12.00	2.87	16.61
			Panel B. Experienced Investors			
Mean	18,909	121.41	18.21	6.19	1.44	-5.51
Standard deviation	31,941	138.91	23.81	4.72	5.01	11.89
10^{th} Percentile	2,618	11.09	1.00	1.00	-0.63	-18.63
Median	9,446	73.00	10.00	5.00	0.66	-4.79
90^{th} Percentile	37,708	289.50	44.00	13.00	2.63	6.95
			Panel C. Estimation of peer effects			
Experience Rate	0.117***	-0.073*	0.092**	0.067**	0.192**	-0.059
	(3.102)	(-1.762)	(2.395)	(2.531)	(2.066)	(-0.106)
Peer Returns^{+}	0.071	-0.088	0.118	0.036	-0.079	-2.995**
	(0.733)	(-0.842)	(1.091)	(0.476)	(-0.395)	(-2.163)
Observations	1,364	1,284	1,364	1,364	554	1,360
R-squared	0.172	0.151	0.157	0.185	0.231	0.319

The table reports information on trading behavior during the 12-months following the start date of each course for new investors (Panel A) and for students with experience (Panel B). Panel C reports the estimation of each outcome variable on the course *Experience Rate* and on a dummy variable that captures whether experienced students in the class had positive returns. The variables *Amount, Holding Period, Days Trading* and *Stocks* are estimated using the natural logarithmic transformation. Control variables are described in the text. The OLS regressions include time (year-month), city, class size, 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%.

-3.21% yearly risk-adjusted returns. The result is not surprising since individual investors who trade actively underperform (Barber & Odean, 2000).

Our crucial finding is that students who interact with high-performing peers in the class, obtain the lowest returns among new investors. The difference in risk-adjusted returns between students attending courses where peers display positive returns and those from other courses is -3.00% during the first-year trading (last column in Table 8-Panel C). As we showed earlier, students exposed to positive peer outcomes disproportionally purchase stocks with lottery characteristics. While such stocks exhibit extreme valuations in the short run, they also have poor subsequent performance (see, e.g., Bali et al., 2011). In Table A.2 in the Appendix, we show that our proxy to classify stocks in the lottery-type category is negatively correlated with the stocks' subsequent returns. It appears that the worse performance of new investors from courses where peers had positive returns is associated with their propensity to buy lottery-like stocks.

In Table 10, we show that the underperformance of new investors is related to their stock selection and not to their trading intensity (e.g., trading amount or frequency). We also split *Peer Returns* into positive and negative regions and present the estimation of the risk-adjusted returns of new investors using different classifications for students with experience. We confirm that new investors from courses where peer outcomes are positive obtain inferior returns. The finding is explained by the type of social interactions in the classroom, rather than by how often they trade, the number of stocks, their trading amount, or for how long they hold the stocks in their portfolios.

In Fig. 3, we present additional graphical evidence. We sort courses by quartiles of *Peer Returns* (measured during the 6-month window before the class) and calculate the average risk-adjusted returns among new investors in each group. According to the figure, 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 course. Notably, for courses where *Peer Returns* are high (in the top quartile), the returns of new investors are low and of the same magnitude as the returns from classmates with trading background. 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* (quartiles 1, 2, and 3), new investors overperform relative to their experienced classmates after the class.

Fig. 3 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 (their average risk-adjusted returns after the course are -5.51%, Table 8-Panel B). These experienced students are not necessarily sophisticated investors; they are simply more active and have some recent trading history relative to their classmates. In fact, extreme pre-course trading returns among experienced students result from high-volatility portfolios. Panel A in Fig. 4 presents the average and the upper and lower bounds of the 99% confidence intervals of *Peer Volatility* sorted by courses according to

Table 10
Peer effects and investor performance.

	1 Year		3 Years	
	(1)	(2)	(3)	(4)
Experience Rate	-0.532	0.467	-0.403	0.225
	(-0.363)	(0.329)	(-0.235)	(0.139)
Max (0, Peer Returns)	-1.874***	-1.594**	-1.716**	-1.673**
	(-2.930)	(-2.525)	(-2.275)	(-2.188)
Min (0, Peer Returns)	-0.187	-0.209	-0.225	0.118
	(-0.371)	(-0.384)	(-0.357)	(0.178)
ln(Amount)		-0.403		-0.577
		(-0.965)		(-1.221)
ln(Holding Period)		-0.082		-0.001
		(-0.186)		(-0.002)
ln(Frequency)		-0.531		-0.212
		(-0.525)		(-0.171)
ln(Stocks)		-1.741		-2.212
		(-1.416)		(-1.449)
Observations	1,359	1,359	1,184	1,184
R-squared	0.327	0.351	0.340	0.362

This table estimates the first-year performance of new investors. The dependent variables are the risk-adjusted returns of new investors during the 12 months following the course start date. Experience Rate is defined as the percentage of students in a class with trading background: students with at least one stock purchase either 1 year (columns 1 and 2) or 3 years (columns 3 and 4) 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, course curriculum, and class size 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%.

