Social Influence in Household Equity Investment: Evidence from Randomized Military Drafts[*]

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Abstract

We provide causal evidence of the peer effect on equity investment in a large-scale natural experiment in Taiwan. We show that retail investors respond to the investment decisions of their military peers who were randomly assigned in compulsory military drafts: retail investors participate more in the stock market, invest more in stocks that peers hold, and obtain more dividend gains and capital gains. Our investigation indicates that retail investors learn valuable information from their peers to make profitable investment decisions. These effects are more pronounced among peers who are more sophisticated and among stocks entailing less behavioral bias. Stocks with more peer clientele outperform stocks with less clientele.

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Introduction

How social interaction drives household financial decision making has been a topic of growing interest. While recent research in economics and finance documents the impact of social interaction on household savings and borrowing decisions, evidence of the impact on household equity investment decisions is still in its nascent stages. Social interactions with peers may provide an important source of information from which households may learn and profit (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992; Ellison and Fudenberg, 1993, 1995; Banerjee and Fudenberg, 2004), or peers' actions may affect households' utility directly (Duesenberry, 1949; Akerlof, 1976; Abel, 1990; Gali, 1994; Bakshi and Chen, 1996; DeMarzo, Kaniel, and Kremer, 2004). Identifying and understanding which channels of social interaction shape households' equity investment decisions—and potentially, by implication, equity investment performance—remain questions of great interest to both scholars of financial economics and practitioners (Kuchler and Stroebel, 2021).

In this paper, we explore how social interaction affects household investment by using a large-scale natural experiment of military peers engaged in compulsory military service in Taiwan. To provide plausible causal evidence, we address the inherent identification challenge in peer effect studies by separating the effect of social interaction on peers' investment choices from the effect of selection into social groups (Manski, 1993), given that social interaction may be formed endogenously with peers that share similar characteristics or preferences. Our study exploits an institutional feature in Taiwan: male Taiwanese are required by law to fulfill compulsory military service, and draftees are randomly assigned to military units as part of this process.[1] This randomized military peer group assignment alleviates endogeneity concerns with respect to peer

[1] The random assignment relies on compulsory military draftees' drawing lotteries in public (i.e., no room for manipulation), and the assignment decision is final. Specifically, the random assignment follows a two-stage process. The first stage consists of draftees drawing a lottery on their individual assignment to the Navy, Army, Air Force, or Coast Guard. The second stage consists of draftees drawing a lottery to a specific military unit within their respective force.

group formation, and therefore isolates the effect of social interaction on investment derived from common characteristics or preferences. Our validation tests provide further evidence for the randomized nature of military peer groups, as each draftee's pre-assignment characteristic is uncorrelated to the military group's average pre-assignment characteristics.

We first examine the effect of social interaction on the extensive margin decision that individuals who participate in the stock market must make. Exploiting randomized military peer groups, we find that peers' stock market participation rate positively impacted individuals during the time of military service as well as after this time of service. Specifically, a one-standard-deviation increase in peers' participation rate increased an individual's likelihood to participate in the stock market by 12.6% in comparison with our sample average. Notably, we do not find any peer effect before military service. In addition, the evidence of peer effects after the military service indicates that such effects are not attributable to peers experiencing common shocks.

Why does social interaction affect individuals' stock market participation? Our investigation of possible mechanisms favors the social learning channel, in which peers are able to learn about valuable equity investment information and opportunities from their peers. In our investigation of heterogeneity in peer effects on participation, we find the effect to be more pronounced when peers are older, have higher incomes, are better educated, or possess more financial literacy before military service. We did not find evidence that directly supports the social utility channel, in which a preference for peers' equity investment decisions depends on the difference between an individual's own investment decisions with those of that individual's peers.

To more fully understand the peer effect on investment decisions, we next investigate the effect of social interaction on the intensive margin, which is an individual's portfolio choice. Using detailed account-level data with over 350 million observations from the Taiwan Stock Exchange (TWSE), we examine if social influence drives investors to hold the same stock as that of their peers. We find that individuals are more likely to invest in the same stock as that of their peers both during as well as after military service. A one-standard-deviation increase in a peer's likelihood to invest in a given stock increases an individual's likelihood to invest in the same stock by 37.2%, relative to the sample average.

As individuals are responsive to peers' investment decisions, we also investigate whether social interaction has a material effect on individuals' investment performance. We observe that peer effect significantly improves individuals' stock market performance both via capital gains and via dividend gains. Interestingly, the effects on the two types of gains feature different degrees of persistency. We find that dividend gains only improve *during* the service year, but neither in years that followed this service year, nor in years that preceded the service year. This finding suggests that peers provided this valuable or profitable information during the time of service, when such profitable information could be communicated to peers within close proximity, potentially due to the sensitive and secretive nature of such information. Utilizing annual data on realized capital gains from trading non-publicly listed stocks, we show that peers' participation contributes to better long-term performance. In addition, we perform a portfolio analysis by sorting stocks into portfolios based on their peer effect exposure. We find that the portfolio with the most peer exposure outperformed the portfolio with the least exposure by a monthly average of 61 to 103 basis points in a three-month holding period. Collectively, our findings suggest that individual investors learn valuable and profitable information from their military peers both during and/or after their time of military service.

Finally, using detailed individual-level holding data, we investigate the heterogeneity of peer effects across stock characteristics in a comprehensive manner that has not yet been explored in the literature. In addition to investor heterogeneity in stock market participation decision across peers' characteristics, we also demonstrate that stocks with higher speculative beta[2], lottery-like

[2] In the empirical asset pricing literature, the CAPM beta measures the sensitivity of stock excessive return to the systematic risk. However, Hong and Sraer (2016) find that high-beta stocks tend to be over-priced due to excessive speculative behavior of the over-confident investors.

attributes, and idiosyncratic volatility exhibit relatively muted peer effects compared to the other stocks. This finding forms the basis for understanding the superior investment performance by peer effects, illustrating how retail investors learn from their peers to avoid stocks associated with higher levels of behavioral bias.

We contribute to the literature on the effect of social interaction on stock market participation or stock purchases by providing causal evidence that investors acquire valuable information from their peers and make similar investment contributions. Prior studies find that stock market participation decisions may be associated with average ownership levels in an individual's community (Brown et al., 2008), the investment performance of one's neighborhood (Kaustia and Knüpfer, 2012), participation decisions of an individual's parents or children (Li, 2014) and family members who work in the finance industry (Knüpfer, Rantapuska, and Spickers, 2023). Stock purchasing decisions could also be correlated with choices made by other traders living in the same city (Feng and Seasholes, 2004), by those in the same neighborhood who also purchase stocks in the same industry (Ivković and Weisbenner, 2007), by those of ones' parents (Knüpfer, Rantapuska, and Sarvimäki, 2023), and by those of one's bank/brokerage recommenders (Balakina et al., 2023).

Our paper differs from the literature in the following three aspects. Firstly, we identify causal peer effects from randomly assigned peer groups while the literature typically finds correlated decisions among endogenously formed peer groups. Though some papers try to make a causal inference by using instrumental variables, such as social capital associated with a neighbor's birthplace (Brown et al., 2008), extended family (Li, 2014), and the investment decisions of a parent's colleagues (Knüpfer, Rantapuska, and Sarvimäki, 2023), it nonetheless remains challenging to verify exclusion restrictions.[3] That said, we are able to test the randomness of peer

[3] One exception is Bursztyn et al. (2014), who use laboratory experiments with fewer than 100 participants on a single pseudo asset to uncover sharp causality of both social learning and social utility on individual investors. In contrast, we use actual stock holdings to conduct a large-scale natural experiment with more than 350,000 investors and 150

group assignments directly by using a detailed panel at the individual level; we also observe no peer effects prior to peer group formation. Secondly, in contrast with the literature that targets peers from particular facilities or neighbors, our sample covers the universe of the young male population in Taiwan and therefore provides external validity to general male individuals in their 20s. Thirdly, we examine the peer effects on both stock market participation and stock selection from a large set of public stocks, while the studies we describe earlier demonstrate peer effects only on participation or on a very limited set of securities.[4]

Our study also contributes to the literature on the welfare implication of peer effects on retail investment. While the literature consistently finds that institutional traders outperform when following peers' investment decisions[5], the corresponding evidence for noninstitutional traders is limited and mixed. On the one hand, Hvide and Östberg (2015) find that peer-pressured portfolios do not exhibit abnormal returns. Additionally, behavioral bias could also socially transmit and impair performance (Heimer, 2016; Hirshleifer, 2020; Han, Hirshleifer, and Walden, 2022). On the other hand, Arrondel et al. (2022) show that information from social groups may help individuals make better forecasts. In a setting of brokerage recommendations, Balakina et al. (2023) show that followers' portfolio quality improves due to diversification through fund investments. Knüpfer, Rantapuska, and Sarvimäki (2023) discover that portfolio characteristics, both expected

assets. Our study thus provides an environment in which individuals can engage with large and diverse groups of people such that the wisdom of crowds emerges, as suggested by Hwang (2023).

[4] Hvide and Östberg (2015) also examine stock-level peer effects but among endogenously formed peer groups, namely coworkers. Unlike the exogenous formation of military peer groups, workplace peer formation can be endogenously affected by individual characteristics and/or preferences. For example, Hvide and Östberg (2015) show that individuals' stock choices may be positively driven by their new colleagues before they start their new jobs, suggesting that both occupation decisions and stock selections may be confounded by unobservable factors mutually shared by individuals and their workplace peers. These unobservable factors may explain our different findings in peer group stock performance, as we document positive dividend gains as well as portfolio performances; in contrast, Hvide and Östberg (2015) find no abnormal returns for peer-pressured portfolios.

[5] The literature that finds institutional investors who make abnormal returns follow their peers includes Cohen, Frazzini, and Malloy (2008) (peers that share common educational backgrounds), Pool, Stoffman, and Yonker (2015) (peers that live geographically close to each other), Sialm, Sun, and Zheng (2020) (funds investing in hedge funds in the same geographical areas), and Kuchler et al. (2022) (institutions residing in regions with high social connectedness). Other seminal papers that document peer effects on investment decisions of institutional investors include Shiller and Pound (1989) and Hong, Kubik, and Stein (2005).

returns and volatility, may be correlated between parents and children. Welfare implications of peer effects on other financial decisions are also mixed. While peer effects improve financial decisions with respect to retirement plan participation (Duflo and Saez, 2002; 2003) and employee stock purchase plans (Ouimet and Tate, 2020), peer effects may negatively affect participation in retirement plans due to discouragement of social comparison (Beshears et al., 2014). We complement this literature by capturing higher dividend gains and abnormal returns from peer-pressured portfolios, and we achieve so using samples less exposed to identification problems.

Lastly, our study contributes to the literature by providing plausible causal evidence in asset pricing. Endogeneity traditionally has been sidelined in asset pricing studies. In recent years, pioneering studies show the causal effect of limit to arbitrage in anomalies (Chu, Hirshleifer, and Ma 2020) and the causal effect of disagreement on asset prices (Chang, Hsiao, Ljungqvist, and Tseng 2023). In turn, our study joins this selective group of papers by showing the causal effect of social influence on an individual's trading behavior and performance.[6]

1. Empirical strategy and data

1.1 Institutional background

Identifying the causal relationship between social interaction and investment decisions is difficult due to the reflection problem (Manski, 1993). One possible reason why researchers may observe common behaviors among a group of individuals is the peer effect. However, people also

[6] In addition to contributing to the literature on asset pricing, our paper contributes to the broad literature on peer effects with respect to general financial decisions. Grinblatt, Keloharju, and Ikäheimo (2008) discover that consumers' automobile purchase decisions may be affected by their neighbors. Using randomized MBA cohorts, Shue (2013) finds that social interaction in alumni networks causes similar corporate acquisition and compensation decisions. Banerjee et al. (2013) find that information about microfinance adoptions can be diffused through an individual's social networks in Karnataka. Meanwhile, Maturana and Nickerson (2019) find evidence that Texas teachers learn about the benefits of mortgage refinancing from nearby teachers, whereas Kalda (2020) shows that financial distress shocks to workplace peers affect individuals' leveraging choices. Using data from Germany, Stolper and Walter (2019) provide evidence that individuals are more likely to follow financial advices from advisors with similar demographic backgrounds. Recent studies use Facebook data to find that social network interactions affect an individual's housing decisions (Bailey et al., 2018), mortgage decisions (Bailey et al., 2019), bank lending behaviors (Rehbein and Rother, 2022), and insurance choices (Hu, 2022). We contribute to this literature by providing plausible causal evidence of social influence among entire generations of young males in Taiwan, which is arguably externally valid across different social and educational backgrounds.

tend to share similar characteristics or face common shocks with their friends. In order to identify causal peer effects, we must exclude the commonality driven by homophily or common shocks.