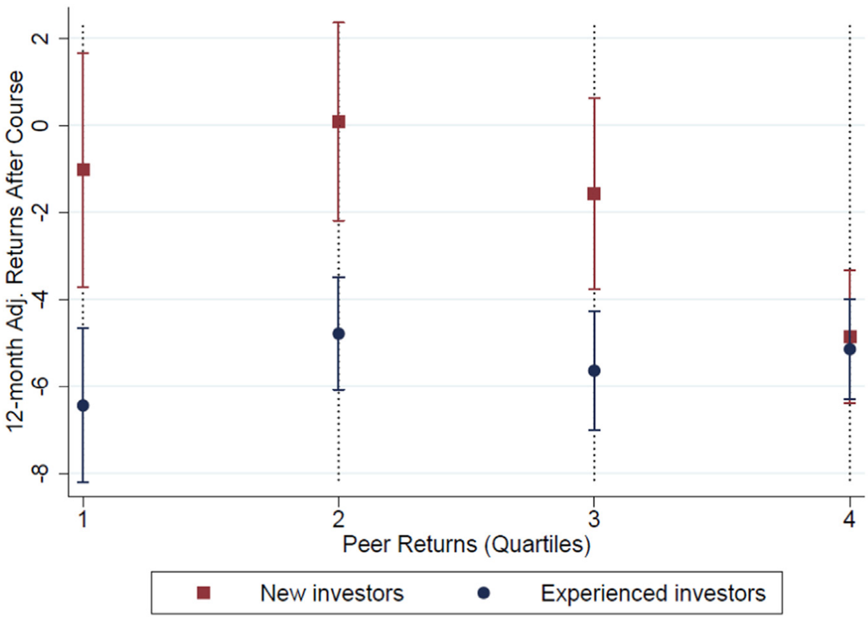

Fig. 3. 12-month portfolio returns after course.
The figure plots the risk-adjusted returns of new investors (squares) and experienced investors (circles) calculated during a 12-month window after the start of a course. The groups are sorted for quartiles of peer returns, calculated during a six-month window prior to the start date of the course. The solid lines represent the upper and lower bounds of 99% confidence intervals.

Peer Returns. The V-shape figure suggests that the monthly standard deviation of the peer returns over a three-year window is precisely the highest for students with large absolute returns. In other words, experienced students with extreme outcomes before the course tend to have portfolios with high idiosyncratic volatility over the long run. Other characteristics, such as the number of trades among experienced classmates, appear to be more similar across courses (Fig. 4-Panel B).

To summarize, students exposed to positive outcomes from peers are more likely to copy the purchases in lottery-type and illiquid stocks from their experienced

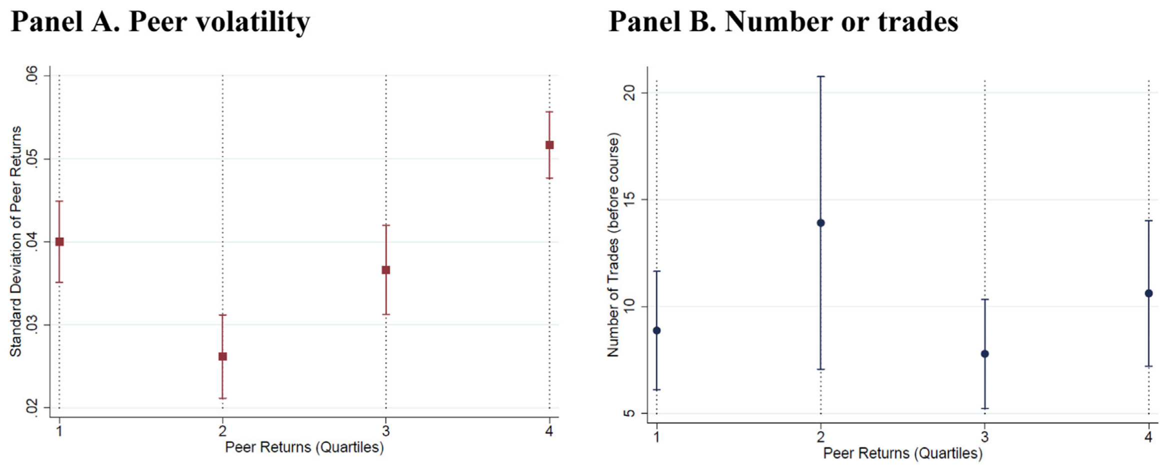

Fig. 4. Portfolios and trading before the beginning of the course.
The graphs plot the standard deviation of monthly returns over a 3-year window for students with trading experience (Panel A) and their yearly number of trades before the course (Panel B). The groups are sorted for quartiles of peer returns, 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.

classmates. Since lottery stocks have low expected returns, new investors from these courses underperform. Other students from courses where peer returns are negative have a smaller propensity to buy lottery stocks. In turn, they outperform both their experienced classmates and new investors from courses where peer returns are positive. Altogether, the evidence suggests that social interactions, particularly when peer outcomes are positive, enhances the attraction to investments with extreme returns but with low subsequent performance.

6. Main channels and robustness tests

In this section, we discuss existing theories that might explain our evidence and we connect our results to other work in the literature. We also present some additional robustness checks and discuss the external validity of our findings.

6.1. Selective communication and negative information neglect

In classroom interactions, 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, Heimer & Simon (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).

Such selective communication would be consistent with our findings, particularly with the evidence that the correlation in stock purchases between experienced peers and new students is exclusive to classrooms where peer outcomes are positive. Relatedly, if negative outcomes such as stock transactions that generate low or negative returns are filtered out to present a positive self-view to others, the information environment in courses without experienced students (*Experience Rate* =0) should be similar to courses where peer outcomes are negative (*Peer Returns*<*0*). To explore this possibility, we compare the stock purchases between new investors that attend courses without experienced classmates to the stock purchases from investors in courses where peers had poor outcomes. We estimate the fraction of new purchases $f_{i,c,t+3,s}$ as a function of stock characteristics in Eq. (3) and classify investors by their classroom interaction: $Peer\ Returns_c^-$ is equal to one if peer returns were negative and zero if no experienced students registered to course c. As we show in Table 11, the coefficients for the interactions between $Peer\ Returns_c^-$ and each stock characteristic are indistinguishable from zero; new investors from courses with no experienced students and from courses with negative peer outcomes seem to purchase stocks with similar attributes.

We also compare the performance of new investors in courses where the Experience Rate is zero to the performance of new investors if peer outcomes are negative. In Fig. 5, the solid line for $X < 0$ are the point estimates of the difference in the first year risk-adjusted returns between new investors from courses where the Experience Rate is zero, and courses where peer returns are below X: $Adj.Ret_c(Experience\ Rate_c = 0) - Adj.Ret_c(Peer\ Returns_c < X)$.[27] According to the figure, the performance of new investors from courses where peer

[27] The estimation controls for investors' gender, age, whether the student took previous courses, and for city and course curriculum fixed effects. The point estimate for X = -10%, is the difference in risk-adjusted returns between new investors from courses with no experienced peers and those from new investors in courses where *Peer Returns* are below -10%.

Table 11
Stock purchases by new investors: *experience Rate* = 0 vs. *Peer Returns* < 0.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOTT x Peer Returns⁻	0.059							0.174
	(0.148)							(0.325)
IVOL x Peer Returns⁻		-0.033						-0.088
		(-0.086)						(-0.162)
BETA x Peer Returns⁻			-1.013					-0.995
			(-1.613)					(-1.573)
SMALL x Peer Returns⁻				-0.62				-0.552
				(-1.062)				(-0.891)
MOM x Peer Returns⁻					-0.624			-0.676
					(-1.434)			(-1.512)
ILLIQ x Peer Returns⁻						-0.107		-0.458
						(-0.358)		(-1.351)
GROWTH x Peer Returns⁻							-0.117	-0.236
							(-0.200)	(-0.393)
Observations	19,863	19,804	19,863	19,863	19,863	19,863	19,863	19,804
R-squared	0.183	0.184	0.184	0.184	0.184	0.183	0.183	0.184

This table shows the estimation of the fraction of purchases in a particular stock by a new investor as a function of stock characteristics and whether experienced students in the class had negative returns ($Peer\ Returns_c^- = 1$) or the class had no experienced students ($Peer\ Returns_c^- = 0$). The dependent variable $f_{i,c,t+3,s}$ is the fraction of purchases by investor i in stock s for 3 months following course c. Control variables are described in the text. The OLS regressions include time-stock, city-stock, course curriculum and class size fixed effects. 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%.