To address this issue, we exploit individual investment decisions within peer groups formed by a randomized military draft assignment. According to the Constitution of Taiwan, every Taiwanese male citizen must fulfill his compulsory military services. Male citizens receive conscription notice once they turn eighteen and cannot be deferred—with one notable exception: if they are still in school.[7] However, deferring military service limits travel abroad, and attempts to bypass compulsory military service may result in imprisonment. The term of the compulsory military service in our sample is twelve months.[8]

Upon being drafted, individuals are required to first draw a lottery publicly to determine their military force assignment (i.e., Navy, Army, Air Force, or Cost Guard), and they then attend a military force training facility for five weeks. In the fifth week of their training, individuals will draw another lottery publicly to determine the specific military units in which they will serve for the rest of their service. The draft lottery is random with no room for manipulation; as a result, compulsory military servicemen and their military unit peers are randomized peer groups by design. Alternatively, draft candidates may apply for substitute military service or reserved officer status in replacement of regular military services.[9] In this paper, we exclude the substitute military service and reserved officer requests and instead focus exclusively on regular military service.

1.2 Sample and data

We obtain tax returns and registered individual wealth information between 2009 and 2017 from the Financial Information Agency (FIA) of the Ministry of Finance. Every individual in Taiwan is assigned with an encrypted unique identifier. Our data consist of a panel of individual

[7] Upon finishing school, both the timing of receiving notification and the timing to be enlisted is uncertain to a draftee, which makes it difficult for draftees to manipulate the randomized assignment.
[8] Starting from 2014, Taiwanese male citizens born after 1994 January must only undergo a four-month military training period. Male citizens born before 1993 must serve in a military unit for at least twelve months.
[9] Draftees could apply for a substitute military service if they have special health conditions, religious conditions, or specific STEM expertise; this substitute service accounts for 8.0% of draftees in 2009. Draftees with college degrees could apply for reserved office upon passing a selective written exam, which accounts for 2.2% of draftees.

incomes and wealth for each year. For the purposes of this study, we observe individual labor income, dividends, and interests, as well as personal wealth (e.g., real estate, vehicles, stock holdings, savings, liquid wealth).[10] We also match stock holdings with stock prices from the Taiwan Economic Journal (TEJ) database at the ex-right date. For stocks that do not distribute dividends, we match them with the closing price on the last trading date in July.[11] For private stocks, we use book value as the stock price.

1.2.1 Identifying military units and compulsory military servicemen

While we cannot directly observe military services due to the anonymous nature of the FIA data, we are nonetheless able to identify military units as well as compulsory military servicemen with the rich information contained in the data and adequate institutional knowledge. Because our dataset allows us to observe encrypted identifiers of companies from which individuals receive labor income, we can identify workplace peers, given that people are paid by the same company. We first identify military units by focusing on significantly underpaid employees, as compulsory military servicemen are greatly underpaid compared to regular salarymen in Taiwan. The minimum monthly wage was 17,880 New Taiwan Dollar (TWD), or the equivalent of 615 USD in 2011. Meanwhile, compulsory military servicemen only received a monthly wage of 5,890 TWD to 6,630 TWD (203 to 228 USD) in 2011.[12] This observation provides us with a method to identify military units and compulsory military servicemen.

We begin by defining potential candidates of compulsory military servicemen. An individual is classified as a candidate if he satisfies the following conditions: (1) birth year < 1994; (2) age between 18 and 25; and (3) annual income between 5,890 TWD to 100,000 TWD.[13] We then apply

[10] The value of housing, land, and vehicles is recorded by FIA by the time the transaction takes place. The value of real estate is adjusted yearly according to the county-specific public assessment prices (PAP). Savings and other liquid wealth (including treasury and corporate bonds) are imputed using interest income items in individual tax returns and the corresponding interest rate, as in Saez and Zucman (2016).

[11] Companies listed on the Taiwan Stock Exchange distribute dividends once per year. The distribution dates are concentrated at the end of July.

[12] Throughout our paper, we use the median spot exchange rate of TWD/USD in 2011 (29.08).

[13] Military servicemen enjoy 1,000 TWD to 2,000 TWD additional compensation each month if they serve in extremely rural areas or outlying islands.

the following filters to salary-paying institutions, so we may identify military units: (1) public sector; (2) employs more than 10 potential candidates; (3) candidate male ratio > 80%; and (4) total employee male ratio > 70%. Lastly, we identify individuals as compulsory military servicemen using the following criteria: (1) one must be a potential candidate; (2) one must be male; and (3) one can only serve in military units that we identified for no more than two consecutive years. Applying the filters above, we identify 25 military units and 349,715 military servicemen that fulfilled their military service in the period 2011-2015. The sample accounts for about 75% of individuals qualified to fulfill compulsory military service within this sample period.

Figures IA.1 and IA.2 in the Internet Appendix show the distributions of employee duration and age among the identified military units (including both identified compulsory military servicemen and professional soldiers) compared to public sectors or other institutions. Figure IA.1 shows that most employees in the identified military units stay for no more than two calendar years, which is significantly different from the duration in the rest of the institutions. Similarly, Figure IA.2 shows that the age distribution of individuals in military units concentrates in the mid-twenties, while the other public sectors have an age distribution that concentrates in the early forties. Figures IA.1 and IA.2 together provide supporting evidence for the method we use to identify military units and compulsory military servicemen.

1.2.2 Summary statistics

Our sample consists of 349,715 individuals enlisted in one of the 25 military units between 2011 and 2015. For each individual, we include 5 years' worth of observations, which begins with 2 years before the service and ends with 2 years after the service. For instance, if a compulsory military serviceman was drafted in 2012, then we include 5 individual-year observations from this serviceman (i.e., from 2010 to 2014).

Table 1 shows the summary statistics of our observations. The average age to begin military service is 22.7 and the median is 23, which means that most individuals were drafted upon finishing college. The standard deviation for age is 2.37 with 21 (24) as the first (third) quartile.

In Table 1, only 0.9% of servicemen were married during our sample period. In terms of education, close to 300,000 servicemen (85.4%) received a college education, and 30,000 of them (9.0%) in particular studied finance-related majors. We also used registration data to determine each military serviceman's financial background, income, and wealth. We compute a serviceman's wealth as the sum of one's savings, real estate, vehicles, and stocks. Table 1 reports that the average serviceman's income is 112 thousand TWD (3.85 thousand USD) and wealth is 435 thousand TWD (14.96 thousand USD). Also, the median income is 68 thousand NTD (2.34 thousand USD) and the median wealth is 0, as most servicemen are recent college graduates with no property registered under their names. In our robustness check, we place a serviceman's wealth with his respective family's wealth and find consistent results.

Table 1 also shows that the average stock market participation rate is 8.1%, which means that one in twelve military servicemen participated in the stock market during our sample period. The average dividend gain is 4.86 thousand NTD (0.17 thousand USD). Finally, we construct a perfectly balanced panel of individual-year-stock observations with 203 stocks from TWSE. The probability that a given stock is held by an investor is 0.08% during our sample period.

1.3 K-means clustering and elbow method

Till this point, we can identify individuals who were drafted in the same year into the same military units. Nevertheless, the cohort size for each military unit-year pairing remains large.[14] As a result, we employ a Machine Learning approach to segment and reduce the group size.

As outlined in section 1.1, once an individual reaches the age of 18 and stops schooling, he would be eligible to receive the conscription notice. The specific timing as to when the individual

[14] With 5 years of drafting and 25 military units, we could form a coarse set of 125 peer groups. Doing so would result in an average of 349,715/125 ≈2,800 group size within each group.

receives this notice remains uncertain, for the notice could arrive in any month following his schooling period. Consequently, compulsory military service members are drafted into military units in multiple waves throughout the year. Fortunately, compulsory military servicemen receive a fixed (and underpaid) monthly labor income, which means that the timing of an individual's draft must be associated with the annual labor income they earn from the military units in the draft year: the higher his income, the more likely it is that he is drafted close to the beginning of his draft year. Therefore, we use a K-means clustering method to partition each military unit-year cohort into *K* subgroups, based on their annual military income in the draft year.

The key coefficient of the K-means clustering is the number of subgroup *K*. Athey and Imbens (2019) highlight that the choice of the group number *K* should not be driven by the data itself, but rather grounded in the institutional context. Thus, we set *K* to be standard annual draft rounds in Taiwan: 2, 3, 4, 6, and 12, with corresponding grouping intervals of 6 months, 4 months, 3 months (a quarter), 2 months, and 1 month, respectively. We proceed to select the optimal *K* from the aforementioned values by using the widely-used elbow method (Agness et al., 2022), which identifies the *K* that incrementally yields the most significant reduction in the within cluster sum of squares. We find that the optimal value of *K* is 4, as indicated in Table IA.1 in the Internet Appendix. The associated partitioned groups will be the baseline groups that we use throughout the paper. Essentially, this process entails subdividing each unit-year group into 4 unit-quarter batches. Within each batch, military servicemen are drafted into the same military unit during the same quarter of their draft year.

Of the 25 military units, 2 comprise fewer than 50 compulsory military servicemen from 2011 to 2015. Thus, we apply the K-means clustering method to the remaining 23 military units for each draft year, which ultimately yields a total of (23×4+2)×5=470 randomized peer groups in our sample. The average group size is then reduced from around 2,800 to around 750 individuals.[15]

1.4 Random assignment of military servicemen

The lottery that assigns draftees to each military force type as well as the lottery that assigns draftees to each military unit after their initial military trainings are random by design. Although draftees may defer compulsory military service until they complete their final degree, the batch of individuals to be drafted itself is also random. Once a draftee graduates with his final degree (usually a high school or college degree), he may receive conscription notice from the Ministry of National Defense shortly after his graduation. Therefore, it is unlikely that the draftee's social status is correlated with the batch being drafted.

An appealing feature of our study is that the randomness in the compulsory military service draft can be verified empirically. Specifically, we can observe the demographic characteristics of the identified draftees before their service. If the assignment towards each military unit is truly random, then we should expect that pre-service characteristics among compulsory military servicemen in the same peer group are uncorrelated. To test the randomness of military assignments, we follow the approach in Jochmans (2023) to examine if the group-average characteristics significantly predict the characteristics of individuals in the same group.

As we discussed in the previous section, our sample consists of 349,715 compulsory military servicemen who fulfilled their service in the period 2011-2015. Using the K-means clustering method, we are able to partition unit-year cohorts into 4 unit-quarter groups. The larger 23 military units and 20 enrollment quarters (2011Q1 to 2015Q4) together with the 2 smaller military units and 5 enrollment years (2011 to 2015) form a total of 470 peer groups. To access the randomness of the military assignments, we follow the peer effect literature (Sacerdote, 2001) to regress each

[15] As indicated in Table IA.1, the general finding (no effect in pre-period and significantly positive effects in during- and post-periods) remain robust in all choices of *K*. With *K=12*, we are able to obtain an even sharper average peer group size of 250 individuals. We lean toward *K=4* simply for the sake of the signal-to-noise ratio.

individual's pre-assignment characteristics on a peer-group's leave-one-out average pre-assignment characteristics. If the assignment is random, then there should be no relationship between the draftee's background and that of his peers (i.e., the coefficient is zero). As emphasized by Guryan, Kroft, and Notowidigdo (2009), this test tends to give a downward-biased estimation of the coefficient because an individual cannot be his own peer; within a given peer group, individuals with high values of a particular characteristic tend to have peers with relatively low values of that particular characteristic, and vice versa. Consequently, positively grouped peers may appear randomly grouped. We follow the test by Jochmans (2023) that corrects for such a bias, which is essentially the total within-group variation of the characteristics' values.

We test the randomness of the assignment with the following characteristics: age upon drafted, household wealth, marriage status, college degrees, college degrees from public universities, college degrees with a concentration in finance-related fields, and labor income before military service. In Panel A of Table 2, we report the distribution of group-average characteristics among the 470 peer groups. The mean number of peers in a given group is 750.45, and the median number is 513.5.

In Panel B of Table 2, we report the results of our random assignments in our peer group formations test. The null hypothesis that the assignments are random is not rejected for all characteristics, consistent with the details for the institution that each draftee randomly draws as well as with the details for the military unit to which he is assigned. Table IA.2 in the Internet Appendix provides additional tests with respect to this randomized process, which we conduct by following Stevenson (2015) and Ouimet and Tate (2020). When we conduct these tests, we find similar results: that the assignments are random.

2. Social interaction and stock market participation

2.1 Baseline results

We begin our analysis by examining the social influence on stock market participation. Given that compulsory military peers are randomized peer groups, we are able to provide plausibly causal evidence on the effect of social influence on equity investment decisions. Our sample consists of a panel of individual-year observations. For each individual, we include 5 annual observations—from 2 years prior to the service to 2 years after the service. Our study focuses on investment decisions conducted by compulsory military servicemen and their peers within the five-year event window. We define the pre-window as the two years prior to military service (window year: −2, −1), during-window as the service year (window year: 0), and the post-window as two years afterwards (window year: +1, +2). We then run the following regression:

$$Participation_{it} = \alpha_0 + \beta_{-1}\, ParPre_{-it} + \beta_0\, ParDuring_{-it} + \beta_1\, ParPost_{-it} + \gamma' X_{it} + c_t + c_w + c_i + \varepsilon_{it}, \quad (1)$$

in which $Participation_{it}$ is a dummy that equals one if individual i holds any stock in calendar year t. $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$ are the leave-one-out average stock market participation rates among i's military peers in year t only before, during, and after the peer-forming period, respectively. Specifically, $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$ interact participation rates among i's peers, Par_{-it}, in year t with a window dummy that equals one when t is before (window year: −2, −1), at (window year: 0), and after (window year: +1, +2) the service year, respectively. β_{-1}, β_0, and β_1 then capture the peer effects before, at, and after the peer group formation year. Our results are robust to alternative definitions of windows.