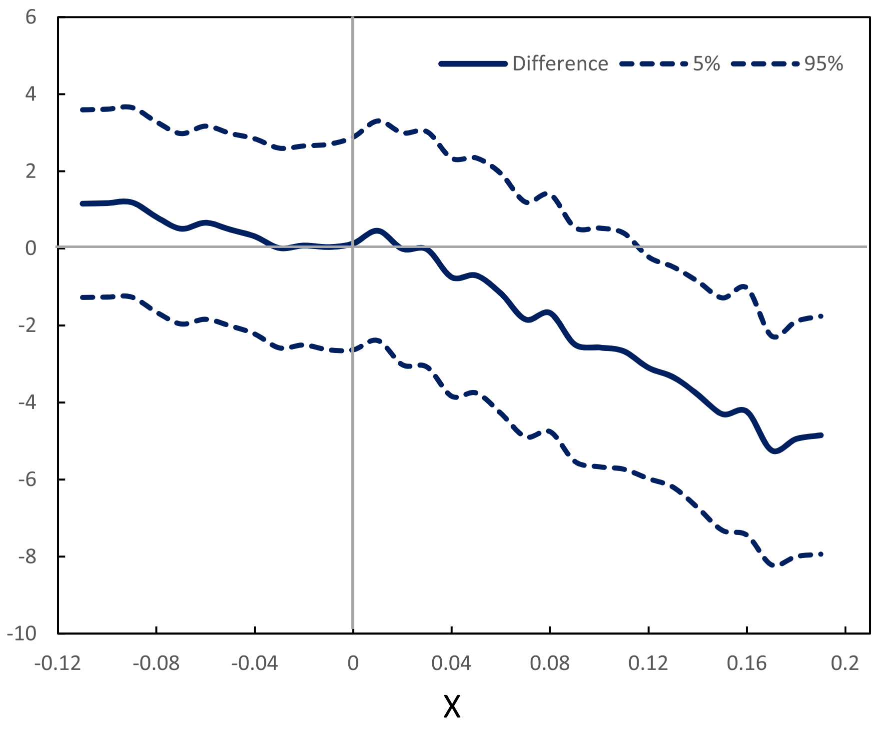

Fig. 5. Performance of new investors: Relative to courses with no experienced students.
For $X < 0$, the solid line depicts the point estimates of the difference in the first-year risk-adjusted returns between new investors from courses without experienced classmates vs. courses where peer returns are below X: $Adj.Ret_c(Experience\ Rate_c = 0) - Adj.Ret_c(Peer\ Returns_c < X)$. For $X \geq 0$, the solid line depicts the point estimates of the difference in the first-year risk-adjusted returns between new investors from courses without experienced classmates vs. courses where peer returns are above X: $Adj.Ret_c(Experience\ Rate_c = 0) - Adj.Ret_c(Peer\ Returns_c > X)$. Dashed lines are the 5% and 95% confidence intervals. The estimation controls for investors' gender, age, whether the student took previous courses, and includes the city and course curriculum fixed effects.

returns are negative is indistinguishable from the performance of new investors that enrolled in courses where there are no students with trading background. The solid line for $X > 0$ refers to the difference in the first year risk-adjusted returns between new investors from courses where the Experience Rate is zero, and courses where peer returns are positive: $Adj.Ret_c(Experience\ Rate_c = 0) - Adj.Ret_c(Peer\ Returns_c > X)$. When peer returns are high (as X increases), new investors from these courses significantly underperform students from courses with no experienced classmates. For example, new investors from courses where *Peer Returns* are greater than 15%, underperform new investors from courses with no experienced peers by 430 basis points per year.

Students in courses where peer outcomes are negative do not appear to observe substantially different kinds of information than students from classrooms with no experienced peers, which would be consistent with the selective communication hypothesis. An alternative explanation is that experienced investors accurately share their performance, but signal receivers ignore negative outcomes –the *Negative Information Neglect* hypothesis. Specifically, if inexperienced students believe they can avoid peers' losses, only positive outcomes would impact market entry and stock selection. 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 disregard negative peer outcomes, assuming that these result from lack of skill or from other unique circumstances that do not apply to them.

When negative outcomes are fully shared, even if these do not affect market participation, they might encourage signal receivers to learn more about stock trading; for example, by raising awareness about the possibility of extreme negative returns. In our setting, conversations about peer returns could prompt students to continue with the curriculum progression. To test this idea, we use the sample of trading courses which have a subsequent level, for example, Stock trading levels 0 and 1. In total, there are 368 of such courses, most of them offered before 2013. We repeat our strategy from Eq. (1), but instead of estimating the likelihood of entering the market, we estimate whether an inexperienced student matriculates for the following course in the program. Our results indicate that positive outcomes from peers, not negative returns, increase the likelihood of continuing with the training series (columns 1 and 2 in Appendix Table B.2). In this case, negative peer outcomes are either not shared, or do not generate additional interest among classmates to continue with the curriculum.

While there are no significant effects from negative peer returns on market participation, stock selection, trading performance, and on course registration, the evidence does not fully rule out the Negative Information Neglect hypothesis. It is possible that the lack of effects from negative outcomes results from a strong bias to communicate positive experiences, and a bias to ignore information in cases where negative outcomes are transmitted.

Even if we were able to correctly measure the strength of each bias in the information transmission process (i.e., Selective Communication vs. Negative Information Neglect), these mechanisms alone cannot explain the documented bias in stock selection; that is, the evidence that students exposed to good outcomes are strongly attracted to lottery-type stocks and to stocks that are less liquid. The lottery anomaly is often explained by models with non-traditional preferences for portfolio skewness (Brunnermeier & Parker, 2005; Barberis & Huang, 2008). A missing element in these models, however, is the extent to which social interactions impact investor behavior. For instance, while individuals might learn about the skewness of returns through their communication with peers, a model solely based on preferences would fail to explain the finding that positive peer outcomes enhance the attraction for stocks with extreme returns. A potential avenue for future research would be to embed communication frictions in preference-based theories. Such a model might be useful to understand the dynamics of asset demand, asset prices, and even, the spillover effects between stocks with similar attributes.

6.2. Risk aversion, loss aversion, and the disposition effect

Individuals that obtain high stock market returns might be more willing to take financial risks (Malmendier & Nagel, 2011). As these investors become less risk-averse when they experience positive outcomes, they may transmit their new risk tolerance to their classmates (Ahern et al., 2014). Such channel may also be asymmetric because previous research on financial loss aversion has shown that stock market losses hurt much less than investors expect, and do not make investors more risk averse (Merkle, 2020). While we do not test directly how risk aversion changes over time for experienced investors, especially for those with recent positive returns, this alternative hypothesis is mostly inconsistent with our evidence. For instance, there are very few differences in stock selection among experienced students based on the performance at the time of the class –experienced peers, regardless from their recent performance, seem to be purchasing the same proportion of lottery stocks, high beta stocks, small stocks, and momentum stocks. The exception are growth stocks, as investors with good outcomes are more likely to buy these after the course, although we also show that new investors are not attracted to this stock characteristic. Moreover, we also show that the three-year returns volatility is large for students with trading background and who recently experienced large absolute returns. It appears that both, peers who exhibit extreme positive returns and those with extreme negative returns, are less risk averse. The lack of effect from negative peer outcomes is mostly consistent with some type of communication bias, while the attraction to specific stock characteristics seems to suggest that there is a bias in stock selection.