Our control variables, X_{it}, include demographic variables such as age, income, and wealth. We follow Fagereng, Gottlieb, and Guiso (2017) and include both the level and the squared term of age to control for potential non-linearity. Controlling for individual income and wealth help us account for participation costs that may discourage individuals from investing in the stock market

(Vissing-Jorgensen, 2003; Grinblatt, Keloharju, and Linnainmaa, 2011; and Cole, Paulson, and Shastry, 2014). X_{it} also includes the average participation of every individual that was born in the same year (birth-year cohort) as individual i. c_i is the individual fixed effect that assumes the rest of the individual-specific unobservable characteristics that may affect his own investment decisions (e.g., deep risk-preference parameters).[16] c_t and c_w are two levels of time fixed effects. c_t is the calendar year fixed effect that absorbs the average stock market participating status in a given calendar year, and c_t could control for market-wide economic conditions that all Taiwanese citizens face in the same year. c_w is the window year fixed effect that assumes the average investment decision that compulsory military servicemen would make in each of the window year. For example, after fulfilling their service, these young male citizens finally begin their careers and start to accumulate wealth, which would lead to increases in stock market participation rates. However, controlling for c_w ensures that the peer effect coefficients will not be affected by such phenomenon.

We report our regression results in Table 3. The standard errors are all two-way clustered at the unit and year level. We find that peers' stock market participation positively affects an individual's participation during the peer formation year. In addition, this effect carries over to the post peer formation years (years after discharge), which suggests a positive effect of social interaction on stock market participation. In column (1), the coefficient is 0.222 (p=0.0070) during the peer formation year and increases to 0.328 (p<0.0002) in the post-formation years. As we show in column (2), we further interact c_t with c_w. Essentially, this interaction, c_{wt}, absorbs all calendar year economic conditions for each window year of the draft year cohorts. Our results remain almost identical. In the specification with all controls (column 4), the coefficient is 0.151 (p=0.0208) during the peer formation year and increases to 0.196 (p<0.0019) in the post-formation years. These effects are also economically significant. A one-standard-deviation increase in peers' stock

[16] Applying a draftee fixed effect alleviates concerns that individuals extrapolate their past experiences when it comes to investment decisions (Malmendier and Nagel, 2011).

market participation leads to a 0.50% increase in individual participation during the service year. Similarly, a one-standard-deviation increase in peers' stock market participation leads to a 1.02% increase in individual participation within two years after discharge. Given that average stock market participation rate among military servicemen in our sample is 8.10%, these increases correspond to increases of 6.17% and 12.59% relative to the unconditional mean. In contrast, Table 3 reports no peer effect before the peer forming year. The coefficient is not statistically significant across all specifications, and the economic magnitude is dramatically smaller when compared with the magnitude post services.

While Manski (1993) raises concerns that positive associations in peer behaviors may be attributed to common background risks shared by individuals in the same peer group or to individuals in the same peer group experiencing common shocks contemporaneously, the absence of a positive association in stock market participation decisions before peer group formation suggests that the effects during and after service should not be driven by other omitted variables. In addition, finding positive and significant effects after military service also diminishes the likelihood that the effect is due to peers experiencing common shocks during the same period, as most individuals will not continue staying in the region where they fulfill compulsory military service after it is dismissed.[17]

Figure 1 provides the dynamics of these peer effects. To further rule out potential pre-trends, we extend our pre-event window to three years and find that all coefficients before service years are qualitatively and statistically indifferent from zero. This further verifies our random assignment setting in the military peer group formation. The peer effect first emerges in the peer forming year (window year: 0) and then carries over to the post peer forming years. Table IA.4 in the Internet

[17] In Hvide and Östberg (2015), individuals who switch jobs exhibit weak but significantly associated investment decisions with their new colleagues *prior to* job switching. In contrast to their findings, the absence of significant results in our study prior to military service offers robust endorsement for the strength of our research design.

Appendix provides details of regression coefficients, and we provide further discussion in Section 5.3.

Collectively, Table 3 and Figure 1 show that the peer effect on stock market participation decisions is persistent. This persistence may come from two channels. First, although military peer groups are randomly assigned, military peers may still maintain relationships with their peers after service; social interaction after service then may lead to a prolonged peer effect on investments. Alternatively, the common knowledge and experience shared in the service year may generate a long-term influence on investment decisions. Although our empirical tests thus far could not separate these two channels, our empirical tests do provide plausible causal evidence of social influence on stock market participation decisions in a large-scale natural experiment.

Finally, we run the identical regression as specification (1) by using samples partitioned via K-means clustering for selected K. We report these results in Table IA.1 in the Internet Appendix. Similar to our baseline model with $K = 4$, results under other K values not only show no peer effects on stock market participation prior to the draft in which military peer groups are formed, but also show a positive and significant peer effect on stock market participation during and after military service. As K increases, the peer effect coefficients for the service period and post-service period decrease slightly. Meanwhile, the t-statistics for these coefficients increase, signifying a disproportionate reduction in the standard errors. Our finding implies that the K-means clustering method enhances the signal-to-noise ratio.

2.2 Potential mechanism

Having established peer effects on stock market participation, we now seek to identify the underlying mechanism driving our empirical discoveries. The literature proposes social learning and social utility as potential mechanisms that account for the influence of peers on investment decisions.[18]

Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) provide seminal work that individuals *learn* useful information from those whom they perceive to possess superior abilities or knowledge. For instance, younger or less educated individuals may gain valuable insights from their elders or more educated peers. Azoulay, Zivin, and Wang (2010) and Waldinger (2010) find that individuals increase their own productivity by learning valuable knowledge in closely-related areas from their peers. Jaffe (1986), Bloom, Schankerman, and Van Reenen (2013), and Tseng (2022) find that firms learn valuable knowledge from their peer firms in closely-related technology areas. Sialm and Tham (2016) meanwhile show the spillover effect of investment across different but affiliated business segments of public firms.

The other competing channel is social utility. Social utility is best described as the preference of individuals to "keep up with the Joneses," whereby individuals mimic their peers and demonstrate preferences that help them directly attain higher utilities, even if their actions themselves do not contribute to utility gain.[19] Abel (1990), Gali (1994), and Campell and Cochrane (1999) provide theoretical models applying social utility channels to explain asset prices. Social utility may drive peer stock market participation since individuals who make similar participation decisions attain higher utility. Hirshleifer and Teoh (2003) provide an overview of social utility channels.

In the upcoming section, we demonstrate that the peer effect we identified supports the social learning channel by showing that individuals are more influenced by peers with characteristics associated with possessing valuable information.

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[18] Other channels proposed in the literature (e.g., enforcement of social norms, belief contagion) are less likely to explain the finding of peer effect on investment; therefore, we do not review these channels here for brevity's sake. For a comprehensive review, please see Kuchler and Stroebel (2021).

[19] Social learning and social utility could potentially intertwine, as individuals may find it more advantageous to align themselves with individuals who appear to possess useful information; therefore, we categorize this scenario as social learning. This classification arises from the core objective of imitating these specific peer types, which is to acquire relatively valuable information.

2.3 Evidence of social learning: Heterogeneity in peer effects

While we cannot explicitly test the social utility mechanism without making further assumptions, we can examine the social learning mechanism by exploring the heterogeneity in the peer effect that we documented in Section 2.1. If compulsory military servicemen are indeed *learning* from their peers, then we expect stronger peer effects from peers who are older, who earn more, who are more educated, or who are financially more sophisticated. Therefore, we test if our baseline result from Section 2.1 is more salient for peers whom individuals are more likely to learn from. To do so, we partition the military peers into groups that individuals are more likely to learn from (older, higher income, more educated, higher financial literacy) and groups that individuals are less likely to learn from (younger, lower income, less educated, lower financial literacy). For the ease of viewing, we combine the peer effect during the peer forming year (previously termed $ParDuring_{-it}$) and years after peer forming (previously termed $ParPost_{-it}$) to repost the peer effect in the periods after the peer groups are formed, $ParFormed_{-it}$. For a given peer characteristic s, we then separate $ParFormed_{-it}$ into two variables, $ParFormed_{-it}^{s,high}$ and $ParFormed_{-it}^{s,low}$, which are the effects from peers of high and low s, respectively. For example, $ParFormed_{-it}^{age,high}$ equals 1 and is the participation rate among older peers during and after the peer forming period, and equals zero otherwise. We run the following specification to explore the heterogeneity in peer effects:

$$Participation_{it} = \alpha_0 + \beta_{-1}\, ParPre_{-it} + \beta_0^{high}\, ParFormed_{-it}^{s,high} + \beta_0^{low}\, ParFormed_{-it}^{s,low} + \gamma' X_{it} + c_{wt} + c_i + \varepsilon_{it}, \quad (2)$$

in which the selected s includes age, income, education, and financial literacy. We measure income as the income before each individual enlisted to avoid any confounding factors.[20] Peers who received high (low) education are those with (without) a college degree. We measure an individual's financial literacy to reflect if he majored in finance, economics, or management in college.

We provide evidence in Table 4 of the social learning mechanism that individuals use to learn information from more knowledgeable peers, which improves their own economic decision making. To validate specification (2), the coefficients in Table 4 column (1) are consistent with our estimation in Table 3 column (4), in which the coefficient for $ParFormed_{-it}$ is significantly positive while the coefficient for $ParPre_{-it}$ is insignificant from 0. From columns (2) through (5), we find positive and significant peer effects from peers who are older, received a higher labor income before enlisting, are more educated, and have higher financial literacy. We also find significantly negative peer effects from peers who received lower labor income before enlisting and who are less educated. The coefficients on $ParPost_{-it}^{s,high}$ and $ParPost_{-it}^{s,low}$ are significantly different for all characteristics s. Table 4 therefore provides supporting evidence for the social learning channel. In sum, it appears that individuals indeed learn from their more knowledgeable and experienced peers.

3. Social influence and portfolio choice

Next, we investigate whether social interaction affects individuals' portfolio choices. Specifically, we examine if individuals are more inclined to invest in the same stock as their peers. Although our dataset comprises the complete universe of personal stock holdings, we focus on publicly traded stocks that are less susceptible to a downward bias in peer effect estimation driven by asymmetric access to private investments. To ensure the robustness of our analysis, we exclusively consider stocks that have been publicly traded on the TWSE throughout the entire

[20] Though most individuals do not have long-term occupations before they fulfill compulsory military services, a fiscal income could potentially proxy for maturity or social experience.

sample period (2009-2017). Additionally, we require that each stock has an average market capitalization larger than 0.01% of the total market capitalization on TWSE. These criteria reduce our sample to 203 stocks. We proceed by conducting a panel regression at the individual-year-stock level:

$$HoldStock_{ist} = \alpha_0 + \beta_{-1}\, StockRatioPre_{-ist} + \beta_0\, StockRatioDuring_{-ist} + \beta_1\, StockRatioPost_{-ist} + \gamma' X_{it} + c_{st} + c_{wt} + c_i + \varepsilon_{ist}, \tag{3}$$

in which $HoldStock_{ist}$ is a dummy equal to one if investor i holds stock s in year t and $StockRatioPre_{-ist}$, $StockRatioDuring_{-ist}$, and $StockRatioPost_{-ist}$ are the share of i's military peers who held stock s in year t when t is before, during, and after the peer forming period, respectively. The covariates included in X_{it} consist of age, the square of age, income, and wealth. We choose not to control for birth cohort as in equation (1) in order to avoid a potential collinearity effect.

To account for various effects, we include the following fixed-effects: c_{st}, c_{wt}, and c_i are the stock-by-calendar year, calendar year-by-window year, and individual fixed effect, respectively. c_{st} absorbs the average stock holding status for a given stock in a specific given year. c_{wt} controls for the average likelihood of an individual holding any stock across all combinations of window years and calendar years. Finally, c_i addresses individual-specific characteristics that could influence one's decision to hold a stock.

Our findings, which we present in Table 5, indicate significant and positive peer effects on stock choice decisions both during and after the peer forming period. These effects echo our findings in Section 2.1. The influence of peers extends beyond stock market participation, affecting the likelihood of individuals investing in the same stocks. For instance, as shown in column (2), a one-percentage-point increase in peers holding a specific stock corresponds to a 0.119% increase in an individual's likelihood of holding that stock during the peer forming period, and a 0.210% increase thereafter.

In columns (3) and (4), we combine the during- and post-peer effects and find consistent results. In column (4), a one-percentage-point rise in the proportion of peers holding a specific stock leads to a 0.186% increase in an individual's likelihood of holding that stock during and after the peer forming period. Notably, a one-standard-deviation increase in the holding ratio during and after the service year results in a significant 37.2% relative increase in the probability of holding the same stock within the same year, as compared to the unconditional mean probability of holding any random stock in any year. Finally, the peer effect is insignificant from zero before the peer formation period, which again serves as a placebo test and is consistent with our finding for market participation.

Our findings provide evidence on the extensive margin of peer effect by including new stock market participant, thereby departing from the literature that examines conditional peer effects among individuals making at least one stock purchase (e.g., Hvide and Östberg, 2015).