An alternative explanation for the lack of effects from negative peer outcomes could be due to the disposition effect. An extensive body of research has shown that investors view realized versus paper returns differently and are more likely to sell to realize gains than losses (e.g., Seru et al., 2009; Heimer, 2016). In our sample, experienced investors are 1.9 times more likely to sell a stock if the price is above the purchase price than if it is below. It could be that experienced investors think of realized gains as “real” and worth talking about, and real gains tend to be winners.

Throughout the paper, we use total portfolio returns, that is, realized and paper gains and losses, to calculate the performance of experienced students in the classroom. We now examine whether the bias from positive peer outcomes originates from the type of returns: realized vs. total returns. To explore this idea, for each experienced stu-

Table 12
Peer outcomes and market participation: total vs. realized returns.

Experience Student Definition =	1 Year				3 Years			
Returns horizon =	6	6	12	12	6	6	12	12
Panel A. Peer outcomes								
Experience Rate	0.030***	0.028***	0.031***	0.029***	0.028***	0.027***	0.028***	0.028***
	(6.266)	(6.090)	(6.436)	(6.205)	(5.734)	(5.555)	(5.722)	(5.542)
Peer Returns		0.014**		0.011**		0.012*		0.006
		(2.320)		(2.045)		(1.775)		(1.107)
Peer Realized Returns	0.004	0.003	0.000	-0.000	0.003	0.002	0.002	0.002
	(0.783)	(0.601)	(0.029)	(-0.025)	(0.560)	(0.370)	(0.446)	(0.396)
Observations	12,114	12,114	12,114	12,114	11,554	11,554	11,554	11,554
R-squared	0.113	0.114	0.114	0.114	0.109	0.109	0.108	0.108
Panel B. Positive vs. negative outcomes								
Experience Rate	0.032***	0.030***	0.033***	0.031***	0.031***	0.029***	0.031***	0.029***
	(6.597)	(6.345)	(6.708)	(6.365)	(6.159)	(5.974)	(6.133)	(5.816)
Max (0, Peer Returns)		0.015**		0.009		0.018**		0.012*
		(2.223)		(1.527)		(2.344)		(1.742)
Min (0, Peer Returns)		0.002		0.005		-0.004		-0.003
		(0.542)		(1.382)		(-1.018)		(-0.964)
Max (0, Peer Realized Returns)	0.001	0.000	-0.001	-0.002	0.001	-0.000	0.001	0.000
	(0.230)	(0.071)	(-0.283)	(-0.295)	(0.157)	(-0.066)	(0.163)	(0.091)
Min (0, Peer Realized Returns)	0.003	0.003	0.001	-0.000	0.001	0.001	0.000	0.000
	(0.666)	(0.615)	(0.150)	(-0.091)	(0.160)	(0.243)	(0.114)	(0.123)
Observations	12,114	12,114	12,114	12,114	11,554	11,554	11,554	11,554
R-squared	0.094	0.095	0.095	0.095	0.093	0.094	0.093	0.093

This table shows the results of regressions on market participation as a function of Realized Peer Returns. Control variables are described in the text. The OLS regressions include time (year-month), city, class size, 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%.

dent, we calculate the realized returns for each sell transaction in 6- and 12-month windows prior to the beginning of the course. We use a First In, First Out basis to calculate returns relative to each stock purchase and then calculate the average returns per investor weighted by transaction size.[28] We then average the returns across investors in the same course and calculate the difference relative to the short-term rate (*Peer Realized Returns*). As expected, realized returns are higher than portfolio returns. The mean for the 12-month window before the course is 5.90%, and the 10th and 90th percentile of the distribution is -2.12% and 23.7%, respectively.

We estimate Eq. (1) using the measure of realized returns for different definitions of investors' experience and for different time windows before the course. Results are presented in Table 12. We do not find evidence that realized returns, rather than total portfolio returns, affect the market participation decision among classmates. This finding might be associated with the specific features of our classroom setting, where social interactions are likely dominated by first impressions. In social groups with closer connections or with repeated interactions, realized gains might be more salient, thus having a stronger effect on peers. Also, relative to the work of Heimer (2016), who studies the disposition effect and social interactions in an online trading platform for individuals making multiple trades every day, our sample of experienced students is considerably less active; individuals make only 10 trades on average during the year before the course, 6 of which are stock purchases and 4 sells. In a setting where active trading is less pronounced, investors could be more likely to talk about their total gains, rather than to focus exclusively on realized earnings. Overall, in our natural experiment, positive portfolio performance, even when returns have not been realized, attracts other individuals to stock trading.