4. Social influence and investment performance

Whereas we provide supporting evidence for social learning in previous sections of this paper, we now seek more direct evidence as to whether individuals improve their investment decisions after assimilating valuable insights from their financially sophisticated peers.

We begin by examining whether following peers' trading decisions increases two distinct types of gains: dividend gains and capital gains. Unlike the indirect inferences of performance that exist in the literature, we use an approach that employs a direct performance measure, which highlights the welfare implications of peer effects on investment choices. We then construct peer-pressure portfolios and test whether these portfolios yield abnormal returns across various holding horizons. Finally, we delve into the heterogeneity of peer effects at the stock level, aiming to comprehend which types of stocks exhibit more pronounced or subdued peer effects. This endeavor allows us to provide micro-level grounding for our findings related to welfare implications.

4.1 Individual investment performance

4.1.1 Dividend Gains

We begin by investigating dividend gains. While we observe individuals' stock holdings at the annual level, we do not observe when individuals purchase or sell stocks, which makes measuring individual investment performance subject to noise or assumptions.[21] Thus, we take advantage of tax return data to measure individuals' performance based on their stock dividend gains. Stock dividend gains are taxable in Taiwan; therefore, we can observe individuals' annual stock market performance. While we do not observe individuals' entire stock market investment performance, we argue that the stock dividend gain is not only a good proxy, but also a novel contribution to the household investment literature. Measuring individual investment performance, we run the following regression:

$$Performance_{it} = \alpha_0 + \beta_{-1}\, ParPre_{-it} + \beta_0\, ParDuring_{-it} + \beta_1\, ParPost_{-it} + \gamma' X_{it} + c_{wt} + c_i + \varepsilon_{it}, \qquad (4)$$

in which we replace the dependent variable of equation (1) with individual stock market performance measured by the total amount of dividends received by individual i in year t. We also include an additional control of the market value of individual stock holdings to control for the size effect.

Table 6 shows that the peer effect is positive and significant during the peer formation period. We find positive and significant coefficients for peer effects on dividend gains across different

[21] A common practice in the literature is to assume an artificial stock holding period (e.g., thirty days) to compute the gain of investors' losses during the holding period. Given that our purpose is to estimate peer effects, this practice introduces measurement errors to both the right-hand and left-hand side variables in our regressions. Therefore, we will begin with alternative methods.

specifications. Column (6) shows that a one-standard-deviation increase in the peer participation rate raises an individual's dividend gain by 5,500 TWD (189.5 USD) during the peer forming period (p=0.0768).[22]

Whereas the peer effect is persistent with respect to stock market participation and portfolio choices, the peer effect on investment performance is transient. In fact, the peer effect disappears after individuals are discharged, and the economic magnitude is small and statistically insignificant. This finding suggests that valuable information was passed among peers (e.g., word-of-mouth communication) in close proximity (Hong, Kubik, and Stein, 2005; Pool, Stoffman, and Yonker, 2015). Such valuable, sensitive information is less likely to be communicated via other means (e.g., texts, email) in a timely manner after being discharged. Thus, this finding suggests that social learning appears to be the leading channel through which peers' affect individuals' investment performance.

We similarly study the heterogeneity of peer effect on investment performance. By running specifications that replace the dependent variable in equation (2) with $Performance_{it}$, we observe that social learning yields better performance Table IA.5 in the Internet Appendix shows that individuals performed better during the peer forming period than peers who are older, earn more labor income, are more educated, or possess more financial literacy.

4.1.2 Capital gains from trading non-publicly listed stocks

While dividend gains tend to capture yields from long-term holdings, our focus shifts to capital gains, which emphasizes gains from short-term trading. It is worth noting that while capital gains from trading publicly listed stocks are exempt from taxation in Taiwan, capital gains from trading non-publicly listed stocks were subject to taxation as part of the capital gains category before

[22] The dividend yield in our sample is 2.87%, which is slightly lower than the value-weighted average dividend yield among all stocks on the Taiwan Stock Exchange (4.15%). This is consistent with the fact that younger adults are more likely to hold growth stocks than value stocks.

2013.[23] Given our limited sample duration, our focus in this subsection will be solely on that of compulsory military servicemen drafted in 2011. We study a sub-sample period spanning from 2009 to 2012 (i.e., covering two years preceding their service and one year afterward). To streamline our analysis, we use Table IA.6 to present our results derived from a simplified version of equation (4), for which we control for regular covariates and the calendar year fixed effect alone.

Table IA.6 indicates a negative and significant coefficient during the service period (in 2011), while a positive and significant coefficient emerges after the service period (in 2012). Specifically, a one-standard-deviation increase in peers' participation rates corresponds to a decrease of 134 NTD in capital gains from trading non-public stocks during the service year as well as a subsequent increase of 286 NTD in capital gains after the service year. Despite the relatively limited occurrence of non-public stock trades in Taiwan, our results suggest that following peers' investment decisions is particularly rewarding when individuals hold onto non-public stocks for periods exceeding one year. According to Barber et al. (2009, 2014), a significant number of Taiwanese retail traders under-perform due to excessive trading. Longer holding periods, particularly for non-public stocks for which acquiring information may be challenging, contribute to enhancing overall investment performance.

4.2 Peer effect portfolio analysis

We next use a portfolio analysis to investigate stock performance. If valuable information is transmitted via peer effects, then we will be able to design a profitable trading strategy of longing stocks with high peer effects and shorting stocks with low peer effects.

$$HoldStock_{ist} = \alpha_0 + \beta_{st,formed}\, StockRatioFormed_{-ist} + \gamma' X_{it} + c_t + \varepsilon_{ist}, \tag{5}$$

[23] Capital gain tax for publicly-listed stocks was also implemented between 2013 and 2014 in Taiwan but was part of the income tax, which cannot be disentangled from the FIA dataset. After 2014, the Taiwanese government removed the capital gain tax for both public and non-public stocks.

We first estimate the peer effect exposure of each individual stock by running equation (5), a simplified version of equation (3), for which we regress $HoldStock_{ist}$ on $StockRatioFormed_{-ist}$, the product of $StockRatio_{-ist}$ and an indicator variable that takes the value of 1 *during* and *post* the service year for each stock at each year. This process allows us to obtain a panel of $\beta_{st,formed}$ coefficients for all 203 stocks from 2011 to 2017. We then sort stocks into terciles based on their peer effect exposure and construct three value-weighted portfolios (low, middle, high). In addition, we construct a hedge portfolio by longing the stocks in the high peer effect exposure portfolio and shorting the stocks in the low peer effect exposure portfolio. We then compute the portfolio returns as well as the risk-adjusted abnormal returns.

Table 7 shows the results of our portfolio analysis. We report monthly average returns for each of the portfolios at the beginning of every August for 3 different lengths of holding periods:[24] 3 months, 6 months, and 12 months. We report raw returns as well as abnormal returns, adjusting for the market factor and the Fama and French (1992) 3 factors. The high peer-effect portfolio exhibits significantly positive monthly raw returns and risk-adjusted abnormal returns for all holding periods. On the other hand, the signs for raw returns and abnormal returns for the low peer-effect portfolio are mixed. The long-short portfolio exhibits significantly positive raw returns and abnormal returns for the 3-month holding periods, ranging from 0.61% to 1.03%, which translate into 7.32% to 12.36% annualized returns. The raw returns of the long-short portfolio for the 6-month and the 12-month holding periods are positive and statistically different from 0, although the corresponding abnormal returns yield mixed results. Collectively, our findings suggest that the superior performance of the peer-effect portfolio is relatively short-lived, consistent with the fact that Taiwanese investors tend to hold stocks in a short horizon (Barber et al., 2009, 2014, 2020). This finding also supports our hypothesis that the peer effects on stock

[24] As we mentioned in Section 1.2, the FIA records stock holding information at the end of every July. Therefore, we construct peer-effect sorted portfolios at the beginning of every August and focus on portfolio performances for different lengths of holding periods.

market participation and stock selection contain profitable information and that learning from peers leads to welfare improvements.

Our portfolio analysis results deviate from recent empirical discoveries regarding the influence of peer effects on investment performance[25]. This discrepancy could stem from the distinction between our research designs and those of previous studies. For instance, Hwang (2023) suggests that homophily within endogenously formed peer groups could explain why peer effects do not enhance retail investors' investment decisions. Coworkers in the same workplace or neighbors in close proximity may already share very similar sets of information; thus, their interaction does not yield much insight.

According to Hwang (2023), the wisdom of the crowd—a concept suggesting that individuals can benefit from collective opinion—requires individuals to interact with a large and diverse group of people for the phenomenon to effectively manifest. Only through such interaction can individuals access valuable information beyond their own sets of information. Our randomized military draft provides an ideal environment in which the wisdom of the crowd could potentially come into play. This context likely accounts for our ability to discern abnormal returns in peer-pressured portfolios. In the next section, we examine the specific types of valuable information that contribute to these abnormal returns.

4.3 Stock peer effect heterogeneity

Our direct performance measures and portfolio analysis collectively suggest that individuals are apt to make improved investment decisions when they engage in substantial interactions with their peers. This leads to an intriguing question: what precisely constitutes the valuable information that these young male citizens acquire from their peers?

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[25] For instance, Hvide and Östberg (2015) discovered that stocks purchased aggressively by coworkers do not exhibit abnormal returns. Similarly, Huang, Hwang, and Lou (2021) demonstrated that trading driven by word-of-mouth does not enhance retail investors' performance.

Given their age and limited experience, our young compulsory military servicemen likely do not possess private corporate information. An alternative explanation could be that they learn to avoid obvious investment mistakes from their financially sophisticated peers. This hypothesis could be substantiated by scrutinizing the specific types of stocks that exhibit more pronounced or weaker peer effects:

$$HoldStock_{ist} = \alpha_0 + \beta_{-1}\, StockRatioPre_{-ist} + \beta_1\, StockRatioFormed_{-ist}$$
$$+\theta\, StockRatioFormed_{-ist} \times I(HighGroup_{st}) + \gamma' X_{it} + c_{st} + c_{wt} + c_i + \varepsilon_{ist}, \quad (6)$$

Equation (6) is an extension of equation (3) in which we examine peer effects at the individual-year-stock level and further interact $StockRatioFormed_{-ist}$ with an indicator variable, denoted as $I(HighGroup_{st})$, which signifies whether stock s belongs to a specific characteristic group in year *t*. The sorting attributes consist of the beta value, MAX, from Bali, Cakici, and Whitelaw (2011), and idiosyncratic volatility measured in June of each year (i.e., one month before the holding status). According to Hong and Sraer (2016), an exceedingly high beta value might prompt speculative behavior among investors. MAX from Bali, Cakici, and Whitelaw (2011) serves as a proxy for lottery-like stocks, which tend to exhibit lower returns in the subsequent months. Lastly, all else being equal, a higher idiosyncratic volatility implies that holding such stocks entails a higher level of non-compensating risk. Stocks in each year are categorized into terciles based on the 3 characteristics. The indicator variable, $I(HighGroup_{st})$, takes the value of one when stock *s* is in the top tercile group in year *t*, and zero otherwise.

Table 8 presents our outcomes of the interaction analysis. Stocks exhibiting elevated beta values, MAX scores, and idiosyncratic volatility display notably diminished peer effects compared to other stocks during and after service years. The effect is about three-quarters for stocks with high beta values, and slightly more than one-half for those with high MAX scores and high idiosyncratic volatility when compared to the remaining stocks. Our findings suggest that the wisdom-of-crowd makes itself manifest in helping young male individuals avoid stocks entailing a higher level of behavioral bias. Through mitigating behavioral bias, individuals can achieve enhanced investment performance.

5. Additional analysis and robustness tests

5.1 Alternative test for random assignment

In this section, we provide additional analyses and robustness tests. We first conduct additional randomization tests following Stevenson (2015) and Ouimet and Tate (2020). In the peer effect literature, the leave-one-out mean method is often used to represent peers' decisions; however, this method incurs a negative bias in the estimated peer effect. This negative bias may result in a false conclusion of randomization when the peer group is indeed not randomized. In addition to that of the Jochmans (2023) method, Stevenson (2015) and Ouimet and Tate (2020) suggest that we could randomly split our sample into two groups, using only half of the sample as our testing sample and using the other part of the sample to construct peer decisions:

$$S_{it} = \alpha + \beta\overline{S_{-\iota t}} + X_{it}\tilde{\beta} + \Phi + \varepsilon_{it} \qquad t = 0, -1, or - 2 \tag{7}$$

Equation (7) is the regression specification to test ex ante randomness. $S_{i,t}$ is the following social status: $Income_{i,t}$, income of individual *i* at year *t*; $Wealth_{it}$, wealth of individual *i* at year *t*; and $HWealth_{it}^{h}$, total household wealth for individual *i* (sum over parents and siblings) at year *t*. $\overline{S_{-\iota t}}$ is the average social status of i's military peers. Control variables X include age and years of education attainment. Φ is a set of fixed effects including employer, draft-year, month-of-birth, county-of-birth, and county-of-enlisting fixed effect. We focus on the time before and during the compulsory military service. Similar to our rationale that we described in Section 1.3, we expect that $\overline{S_{-\iota t}}$ has no predictive power on S_{it} in years before the service if the assignment is truly random.

Table IA.2 in the Internet Appendix presents our results of this randomness testing. After we control for age, education, and various fixed effects, we find that individual wealth, family wealth, finance majors, and individual income are not associated with those of military peers prior to enlisting. During the enlisting year, individual income is positively and significantly associated with the income of military peers. This association reflects the fact the compulsory military servicemen are all severely underpaid when compared to regular salarymen. In sum, this set of additional randomness tests supports our findings in Section 1.3 that military peer groups are indeed randomized peer groups.

5.2 Placebo Tests

In Section 1.3 and Section 5.1, we showed that the assignments for compulsory military peers to military units are random. To examine that our findings stem from the influence of randomized military peers, we next perform additional placebo tests. Specifically, we create artificial military peers by randomly assembling military servicemen. This approach allows us to demonstrate the absence of a peer effect on both stock market participation and dividend gains originating from these artificially created military peer groups.

We construct artificial military peer groups by randomly assigning military servicemen drafted in the same draft year into different units. We then estimate the placebo leave-one-out average participation rates accordingly. Table IA.3 in the Internet Appendix reports the peer effects on stock market participation decisions and stock dividend gains derived from placebo military peers following the same specifications as in equation (1) and equation (4). Our observation reveals that none of the coefficients—whether before, during, or after the service year—are statistically distinct from 0, which implies the absence of peer effects stemming from artificial military peer groups.

Our placebo tests offer supplementary evidence affirming that our model specifications effectively account for potential confounding factors. Moreover, these placebo tests corroborate that the notable peer effects we observe in our study result from peer assignments established during the military draft process.

5.3 Representativeness of our sample

An important consideration when employing randomized controlled trials (RCTs) and natural experiments is the issue of external validity. While establishing a definitive causal connection between specific variables of interest, findings may be context-specific and hence exclusively applicable to only the precise observations within a given, specific analysis. However, this concern is somewhat mitigated in our study due to the extensive coverage of observations, encompassing the entire population of young male citizens in Taiwan. Given this broad scope, our findings are likely to be applicable to young males in various regions globally.

Another concern researchers might raise pertains to the representativeness of both the Taiwanese market and its citizens. In terms of the Taiwanese market, the TWSE weighted index (TWII) has a Sharpe ratio of 0.584 from 2009 to 2017. This value closely resembles the Sharpe ratio of the US stock market, which is 0.513 during the same period. This similarity suggests that investment opportunities in Taiwan are neither distinctive nor atypical.

To demonstrate the similarity between Taiwanese investors and those in other countries, we focus on a specific aspect of the stock market participation life cycle that has been identified in the literature. Using Norwegian administrative data, Fagereng, Gottlieb, and Guiso (2017) reveal that participation rates display a hump-shaped trend with age, peaking in the age range of 55 to 60. In Figure 2, we endeavor to replicate this pattern by using the Taiwanese population. We discover that stock market participation rates among Taiwanese citizens not only exhibit a comparable hump-shaped pattern, but also possess nearly identical magnitudes. Specifically, stock market participation rates in both countries hover around 20% when investors are in their 20s, reach a peak of 50% to 60% when investors are in their 50s, and subsequently decline to around 30% when investors are in their 70s.

This alignment in investment opportunities and stock market participation characteristics underscores the resemblance between Taiwanese investors and their global counterparts. Consequently, the outcomes we highlight in our paper, particularly those pertaining to the causal peer effect and economic implications, hold relevance for individuals across various regions.

5.4 Dynamics of the peer effect

This section studies the dynamics of peer effects on investment decisions previewed in Figure 1. We extend our pre-assignment year to three years to allow for additional observations to study trends before military assignment. We run the following regression to identify the peer effect in each year:

$$Participation_{it} = \alpha_0 + \sum_{f=-3}^{2} \beta_f Par_{-it} \mathbf{1}_i(t,f) + \gamma' X_{it} + c_{wt} + c_i + \varepsilon_{it}, \qquad (8)$$

This specification essentially involves interacting year dummies with the leave-one-out mean participation rates of military peers. The estimated β_f coefficients encapsulate the peer effects for each year. The β_f coefficients estimated across difference specifications are presented in Table IA.4 in the Internet Appendix. We observe that all peer effect coefficients before the service year are statistically insignificant; in contrast, the coefficients during and after service are consistently positive and statistically significant. The economic magnitudes of the peer effects during and after service align with the corresponding coefficients in Table 3, reinforcing the robustness of our documented peer effects and underscoring the validity of our pre-trend. We plot Figure 1 based on the coefficients that we estimate in Table IA.4 column (4).

6. Conclusion

Using a large-scaled natural experiment, we provide plausible causal evidence of social influence on retail investors' stock investment decisions and performance. We use compulsory military training for young male adults, coupled with the random assignment of draftees into military units, as our identification strategy for identifying peer effects. We find that retail investors respond to investment decisions made by their military peers. Retail investors are more likely to participate in the stock market if their peers do, more likely to invest in the same stock as their peers do, and are more likely to perform better in the stock market. While peer effects on participation and portfolio choices carry over after service years, the effect on performance is more transient and requires closer interaction.

Our investigation of possible channels favors the explanation that retail investors learn valuable information from their peers. The increases in participation and performance are more pronounced for retail investors who are older, earn more, are better educated, and possess more financial literacy than their peers. In addition, stocks with more peer clientele outperform stocks with less clientele for a 3-months holding period. Stocks with higher speculative beta, lottery-like properties, and idiosyncratic risk exhibit weaker peer effects. Our findings speak directly to the recent call for more empirical evidence on whether social influence drives individuals to make better decisions (Bikhchandani et al., 2021; Kuchler and Stroebel, 2021; Hwang, 2023). Our findings suggest that social interaction during the time of military service leads to a transmission of valuable equity investment-related information from military peers to individuals.

This paper provides plausible causal evidence of peer effects on stock market participation decisions, portfolio choice decisions, and trading performance. Our central findings—that peers affect market participation decisions persistently and that peers provide profitable information in the short-term—highlight a previously undocumented temporal variation along different dimensions of peer effects. Future studies that explore modeling household investment decisions should consider word-of-mouth elements and incorporate transient peer effects on investment performance.

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Appendix A: Variable Definitions

Dependent variables

Participation$_{it}$ is an indicator variable that takes the value of 1 if individual *i* holds any public stock in year *t*, and 0 otherwise.

Dividend$_{it}$ is the stock dividend gain in thousand NTD that individual *i* receives in year *t*.

HoldStock$_{ist}$ is an indicator variable that takes the value of 1 if individual *i* holds stock *s* in year *t*, and 0 otherwise.

Participation rates and stock holding ratios

Par$_{-it}$ is the leave-one-out average participation rate of individual *i*'s military peers in year *t*.

ParPre$_{-it}$ is the leave-one-out average participation rate of individual *i*'s military peers during years before the service. Specifically, it is calculated as the product of ***Par***$_{-it}$ and an indicator variable that takes the value of 1 during years before the service ($t=-1$ *or* -2), and 0 otherwise.

ParDuring$_{-it}$ is the leave-one-out average participation rate of individual *i*'s military peers during the service year. Specifically, it is calculated as the product of ***Par***$_{-it}$ and an indicator variable that takes the value of 1 during the service year ($t=0$), and 0 otherwise.

ParPost$_{-it}$ is the leave-one-out average participation rate of individual *i*'s military peers during years after the service. Specifically, it is calculated as the product of ***Par***$_{-it}$ and an indicator variable that takes the value of 1 during years after the service ($t=1$ *or* 2), and 0 otherwise.

ParFormed$_{-it}$ is the leave-one-out average participation rate of individual *i*'s military peers *after* the military peer group is *formed*. Specifically, it is calculated as the product of ***Par***$_{-it}$ and an indicator variable that takes the value of 1 *during and after* the service year ($t=0$, *1 or 2*), and 0 otherwise.

Par$^{Birth\ Cohort}$ is the leave-one-out average participation rate among military servicemen who share the same birth year with individual *i*.

StockRatio$_{-ist}$ is the leave-one-out average ratio of individual *i*'s military peers that hold stock *s* in year *t*.

StockRatioPre$_{-ist}$ is the leave-one-out average ratio of individual *i*'s military peers that hold stock *s* during years before the service. Specifically, it is calculated as the product of ***StcokRatio***$_{-ist}$ and an indicator variable that takes the value of 1 during years before the service ($t=-1$ *or* -2), and 0 otherwise.

StockRatioDuring$_{-ist}$ is the leave-one-out average ratio of individual *i*'s military peers that hold stock *s* during the service year. Specifically, it is calculated as the product of ***StcokRatio***$_{-ist}$ and an indicator variable that takes the value of 1 during the service year ($t=0$), and 0 otherwise.

StockRatioPost$_{-ist}$ is the leave-one-out average ratio of individual *i*'s military peers that hold stock *s* during years after the service. Specifically, it is calculated as the product of ***StcokRatio***$_{-ist}$ and an indicator variable that takes the value of 1 during years after the service ($t=1$ *or* 2), and 0 otherwise.

StockRatioFormed$_{-ist}$ is the leave-one-out average ratio of individual *i*'s military peers that hold stock *s after* the military peer group is *formed*. Specifically, it is calculated as the product of ***StcokRatio***$_{-ist}$ and an indicator variable that takes the value of 1 during and after the service year (*t=0, 1 or 2*), and 0 otherwise.

Demographic variables

Age is calculated as the difference between individual *i*'s birth year and the year of observation.

Income is the labor income individual that *i* receives (in thousand NTD) in the year of observation.

Wealth is the sum of assets, savings, real estate, vehicles, and equities, and is measured in thousand NTD. The value of real estate and vehicles are recorded by FIA by the time the transaction takes place. The value of real estate is adjusted yearly according to county-specific public assessment prices (PAP). Savings are imputed using the interest income items in individual tax returns and the corresponding interest rate as in Saez and Zucman (2016). The value of each stock holding is calculated as the product of the number of shares individual *i* holds in year *t* and the closing price of the stock before the ex-right dates. If the stock is not public, we simply adapt the book value as the price.

College is an indicator variable that takes the value of 1 if individual *i* holds a bachelor's degree.

Finance is an indicator variable that takes the value of 1 if individual *i* holds a bachelor's degree in the field of finance, economics, or management.

Marriage is an indicator variable that takes the value of 1 if individual *i* is married.

Return measures

Raw Return is the total monthly stock/portfolio return.

Risk-Free Rate is the one-year fixed rate (at monthly frequency) on the First Bank, following the definition in the Taiwan Economic Journal (TEJ).

Excess Return for a stock/portfolio is the difference between its **Raw Return** and the **Risk-Free Rate**.

CAPM α is the abnormal monthly return by regressing a stock's/portfolio's **Excess Return** on the stock market excess return. The stock market return is calculated as the marketcap-weighted **Raw Returns** of all stocks on the Taiwan Stock Exchange (TSE) and the Taipei Exchange (OTC).

3-Factor α is the abnormal monthly return by regressing a stock's/portfolio's **Excess Return** on the 3 Fama and French (1992) 3 factors: MKT, SMB, and HML.