6.3. Survey check

To shed more light on the role of social interactions within the classroom, we use the answers from the electronic survey. We ask former students if they engaged in informal discussions about stock trading with classmates. Among the respondents, 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 re-

[28] Measuring realized returns is not straightforward. For example, it is not obvious how to average the performance between a stock that was sold today for a 10% gain relative to the purchase price a year earlier, to a stock sold for the same gain but which was originally bought only a week earlier. To calculate realized returns, we try multiple measures. First, we use the raw rate of return for each transaction (price of sell relative to the purchase price) and calculate the value-weighted average for all stock sells in the period (results reported in the text). Second, we annualized the rate of return for each transaction and calculated the value-weighted average. Third, we calculate realized gains relative to the price of the stock at the beginning of period, rather than the purchase price (unless the stock was first purchase during the measurement period). The results are similar for the three measures, so we only present the first one for brevity.

turns 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 stronger when peer outcomes are positive.

We test the decision to start trading stocks using the sample of survey respondents. We augment our baseline model (Eq. 1) by interacting our main covariates with a dummy variable that captures if the student had investment conversations with classmates ($talks_i$) as follows:

$$\begin{aligned} y_{ict} = {} & \alpha + \theta talks_i + \beta_2 talks_i \cdot Experience\ Rate_c \\ & + \gamma_1 talks_i \cdot Peer\ Returns_c \\ & + \beta_2 ExperienceRate_c + \gamma_2 PeerReturns_c + \boldsymbol{Q}'\Omega_t \\ & + \boldsymbol{M}'\Psi_c + \boldsymbol{Z}'\Gamma_i + \mu_t + \rho_n + \delta_p + \gamma_l + \ \varepsilon_{i,c} \end{aligned} \tag{4}$$

We use a 6-month window to measure *Peer Returns* and estimate Eq. (4) using as dependent variable our definition of market entry as well as first-year returns of new investors. We use the same set of controls described in Section 3 and include dummy variables for each income and education group of the student reported in the survey. Table 13 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 of the small sample size; only 63 students that answered the survey started trading actively after their training.[29]

The results using the survey sample are important for two reasons. First, we confirm that people react to peer gains rather than to peer losses. Second, it further emphasizes the role of social interactions as a major driver of our results. We show that students who react to peer gains are precisely those who report having investment conversations with classmates.

[29] We do not include class size fixed effects in columns 3 and 4 as there is not enough variation in average returns and class sizes to identify the effects with this small sample.

6.4. Teacher effects

Informal communication might be present among students and between teachers and students. If teachers share their own trading history with students, it might impact stock market participation. To further examine how information is transmitted in the classroom, we study the role of the class instructor on investment choices.

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 (Eq. 1). 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.[30] Columns (3) and (4) in Table B.2 report 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 4).

The absence of teacher effects could be explained as follows: teachers might avoid discussing personal investment stories with students to focus exclusively on the course material. Alternatively, students might disregard information about teachers' outcomes. For example, since teachers are experts in 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. In unreported results, we estimate Eqs. (2) and (3) replacing Peer Returns for Teacher Returns, and Peer Purchases for Teacher Purchases. We do not find any evidence that new investors buy the same stocks as their class instructor after the start of the course.

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 be 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

[30] 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.

Table 13
Social interactions: survey findings.

	Market Participation		First Year Returns	
	(1)	(2)	(3)	(4)
Experience Rate	0.963	1.005	-0.912	-0.481
	(1.431)	(1.451)	(-1.348)	(-0.763)
Talks	-0.017	0.013	0.355**	-2.846
	(-0.400)	(0.299)	(2.167)	(-0.700)
Peer Returns	-0.062*		1.804	
	(-1.689)		(1.375)	
Experience Rate x Talks	-1.081	-1.126	0.957	0.523
	(-1.603)	(-1.623)	(1.341)	(0.763)
Peer Returns x Talks	0.076**		-1.791	
	(1.987)		(-1.416)	
Max (0, Peer Returns)		-0.056**		9.397
		(-2.326)		(0.758)
Max (0, Peer Returns) x Talks		0.070**		-9.394
		(2.528)		(-0.762)
Min (0, Peer Returns)		0.060		0.014
		(0.877)		(0.399)
Min (0, Peer Returns) x Talks		-0.053		-0.656
		(-0.733)		(-0.277)
Observations	744	744	63	63
R-squared	0.295	0.296	0.893	0.893
Controls	Yes	Yes	Yes	Yes
Time, City, Curriculum FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	No	No

This table shows the results of regressions on market participation (columns 1 and 2) and first year risk-adjusted 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 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. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

have positive returns could be more encouraging of stock trading. In column 5 of Table B.2, 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 is driving the market participation decision and the correlation in stock purchases.