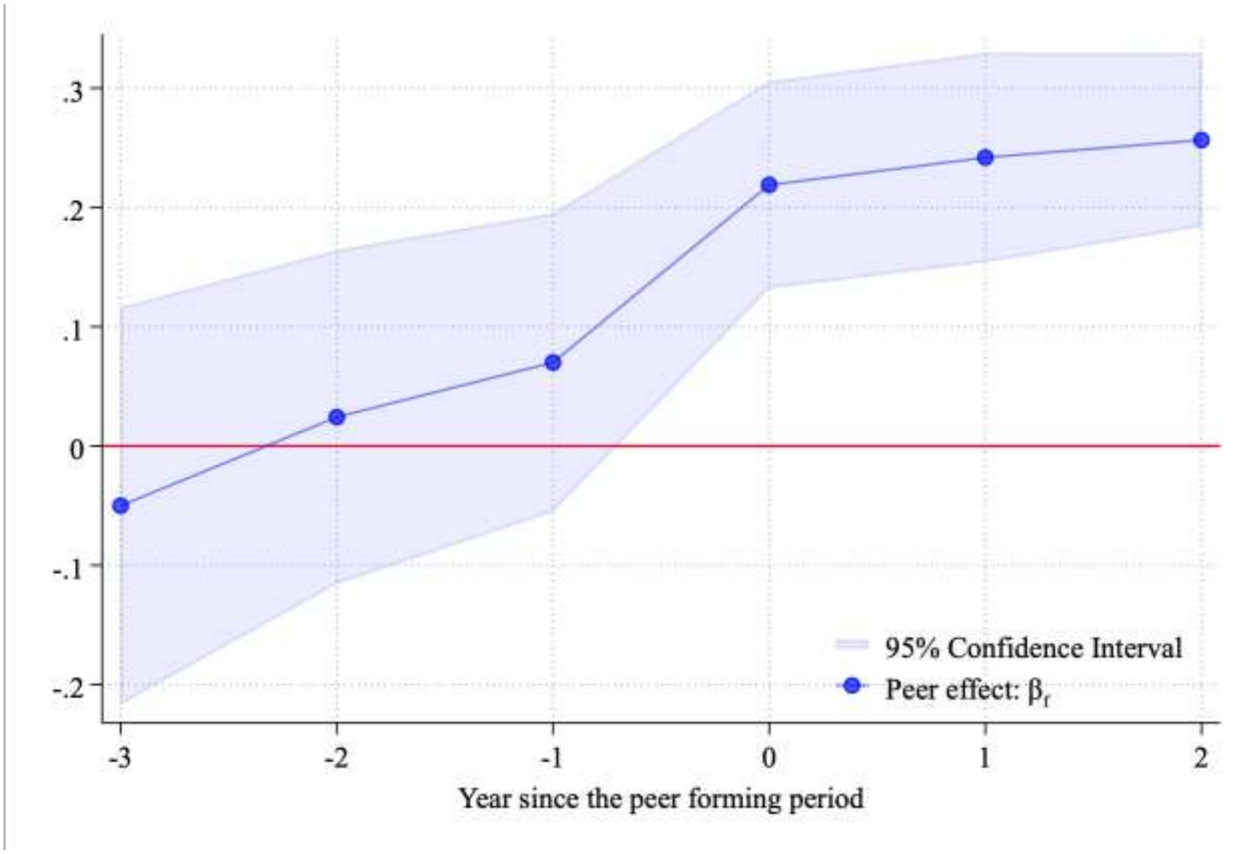

Figure 1. Dynamics of the Peer Effect on Stock Market Participation

The figure plots the year-by-year peer effect coefficients $\widehat{\boldsymbol{\beta}_f}$ estimated from the following regression: $\boldsymbol{Participation_{it}} = \boldsymbol{\alpha_0} + \sum_{f=-3}^{2} \boldsymbol{\beta_f}\, \boldsymbol{Par_{-it}} \mathbf{1}_i(\boldsymbol{t}, \boldsymbol{f}) + \boldsymbol{\gamma}' \boldsymbol{X_{it}} + \boldsymbol{c_{wt}} + \boldsymbol{c_i} + \boldsymbol{\varepsilon_{i,t}}$, in which $\boldsymbol{Par_{-i,t}}$ is the participation rate of peers in year $\boldsymbol{t}$. We use $\boldsymbol{f}$ to denote the year since the peer forming year. $\mathbf{1}_i(\boldsymbol{t}, \boldsymbol{f})$ is an indicator variable equal to 1 if year $\boldsymbol{t}$ equals $\boldsymbol{f}$ since $\boldsymbol{i}$'s peer formation year.

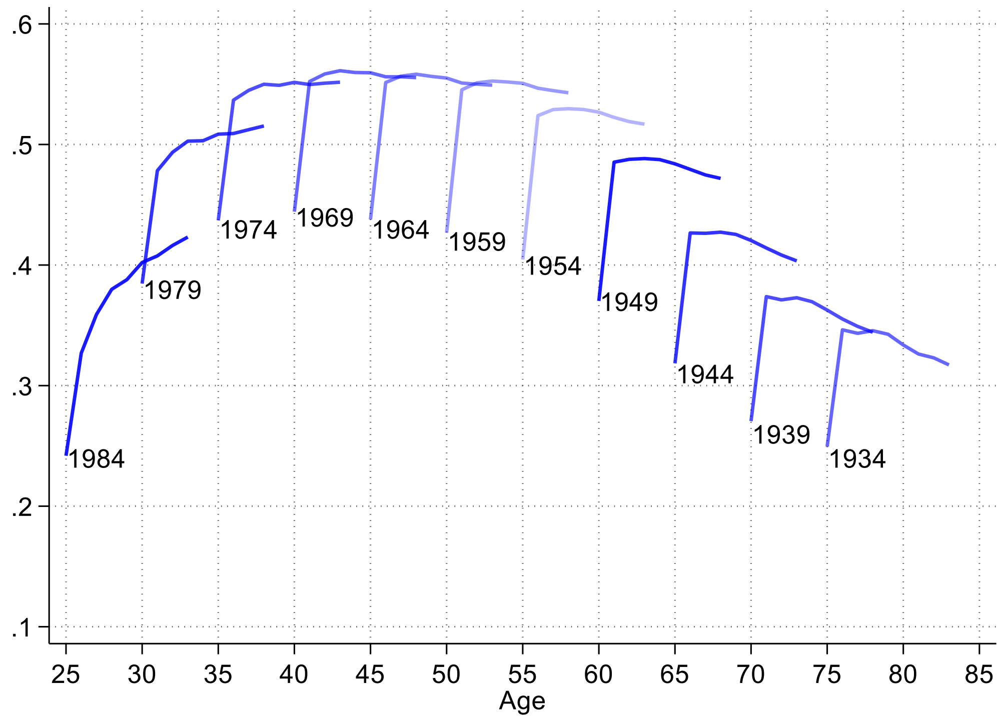

Figure 2. Stock Market Participation Rates across Age

This figure plots the mean stock market participation rates by age for 5-year age cohorts over the period 2009 to 2017 as in Fagereng, Gottlieb, and Guiso (2017). For example, the 1984 (1979) curve stands for the average stock market participation rates from 2009 to 2017 among all Taiwanese citizens born between 1980 and 1984 (1975 and 1979).

Table 1
Summary Statistics

This table provides summary statistics of the main variables in our analysis. The sample consists of 349,715 compulsory military servicemen enrolled between 2011 and 2015. For each individual, we include 5 years' worth of observations: from 2 years before service to 2 years after service. The dependent variables include the following: $Participation_{it}$, an indicator variable that captures whether individual i participates in the stock market in year t; $Dividend\ Gain_{it}$, the stock dividend (in thousand dollars) that individual i receives in year t; and $HoldStock_{ist}$, an indicator variable that takes the value of 1 if individual i holds stock s in year t, and 0 otherwise. The main explanatory variables are $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$ ($HoldStockPre_{-ist}$, $HoldStockDuring_{-ist}$, and $HoldStockPost_{-ist}$), the leave-one-out average participation rates, Par_{-it}, (stock holding ratio for stock s, $StockRatio_{-ist}$) of individual i's military peer before, during, or after that peer's service. $ParFormed_{-it}$ ($HoldStockFormed_{-ist}$) is the leave-one-out average participation rate (stock holding ratio for stock s) of individual i's military peer during and after service year. $Par^{\text{Birth Cohort}}$ is the average participation rate among individual i's birth cohort (all servicemen who share the same birth year with i). Other demographic variables include individual i's age, income (in thousand dollars), wealth (in thousand dollars), and indicator variables that capture if one holds a bachelor's (and advanced) degree, if one holds a bachelor's (and advanced) degree in areas related to finance, economics, and management, and if one is married. Wealth is the sum of savings, value of vehicles, value of real estate, and stocks in market prices.

	N	Mean	Std.	Min	p25	p50	p75	Max
Dependent Variables								
$Participation_{it}$	1,748,575	0.081	0.273	0	0	0	0	1
$Dividend\ Gain_{it}$	1,748,575	4.86	394.04	0	0	0	0	409,710.21
$HoldStock_{ist}$	354,960,725	0.0008	0.0280	0	0	0	0	1
Military Peer Participation Rates								
Par_{-it}	1,748,575	0.081	0.028	0	0.061	0.078	0.098	0.254
$ParPre_{-it}$	1,748,575	0.025	0.032	0	0	0	0.056	0.201
$ParDuring_{-it}$	1,748,575	0.016	0.033	0	0	0	0	0.220
$ParPost_{-it}$	1,748,575	0.040	0.052	0	0	0	0.090	0.254
$ParFormed_{-it}$	1,748,575	0.056	0.050	0	0	0.069	0.097	0.254
$StockRatio_{-ist}$	354,960,725	0.0008	0.0018	0	0	0	0.0009	0.1429
$StockRatioPre_{-ist}$	354,960,725	0.0002	0.0009	0	0	0	0	0.1429
$StockRatioDuring_{-ist}$	354,960,725	0.0002	0.0008	0	0	0	0	0.1250
$StockRatioPost_{-ist}$	354,960,725	0.0004	0.0014	0	0	0	0	0.1250
$StockRatioFormed_{-ist}$	354,960,725	0.0005	0.0016	0	0	0	0.0005	0.1250
Other Cohort Participation Rates								
$Par^{Birth\ Cohort}$	1,748,575	0.081	0.039	0.008	0.055	0.076	0.105	0.418
Other Variables								
Age	1,748,575	22.70	2.37	16	21	23	24	39
Income	1,748,575	112.29	143.07	0	6.75	68.26	163.98	21730.38
Wealth	1,748,575	435.39	3302.96	0	0	0	598310.40	886951.74
College	1,748,575	0.854	0.354	0	1	1	1	1
Finance	1,748,575	0.090	0.286	0	0	0	0	1
Marriage	1,748,575	0.009	0.094	0	0	0	0	1

Table 2
Average Peer Group Characteristics and Test of Randomness

This table provides summary statistics of average group characteristics across military draft groups (Panel A) and the Jochmans (2023) test for random assignment (Panel B). Our sample consists of 25 military units that intake drafted military servicemen from 2011 to 2015. Except for 2 military units that intake fewer than 50 compulsory military servicemen during this time period, we conduct a K-means clustering method and subdivide each unit-year peer group into 4 based on the expected quarter that one is drafted. Our sample comprises a total of 470 peer groups ((23×4+2) ×5=470). *N* is the total number of individuals for the 470 peer groups. *Age*, *Wealth* (in thousand TWD), *College* (ratio of servicemen with college degrees), *Finance* (ratio of servicemen with finance-related college degrees), and *Marriage* (ratio of married servicemen) are the average characteristics of each group by the time that military service begins. *Income* is the average income (in thousand TWD) one-year before the peer-forming year. In Panel B, we report *t*-statistics and corresponding *p*-values of the Jochmans (2023) random assignment tests. The null hypothesis is that individuals are randomly assigned into groups.

	Panel A: Distribution of Peer Group Means							**Panel B**: Tests of Randomness Jochmans (2023)		
	mean	Std.	min	p25	p50	p75	Max	*t*-statistic	*p*-value (two-tail)	*p*-value (right-tail)
N	750.45	771.33	8	182	513.5	1,095	6,048			
Age	22.92	0.85	20.25	22.51	22.88	23.22	27.05	−1.3947	0.1631	0.9185
Income	71.06	29.29	0.20	61.15	69.50	79.42	169.21	−0.7619	0.4461	0.7769
Wealth	8,504.05	2,597.97	1,869.33	6,724.63	8,178.13	9,962.93	23,900	0.3675	0.7132	0.3566
College	0.86	0.15	0.22	0.77	0.91	0.98	1.00	0.0768	0.9388	0.4694
Finance	0.08	0.04	0.00	0.06	0.09	0.11	0.21	0.0705	0.9438	0.4719
Marriage	0.008	0.019	0.000	0.001	0.003	0.007	0.222	0.1793	0.8577	0.4289

Table 3
Peer Effect on Stock Market Participation Decisions

This table reports the panel regression of compulsory military servicemen' stock market participation decisions on the participation rate of their military peers along with a set of control variables and fixed effects in a $[-2, 2]$ event window. The dependent variable, $Participation_{it}$, is an indicator variable that equals 1 if individual i holds any stock in year t. The independent variables, $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$, are the participation rates of military peers in year t when t is within the two-year window before, at, and within the two-year window after the peer forming period, respectively, and zero otherwise. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year fixed effect, window year fixed effect, and participation rates of individual i's birth cohort. t-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$Participation_{it}$			
	(1)	(2)	(3)	(4)
$ParPre_{-it}$	0.055	0.054	0.046	0.032
	[0.84]	[0.82]	[0.67]	[0.50]
$ParDuring_{-it}$	0.222***	0.221***	0.179**	0.151**
	[3.60]	[3.55]	[3.13]	[2.87]
$ParPost_{-it}$	0.328***	0.326***	0.233***	0.196***
	[6.66]	[6.61]	[5.17]	[4.58]
Controls			yes	yes
Birth Cohort Par_{-it}				yes
Individual FE	yes	yes	yes	yes
Calendar Year FE	yes			
Window Year FE	yes			
Calendar Year × Window Year FE		yes	yes	yes
N	1,748,575	1,748,575	1,748,575	1,748,575
Adj. R2	0.736	0.736	0.737	0.737

Table 4
Heterogeneity in Peer Effects on Participation

This table reports the panel regression of compulsory military servicemen' stock market participation decisions on the participation rates of military peers of different characteristics along with a set of control variables and fixed effects in a [−2, 2] event window. The dependent variable, $Participation_{it}$, is an indicator variable that equals 1 if individual i holds any stock in year t. $ParPre_{-it}$ is defined as in Table 3. $ParFormed_{-it}$ is the military peers' participation rate in year t when t is at or after the peer forming period, and 0 otherwise. The independent variables are the participation rates of individual i's military peer subgroups of high/low past labor income, high/low age, with/without a college degree, and with/without a college degree in finance or economics-related areas during and after the military peer group formation. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year fixed effect, window year fixed effect, and participation rates of individual i's birth cohort. t-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. The F-statistic tests the null hypotheses that the coefficients for participation rates from high/low and with/without groups are the same. ***p<0.01, **p<0.05, *p<0.1.

	$Participation_{it}$				
	(1)	(2)	(3)	(4)	(5)
$ParPre_{-it}$	0.052	0.056	0.018	0.014	0.035
	[0.89]	[0.82]	[0.26]	[0.17]	[0.57]
$ParFormed_{-it}$	0.198***				
	[4.77]				
$ParFormed_{-it}^{age,high}$		0.244***			
		[9.64]			
$ParFormed_{-it}^{age,low}$		−0.016			
		[−0.43]			
$ParFormed_{-it}^{income,high}$			0.250***		
			[10.61]		
$ParFormed_{-it}^{income,low}$			−0.099**		
			[−2.91]		
$ParFormed_{-it}^{education,high}$				0.408***	
				[9.38]	
$ParFormed_{-it}^{education,low}$				−0.069*	
				[−2.07]	
$ParFormed_{-it}^{finance,high}$					0.122***
					[7.09]
$ParFormed_{-it}^{finance,low}$					0.058***
					[3.36]
Control	yes	yes	yes	yes	yes
Birth Cohort Par_{-it}	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes	yes
F-Statistic of coefficients difference		30.44	113.28	55.85	3.78
p-value		0.0006	0.0000	0.0001	0.0879
N	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575
Adj. R2	0.737	0.737	0.737	0.737	0.737

Table 5
Peer Effect on Stock Choice Decision

This table reports the panel regression of the stock holding decisions of compulsory military servicemen on the ratio of military peers holding the same stock in the same year along with a set of control variables and fixed effects in a [−2, 2] event window. The dependent variable, $HoldStock_{ist}$, is an indicator variable that equals 1 if individual i holds stock s in year t. The independent variables, $StockRatioPre_{-ist}$, $StockRatioDuring_{-ist}$, and $StockRatioPost_{-ist}$ are the stock holding ratios of stock s among individual i's military peers in year t when t is within the two-year window before, at, and within the two-year window after the peer forming period, respectively, and zero otherwise. The independent variable, $StockRatioFormed_{-ist}$, is the stock holding ratio of stock s among individual i's military peers in year t when t is at or within the two-year window after the peer forming period, and zero otherwise. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year × stock fixed effect, and calendar year × window year fixed effect. t-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$HoldStock_{ist}$			
	(1)	(2)	(3)	(4)
$StockRatioPre_{-ist}$	0.040	0.046	0.042	0.047
	[1.46]	[1.69]	[1.49]	[1.72]
$StockRatioDuring_{-ist}$	0.119**		0.119**	
	[2.50]		[2.50]	
$StockRatioPost_{-ist}$	0.210***		0.209***	
	[3.79]		[3.78]	
$StockRatioFormed_{-ist}$		0.189***		0.186***
		[4.02]		[4.01]
Control			yes	yes
Individual FE	yes	yes	yes	yes
Stock × Calendar Year FE	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes
N	354,960,725	354,960,725	354,960,725	354,960,725
Adj. R2	0.049	0.049	0.049	0.049

Table 6
Peer Effect on Stock Dividends

This table reports the panel regression of compulsory military servicemen' stock dividend gains on the participation rate of military peers along with a set of control variables and fixed effects in a $[-2,2]$ event window. The dependent variable is the total dividend (in thousand TWD) received by individual *i* in year *t*. The independent variables $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$ are defined as in Table 3. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year × window year fixed effect, participation rate of individual *i*'s birth cohort, and the total value of stocks (in thousand TWD) held by individual *i* in year *t*. *t*-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$Dividend\ Gain_{it}$ (in thousand TWD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$ParPre_{-it}$	43.98	43.98	50.45	42.37	42.37	46.19
	[0.35]	[0.35]	[0.40]	[0.30]	[0.30]	[0.31]
$ParDuring_{-it}$	171.5*	171.5*	170.6*	167.8*	167.8*	167.0*
	[2.06]	[2.06]	[2.08]	[2.02]	[2.02]	[2.03]
$ParPost_{-it}$	23.57	23.57	15.74	18.74	18.74	13.36
	[0.25]	[0.25]	[0.16]	[0.19]	[0.19]	[0.13]
Total Value of Holding Stocks				0.0287**	0.0287**	0.0284**
				[3.19]	[3.19]	[3.26]
Control		yes	yes		yes	yes
Birth Cohort Par_{-it}			yes			yes
Individual FE	yes	yes	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes	yes	yes
N	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575
Adj. R2	0.331	0.331	0.331	0.333	0.333	0.333

Table 7
Peer-Pressured Portfolio Performance

This table reports cumulative portfolio returns constructed by using the level of peer pressures. We conduct the stock picking test for each stock at each year (July). Stocks are sorted into peer-pressure tercile portfolios (low, mid, and high) at the end of each July. We report raw returns and abnormal returns from CAPM as well as the Fama and French (1992) 3-factor model. The returns are monthly average returns for different holding periods. *t*-statistics (in brackets) are calculated from Newey-West standard errors with 5 lags. ***p<0.01, **p<0.05, *p<0.1.

Holding Period	Returns (%)	Low (1)	Mid (2)	High (3)	High - Low (3) − (1)
3 months	Raw Return	−0.519	0.191	0.276	0.795***
		[−0.98]	[0.20]	[0.59]	[5.69]
3 months	CAPM α	0.208	1.298***	0.814***	0.606**
		[1.10]	[13.74]	[6.90]	[3.57]
3 months	3-Factor α	−0.651**	0.866*	0.377**	1.028***
		[−3.20]	[2.23]	[3.01]	[5.40]
6 months	Raw Return	−0.006	0.500	0.386*	0.393**
		[−0.01]	[0.87]	[2.34]	[3.26]
6 months	CAPM α	0.302	1.132***	0.657**	0.356***
		[1.66]	[22.37]	[3.42]	[3.95]
6 months	3-Factor α	1.318***	1.849***	0.936**	−0.382***
		[4.12]	[13.30]	[2.96]	[−4.12]
12 months	Raw Return	0.454**	0.705*	0.728***	0.273***
		[2.66]	[2.08]	[4.52]	[5.53]
12 months	CAPM α	0.475***	0.742***	0.746***	0.270***
		[5.45]	[5.34]	[7.78]	[5.25]
12 months	3-Factor α	0.394	−7.321**	0.017	−0.376
		[0.55]	[−3.39]	[0.01]	[−0.24]

Table 8
Peer Effect on Stock Choice Decision

This table reports the panel regression of the stock holding decisions of compulsory military servicemen on the ratio of military peers holding the same stock in the same year along with a set of control variables and fixed effects in a [−2, 2] event window. The dependent variable, $HoldStock_{ist}$, is an indicator variable that equals 1 if individual *i* holds stock *s* in year *t*. The independent variables, $StockRatioPre_{-ist}$ and $StockRatioFormed_{-ist}$, are defined as in Table 5. $HighGroup_s$ is an indicator variable that takes the value of one if stock s is within the top tercile Beta/MAX/IVol group at the end of June in year *t*, and zero otherwise. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year × stock fixed effect, and calendar year × window year fixed effect. *t*-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$HoldStock_{ist}$					
	Beta Group		MAX Group		IVol Group	
	(1)	(2)	(3)	(4)	(5)	(6)
$StockRatioPre_{-ist}$	0.047	0.049	0.050^{*}	0.051^{*}	0.049	0.051^{*}
	[1.77]	[1.79]	[1.88]	[1.91]	[1.85]	[1.88]
$StockRatioFormed_{-ist}$	0.204^{***}	0.204^{***}	0.210^{***}	0.209^{***}	0.204^{***}	0.203^{***}
	[4.22]	[4.22]	[4.25]	[4.24]	[4.19]	[4.18]
$StockRatioFormed_{-ist}$	-0.048^{**}	-0.049^{**}	-0.098^{***}	-0.099^{***}	-0.088^{***}	-0.089^{***}
$\times HighGroup_{st}$	[−2.70]	[−2.71]	[−4.18]	[−4.17]	[−3.90]	[−3.90]
Control		yes		yes		yes
Individual FE	yes	yes	yes	yes	yes	yes
Stock × Calendar Year FE	yes	yes	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes	yes	yes
$HighGroup_{st}$	*Absorbed by the stock × calendar year fixed effects.*					
N	354,960,725	354,960,725	354,960,725	354,960,725	354,960,725	354,960,725
Adj. R2	0.049	0.049	0.049	0.049	0.049	0.049

INTERNET APPENDIX

for

Social Influence in Household Equity Investment: Evidence from Randomized Military Drafts

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(NOT INTENDED FOR PUBLICATION)

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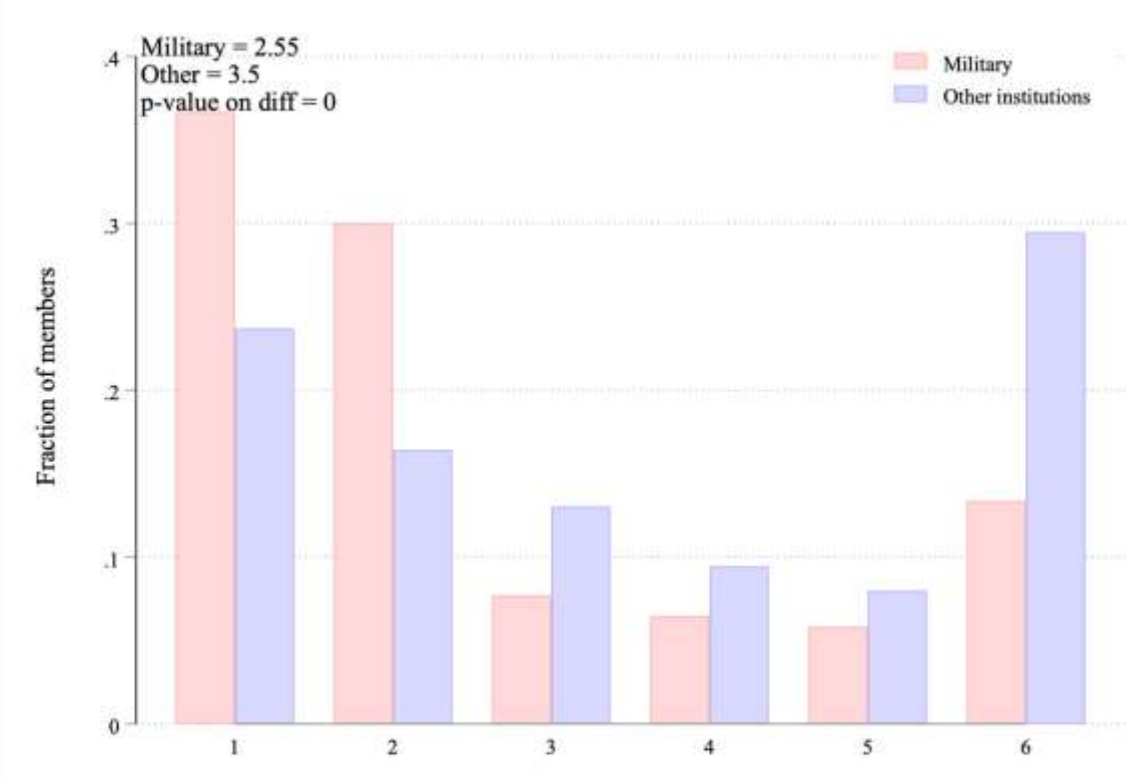

Figure IA.1. Distribution of Employment Duration of Identified Military Units. This figure shows employees' job duration distribution among general public institutions and institutions that we identify as military units. We report the average employee job duration and *p*-values that test the difference between the two groups.

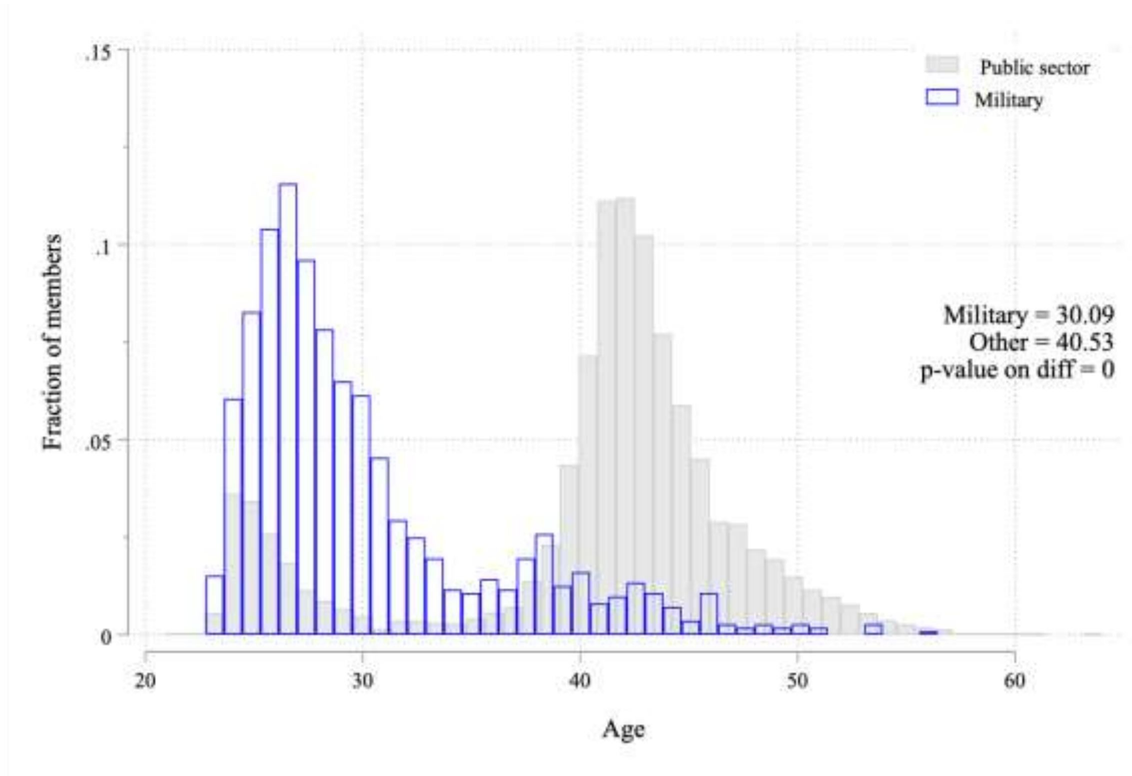

Figure IA.2. Age Distribution of Identified Military Units. This figure shows employees' age distribution among general public institutions and institutions that we identify as military units. We report average employee ages and *p*-values that test the difference between the two groups.