6.5. External validity

A final important concern regards the external validity of the findings. The strong peer effects from positive outcomes on market participation and stock selection are estimated using a particular sample of peers. The groups in our study resemble exogenously formed groups and most classmates do not know each other before taking the course. Selective communication and negative information neglect are likely more pronounced in our setting than among groups with close connections. For example, self-presentation concerns are more pervasive when people interact with strangers,[31] and, negative outcomes from close friends might not be fully discarded, impacting decisions when information about these outcomes is transmitted. While we expect some information transmission biases to be attenuated in groups with strong social ties, in several social settings (e.g., among coworkers or in online social networks), people might still benefit from self-enhancement strategies, favoring the transmission of positive outcomes. At the same time, in many of these settings, signal receivers might partially disregard the information about negative outcomes from peers. In such cases, positive outcomes might have a disproportional effect on the choices of other members of the group, such as the ones documented here.

7. Conclusions

This paper examines how social interactions—in particular, informal word-of-mouth communication among peers—affect investor behavior. We examine the decision to trade stocks among students in a financial education program. The setting is empirically attractive due to the conditional quasi-random assignment of individuals to groups where peers have experienced different outcomes. In addition, as opposed to laboratory experiments that rely on small pecuniary rewards, our natural experiment involves a high stake setting where individuals are making real stock transactions.

We find that individuals react more to peer gains than to peer losses when they decide to participate in the stock

[31] 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).

market, and when they choose what types of stocks to buy. Students enrolled in courses where peers have positive returns are more likely to start trading and they purchase similar stocks as their experienced classmates. Our evidence further suggests that new investors exposed to the positive accounts from peers are disproportionally attracted to lottery-type stocks and to stocks with low liquidity. In the case of lottery securities, since these have low subsequent returns, new investors from courses where peer outcomes are positive systematically underperform investors from other courses.

Our evidence suggests that communication among individuals strengthens the demand for specific types of stocks. While models of investors with non-traditional preferences could explain the attraction to stocks with extreme outcomes, they do not address how social interactions affect investors behavior. To the extent that biases in communication induce people to react more strongly to peer gains than to peer losses, introducing such frictions into preference-based theories could be a productive avenue for future research. This new class of models could have the potential to explain the feedback effects between asset prices and the intensity of social interactions.

Declaration of Competing Interest

There is no conflicts of interest.

Data availability

The data that has been used is confidential.

Appendix A. Stock Characteristics

Firm size: The firm size is defined as the market value of equity at the end of the month. Small stocks (SMALL) are firms in the bottom quartile of size.

Book-to-market: We compute a firm's book-to-market ratio in month t using the market value of its equity at the end of December of the previous year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in the prior calendar year. Growth stocks (GROWTH) are companies in the bottom quartile of book-to-market ratio.

Intermediate momentum: Following Jegadeesh & Titman (1993), we define momentum as the cumulative return of the stock over the previous 11 months starting two months ago, that is, the cumulative return from from t-12 to month t-2. Stocks with high momentum (MOM) are those in the top quartile of the momentum distribution each month.

Illiquidity: Following Amihud (2002), we measure stock illiquidity as the ratio of the absolute monthly stock return to its dollar trading volume, $|R_{s,t}|/VOLD_{s,t}$, where $R_{s,t}$ is the return on stock s in month t, and $VOLD_{s,t}$ is the respective monthly trading volume in dollars (scaled by 10^6). Illiquid stocks (ILLIQ) are those in the top quartile of the illiquidity distribution each month.

Market beta: At the end of each month t and for each stock s, we estimate a single-factor market model: $R_{s,d} - r_{f,d} = \alpha_{s,t} + \beta_{s,t}(R_{m,d} - r_{f,d}) + \varepsilon_{s,d}$, where $R_{s,d}$, $R_{m,d}$, $r_{f,d}$ are the daily stock returns, market returns, and risk-free rate for a range of 502 days prior to the last day of the measurement month. High beta stocks (BETA) are those in the top quartile of the distribution of the estimated betas.

Idiosyncratic volatility: Using the estimated $\alpha_{s,t-1}$ and $\beta_{s,t-1}$ for the previous month, we calculate the daily idiosyncratic returns of stock s in month t as $\varepsilon_{s,d} = R_{s,d} - r_{f,d} - \alpha_{s,t-1} - \beta_{s,t-1}(R_{m,d} - r_{f,d})$. The idiosyncratic volatility is defined as $IVOL_{s,t} = \sqrt{var(\varepsilon_{s,d})}$. High idiosyncratic volatility stocks (IVOL) are classified as those in the top quartile of the idiosyncratic volatility distribution for each month.

Lottery stocks: Following Bali et al. (2011), we measure the average of the largest five daily returns within a month for each stock (MAX). Lottery-type stocks (LOTT) are those in the top quartile according to the distribution of MAX each month.

Tables A.1 and A.2

Table A.1
Stocks characteristics: Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Mean	Std. Dev.
(1) MAX	1.00									2.29	2.65
(2) Id. Volatility	0.42	1.00								2.41	3.62
(3) Beta	0.09	-0.02	1.00							0.77	0.27
(4) *ln*(Mkt. cap.)	-0.21	-0.26	0.11	1.00						28.41	2.26
(5) Momentum	-0.16	-0.18	-0.06	0.20	1.00					1.03	0.31
(6) Illiquidity	0.11	0.57	-0.09	-0.22	-0.15	1.00				0.06	0.28
(7) Book-to-mkt	0.25	0.39	0.04	-0.46	-0.25	0.43	1.00			1.09	1.15
(8) Returns	-0.13	0.07	-0.03	0.01	-0.03	0.04	0.05	1.00		0.35	11.49
(9) Risk-Adj. Ret.	-0.14	0.07	-0.02	0.01	-0.02	0.04	0.05	0.93	1.00	0.03	10.72

This table contains the correlation matrix, the mean and standard deviation of the monthly stock characteristics. The sample period is January 2006 to December 2017.