Table IA.1
K-Means Clustering and Elbow Method

This table reports the panel regression of compulsory military servicemen' stock market participation decisions on the participation rate of their military peers along with a set of control variables and fixed effects in a [−2, 2] event window as in Table 3, but with coarser or finer military peer group sizes. Column (1) reports the results for which we simply use the 25 military units and 5 year-waves of drafting to construct 125 peer groups. From column (2) to column (6), we conduct the K-means clustering method on individuals' military labor income in the draft year (as a proxy for within-draft-year service length) to break peer groups into 2, 3, 4, 6, and 12 subgroups. *t*-statistics (in brackets) are calculated from standard errors clustered at the unit level. ***p<0.01, **p<0.05, *p<0.1.

K=	1	2	3	4	6	12
	(1)	(2)	(3)	(4)	(5)	(6)
$ParPre_{-it}$	0.013	-0.018	0.032	0.032	-0.002	-0.015
	[0.19]	[-0.46]	[0.78]	[0.84]	[-0.08]	[-0.60]
$ParDuring_{-it}$	0.134**	0.095**	0.164***	0.151***	0.108***	0.077***
	[2.24]	[2.27]	[4.85]	[4.86]	[4.29]	[3.69]
$ParPost_{-it}$	0.183***	0.136***	0.214***	0.196***	0.169***	0.127***
	[3.57]	[3.66]	[7.33]	[7.45]	[7.97]	[7.09]
Birth Cohort Par_{-it}	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Year × Window Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Within-Cluster Sum of Square	5342.01	5015.75	4745.12	4466.74	4361.91	4410.24

Table IA.2
Regression of Individual Characteristics on Peers' Characteristics

This table reports the cross-sectional regression of compulsory military servicemen' individual characteristics x_{it} on peers' characteristics $\bar{x}_{-it}$ along with a set of control variables two-years before, one-year before, and during the peer-forming year. Peer statistics are calculated from a randomly selected half of the samples. We then use the other half of the samples for our regression analysis. $Wealth_{it}$ is individual wealth, whereas $HWealth_{it}$ refers to household wealth. Controls include age and years in education. Fixed effects include employer, draft-year, month-of-birth, county-of-birth, and county-of-enlisting fixed effect. Robust t-statistics are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

	$Wealth_{it}$	$Wealth_{it}$	$HWealth_{it}$	$HWealth_{it}$	$Income_{it}$	$Income_{it}$
t is two-years before *i*'s peer-forming year						
$\overline{Wealth}_{-it}$	0.086	0.141				
	[0.67]	[0.96]				
$\overline{HWealth}_{-it}$			−0.012	−0.133*		
			[−0.22]	[−1.86]		
$\overline{Income}_{-it}$					0.110	−0.093
					[1.23]	[−0.85]
N	87,274	50,849	87,274	50,858	87,274	50,889
t is one-years before *i*'s peer-forming year						
$\overline{Wealth}_{-it}$	0.038	0.270				
	[0.20]	[0.97]				
$\overline{HWealth}_{-it}$			−0.010	0.175		
			[−0.06]	[1.43]		
$\overline{Income}_{-it}$					0.150	−0.154
					[1.58]	[−1.28]
N	87,273	50,847	87,273	50,926	87,273	50,943
t is *i*'s peer-forming year						
$\overline{Wealth}_{-it}$	0.014	0.115				
	[0.09]	[0.53]				
$\overline{HWealth}_{-it}$			0.13	0.136		
			[0.91]	[0.91]		
$\overline{Income}_{-it}$					0.480***	0.395***
					[5.94]	[4.07]
N	87,274	50,905	87,274	51,025	87,274	50,905
Control	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3
Placebo Tests for Peer Effects

This table reports the panel regression of compulsory military servicemen' stock market participation decisions and stock dividend gains on the participation rate of *placebo* military peers along with a set of control variables and fixed effects in a [−2, 2] event window. The dependent variable from column (1) to (3), $Participation_{it}$, is an indicator variable that equals 1 if individual *i* holds any stock in year *t*. The dependent variable from column (4) to (6) is the total dividend (in thousand TWD) received by individual i in year t. The independent variables $ParPre_{-it}^{placebo}$, $ParDuring_{-it}^{placebo}$, and $ParPost_{-it}^{placebo}$, are the participation rates of $placebo$ military peers in year t when t is within the two-year window before, at, and within the two-year window after the peer forming period, respectively, and equal to zero otherwise. The placebo military peers are randomly selected from compulsory military servicemen drawn in the same year but not necessarily into the sample military units. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year fixed effect, window year fixed effect, and the participation rate of individual *i*'s birth cohort. t-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$Participation_{it}$			$Dividend\ Gain_{it}$ (in thousand TWD)		
	(1)	(2)	(3)	(4)	(5)	(6)
$ParPre_{-it}^{placebo}$	−0.055	−0.053	−0.050	−9.9	−9.1	−8.9
	[−1.09]	[−1.07]	[−1.00]	[−0.13]	[−0.12]	[−0.11]
$ParDuring_{-it}^{placebo}$	−0.002	−0.001	0.002	−222.2	−221.4	−221.3
	[−0.04]	[−0.01]	[0.04]	[−0.83]	[−0.82]	[−0.82]
$ParPost_{-it}^{placebo}$	−0.104	−0.102	−0.099	−58.2	−57.5	−57.4
	[−1.38]	[−1.35]	[−1.33]	[−1.10]	[−1.21]	[−1.17]
Total Value of Holding Stocks				0.0287**	0.0284**	0.0284**
				[3.31]	[3.24]	[3.26]
Control		yes	yes		yes	yes
Birth Cohort Par_{-it}			yes			yes
Individual FE	yes	yes	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes	yes	yes
N	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575
Adj. R2	0.737	0.737	0.737	0.333	0.333	0.333

Table IA.4
Dynamics of Peer Effect on Stock Market Participation Decisions

This table reports the panel regression of compulsory military servicemen' stock market participation decisions on the participation rate of military peers along with a set of control variables and fixed effects in a [−3,2] event window. The dependent variable, $Participation_{it}$, is an indicator variable that takes the value of 1 if individual i holds any stock in event year t, $t \in [-3:+2]$. The independent variables T^{-3}, T^{-2}, T^{-1}, T^{0}, T^{+1}, and T^{+2} are the participation rates of individual i's military peer groups from year −3 to +2 when individual i falls in the corresponding event year, and zero otherwise. The control variables are age, age^2, income, wealth, individual fixed effect, calendar year fixed effect, window year fixed effect, and the participation rate of individual i's birth cohort. t-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$Participation_{it}$			
	(1)	(2)	(3)	(4)
T^{-3}	−0.086	−0.085	−0.042	−0.050
	[−1.13]	[−1.10]	[−0.50]	[−1.05]
T^{-2}	0.022	0.019	0.032	0.024
	[0.29]	[0.26]	[0.44]	[0.34]
T^{-1}	0.116	0.110	0.089	0.070
	[1.86]	[1.72]	[1.41]	[1.10]
T^{0}	0.328***	0.324***	0.251***	0.219***
	[6.31]	[6.10]	[5.35]	[4.93]
T^{+1}	0.384***	0.379***	0.279***	0.242***
	[7.16]	[6.85]	[6.40]	[5.39]
T^{+2}	0.445***	0.444***	0.293***	0.257***
	[10.75]	[10.56]	[7.70]	[6.92]
Control			yes	yes
Birth Cohort Par_{-it}				yes
Individual FE	yes	yes	yes	yes
Calendar Year FE	yes			
Window FE	yes			
Calendar Year × Window Year FE		yes	yes	yes
N	2,098,290	2,098,290	2,098,290	2,098,290
Adj. R2	0.667	0.667	0.669	0.669

Table IA.5
Heterogeneity in Peer Effects on Dividend Gains

This table reports the panel regression of compulsory military servicemen' stock dividend gains on the participation rates of military peers of different characteristics along with a set of control variables and fixed effects in a [−2,2] event window. The dependent variable is the total dividend return (in thousand TWD) received by individual *i* in year *t*. For a given peer characteristic s, we separate $ParDuring_{-it}$, which we defined in Table 3, into two variables, $ParDuring_{-it}^{s,high}$ and $ParDuring_{-it}^{s,low}$, and report the effect from peers of high and low s, respectively. s includes age, income, education, and financial literacy, which are all defined as in Table 4. The control variables are age, age^2, income, wealth, individual fixed effect, the participation rate of individual *i*'s birth cohort, and the total value of stocks (in thousand TWD) held by individual *i* in year *t*. *t*-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. The *F*-statistic tests the null hypotheses that the coefficients for participation rates from the high/low and with/without groups are the same. ***p<0.01, **p<0.05, *p<0.1.

	$Dividend\ Gain_{it}$ (in thousand TWD)				
	(1)	(2)	(3)	(4)	(5)
$ParPre_{-it}$	30.386	30.889	27.511	37.965	25.685
	[0.25]	[0.25]	[0.22]	[0.32]	[0.21]
$ParDuring_{-it}$	168.240*				
	[2.09]				
$ParDuring_{-it}^{age,high}$		112.160*			
		[2.13]			
$ParDuring_{-it}^{age,low}$		56.434			
		[0.94]			
$ParDuring_{-it}^{income,high}$			148.290		
			[1.75]		
$ParDuring_{-it}^{income,low}$			28.655		
			[0.32]		
$ParDuring_{-it}^{education,high}$				116.543	
				[1.78]	
$ParDuring_{-it}^{education,low}$				41.413*	
				[1.99]	
$ParDuring_{-it}^{finance,high}$					109.858
					[1.49]
$ParDuring_{-it}^{finance,low}$					53.916
					[0.71]
$ParPost_{-it}$	8.785	8.465	7.474	13.543	5.216
	[0.11]	[0.05]	[0.08]	[0.16]	[0.07]
Total Value of Holding Stocks	yes	yes	yes	yes	yes
Control	yes	yes	yes	yes	yes
Birth Cohort Par_{-it}	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes
Calendar Year × Window Year FE	yes	yes	yes	yes	yes
F-Statistic		0.58	0.58	1.63	0.25
p-value		0.4458	0.4542	0.2032	0.6173
N	1,748,575	1,748,575	1,748,575	1,748,575	1,748,575
Adj. R2	0.333	0.333	0.333	0.333	0.333

Table IA.6
Peer Effects on Capital Gains

This table reports the panel regression of compulsory military servicemen' capital gain from non-publicly-traded stocks on the participation rate of their military peers along with a set of control variables and fixed effects in a [−2, 1] event window. The dependent variable, $Capital\ Gain_{it}$, is the capital gain from non-publicly-traded stocks (in thousand TWD) that individual *i* earns in year *t*. The information for capital gain from non-publicly-traded stocks is available up to 2012. Thus, we study the sample of individuals drafted in 2011 and focus on the event year window [−2, 1]. The independent variables, $ParPre_{-it}$, $ParDuring_{-it}$, and $ParPost_{-it}$, are the participation rates of military peers in year t when t is within the two-year window before, at, and the year window after the peer forming period, respectively, and zero otherwise. The control variables are age, age^2, income, wealth, calendar year fixed effect, the participation rates of individual *i*'s birth cohort, and the total value of non-publicly-traded stocks (in thousand TWD) held by individual *i* in year *t*. *t*-statistics (in brackets) are calculated from standard errors two-way clustered at the unit and calendar year level. ***p<0.01, **p<0.05, *p<0.1.

	$Capital\ Gain_{it}$ (in thousand TWD)			
	(1)	(2)	(3)	(4)
$ParPre_{-it}$	0.082	−0.825	−0.678	−0.684
	[0.10]	[−0.86]	[−0.74]	[−0.71]
$ParDuring_{-it}$	−2.477*	−3.967**	−4.112**	−4.058**
	[−1.83]	[−2.52]	[−2.52]	[−2.46]
$ParPost_{-it}$	7.610**	5.664**	5.221*	5.201*
	[2.35]	[1.97]	[1.87]	[1.86]
Calendar Year FE	yes	yes	yes	yes
Control		yes	yes	yes
Birth Cohort Par_{-it}			yes	yes
Total Value of Holding Stocks				yes
N	377,748	377,748	377,748	377,748
Adj. R2	0.0000	0.0002	0.0002	0.0016