Table A.2
Cross-section return regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MAX	-0.577**							-1.011**
	(-2.663)							(-2.234)
Id. Volatility		0.203						0.522
		(0.944)						(1.269)
Beta			-0.072					-0.817
			(-0.700)					(-0.888)
ln(Mkt cap.)				0.088				0.169
				(1.007)				(1.073)
Momentum					-0.094			0.075
					(-1.464)			(0.728)
Illiquidity						0.862		-1.297
						(1.392)		(-0.795)
Book-to-market							0.333***	0.752***
							(3.583)	(2.842)
Observations	4,097	4,072	4,097	4,069	4,097	4,097	4,069	4,044
R-squared	0.072	0.059	0.054	0.055	0.054	0.054	0.056	0.100

Each month in the sample, we run a firm-level cross-sectional regression of the single-factor market-adjusted returns in that month on a subset of lagged predictor variables in the previous month. The table reports the time-series average of the cross-sectional regression slope coefficients and the associated Newey-West (1987) adjusted t-statistics (in parenthesis). * denotes significance at the 10% level; ** at 5%; and *** at 1%.

Appendix B. Other tables

Tables B.1 and B.2

Table B.1
Market participation: Alternative definition of peer returns.

Experience Student Definition =	1 Year			3 Years		
Returns horizon =	6	12	36	6	12	36
Panel A. Linear peer effects						
Experience Rate	0.024***	0.026***	0.025***	0.023***	0.027***	0.027***
	(4.837)	(5.337)	(4.829)	(4.409)	(5.128)	(4.820)
Peer Returns	0.021***	0.012*	0.013**	0.019**	0.006	0.005
	(2.994)	(1.929)	(2.127)	(2.539)	(0.859)	(0.759)
Panel B. Non-linear peer effects						
Experience Rate	0.025***	0.027***	0.024***	0.025***	0.028***	0.027***
	(4.880)	(5.342)	(4.441)	(4.676)	(5.243)	(4.631)
Max (0, Peer Returns)	0.022***	0.017**	0.011	0.023***	0.009	0.010
	(2.937)	(2.442)	(1.599)	(3.018)	(1.281)	(1.281)
Min (0, Peer Returns)	0.003	0.004	0.001	-0.002	-0.001	-0.002
	(0.914)	(1.245)	(0.285)	(-0.542)	(-0.542)	(-0.533)
Observations	12,114	12,114	12,114	12,114	12,114	12,114
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Curriculum FE	Yes	Yes	Yes	Yes	Yes	Yes
Size 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 the returns of the best performing student with trading background in a given course, calculated in a 6, 12, and 36-month window. The estimation in Panel B is performed with a piecewise linear model that employs a single change in the slope of peer returns at zero. Other control variables are described in the text. The OLS regressions include time (year-month), city, course curriculum, and class size 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 B.2
More courses and teacher effects.

	More courses		Teacher Effects		
	(1)	(2)	(3)	(4)	(5)
Experience Rate	0.216***	0.198***	0.021***	0.022***	0.021***
	(2.929)	(2.659)	(3.868)	(3.092)	(3.072)
Peer Returns	0.472***				
	(5.248)				
Max (0, Peer Returns)		0.673***	0.014**	0.025***	0.024**
		(6.024)	(1.998)	(2.597)	(2.353)
Min (0, Peer Returns)		-0.232	0.004	0.011	0.012
		(-1.045)	(0.901)	(1.427)	(1.535)
Max (0, Teacher Returns)				-0.013	-0.019
				(-1.462)	(-1.583)
Min (0, Teacher Returns)				-0.001	0.001
				(-0.112)	(0.096)
Max (0, Teacher Returns)					-0.010
					(-0.425)
Min (0, Teacher Returns)					-0.004
					(-0.523)
Teacher Experience: *ln*(hours)			0.013	0.000	0.002
			(0.886)	(0.021)	(0.069)
Observations	4,862	4,862	12,113	6,822	6,822
R-squared	0.167	0.168	0.105	0.102	0.102
Controls	Yes	Yes	Yes	Yes	Yes
Time, City, Curriculum, Size FE	Yes	Yes	Yes	Yes	Yes
Teacher FE	No	No	Yes	Yes	Yes

Columns (1) and (2) display the estimates of the likelihood that an inexperienced student matriculates for a course in the following level. Columns (3)-(5) shows the results of regressions on market participation when including teacher fixed effects and teacher returns. 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. T-statistics in parentheses, calculated from clustering standard errors at the course level. * denotes significance at the 10% level; ** at 5%; and *** at 1%.

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