# Peer Effects in Multi-Layer Networks: Evidence from Financial Behavior

Olga Balakina*          Gabriela Stockler†

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**Abstract**

We examine the simultaneous peer effects of co-workers, family, and neighbors in financial behavior using Danish registry data. We find that neighbors exert the strongest influence, followed by co-workers and family members. Peer effects are stronger for stocks than for mutual funds, and among experienced investors. While co-workers primarily influence buying decisions, neighbors affect both buying and selling, suggesting distinct channels of influence across peer groups. A multi-layer network model formalizes our empirical results, showing that an investor's trading activity depends on her centrality within and across network layers. Our findings provide new insights into the drivers and implications of peer effects in financial markets.

*Department of Household Finance, Leibniz Institute for Financial Research SAFE. Email: balakina@safe-frankfurt.de

†Universitat Pompeu Fabra and BSE. Email: stockler.gab@gmail.com.

# 1 Introduction

Financial decisions are rarely made in isolation. Individuals are embedded in multiple social relationships each of which may influence their investment behavior in distinct ways. A growing body of research shows that peer effects shape stock market participation, investment in individual assets, and overall investments styles and activity[1]. However, most studies analyze only one peer group at a time, overlooking the fact that individuals are simultaneously exposed to multiple and potentially conflicting social influences. This paper addresses this gap by looking into a *multi-layer social network* and jointly estimating peer effects arising from the network layers. In doing so, it reveals how different social ties interact to shape financial decision-making.

We use granular Danish administrative data to recover an individual-level social network, portfolio, and trading activity. We identify three network layers, or peer groups - co-workers, family, and neighbors. Then, we employ an instrumental variable (IV) strategy to estimate the peer effects of these groups on various individual trading metrics. We are able to discriminate between stock and mutual funds, and buying and selling activities.

Our main contributions are twofold. The first is on the empirical front. Our empirical results reveal that peer effects are strong, positive, and heterogeneous across the three social groups. Peer effects also vary with the asset class and the type of trading activity.

Neighbors exert the strongest influence on trading behavior, followed by co-workers and family members. Peer effects are more pronounced for stock investments than for mutual funds, likely due to greater visibility and active management of stocks compared to the relatively passive nature of mutual funds. Importantly, while co-workers primarily affect buying behavior, neighbors influence both buying and selling decisions, highlighting the heterogeneous nature of social influence across different networks. Furthermore, peer effects intensify among experienced investors, suggesting that prior market participation enhances

[1] Hong et al. (2004); Shiller (2017); Kaustia and Knüpfer (2012); Georgarakos et al. (2013); Hvide and Östberg (2015); Ouimet and Tate (2019); Haliassos et al. (2020); Maturana and Nickerson (2019); Pedersen (2022); Knüpfer et al. (2022); Han et al. (2022)

social responsiveness rather than diminishing it.

This paper also makes a theoretical contribution by developing a formal model that captures how different layers of a social network shape an individual's decision in distinct yet interconnected ways. By incorporating strategic interactions within a multi-layer network, our model extends the classical peer effects literature by allowing for heterogeneous influence channels in a single activity. We derive closed-form equilibrium results and find that an individual's decision is determined by her *multi-layer centrality*, which measures her influence in the multi-layer structure.

Our study builds upon the broader literature on financial decision-making and social influence. While prior research has examined the role of a particular social network in isolation in shaping financial behavior of a single asset class, relatively little is known about the concurrent effects of different peer groups[2] on different investment decisions across different types of assets.[3] To the best of our knowledge, we are the first to uncover the heterogeneous and joint nature of peer effects coming from different social groups in a financial setting. Additionally, we investigate both the extensive and the intensive margins of trading within and across asset classes.

Our findings have important implications for financial market dynamics, as we have seen a rapid digitalization of financial services and the rise of social investing platforms, what has further amplified the importance of social interactions in financial markets. For example, the recent case of GameStop and coordinated trades show how powerful the combination of more accessible stock investment, information and social interactions can be (Pedersen, 2022). Understanding how different social environments influence investment behavior can inform policy discussions on investor protection, financial education, and the potential risks of herding behavior in asset markets.

[2]Even in the few examples where we can observe multiple networks, like in Zhang et al. (2018) and Arrondel et al. (2020), and identify peer effects, there is no information on trading or portfolio composition.

[3]Given the lack of individual-level detailed information in portfolio and trading activity, many studies focus on stock market participation or investments in single assets. However, the literature on financial mistakes (e.g. Heimer, 2016) shows that it is the financial re-balancing and the reaction to information that matters, not the participation in an asset class itself.

The remainder of the paper is structured as follows. Section 2 escribes the data and network construction. Section 3 outlines the empirical strategy, including the instrumental variable approach. Section 4 presents the empirical results, emphasizing the heterogeneity in peer effects across networks and trading behaviors.. Section 5 introduces the multi-layer network model, deriving equilibrium conditions for trading behavior. Section 6 concludes with policy implications and directions for future research.

## 2 Data, Networks and Summary statistics

Our empirical analysis is based on detailed administrative records from Denmark, which provide comprehensive data on individual investment behavior, demographic characteristics, and social networks. The dataset includes information on financial holdings and transactions, including stock and mutual fund purchases, portfolio composition, and trading activity. These records are linked to demographic and employment data, allowing us to control for factors such as income, education, age, and occupation. Crucially, the dataset also enables the construction of multi-layer social networks, capturing peer relationships based on residential, workplace, and family ties.

A key advantage of this dataset is its accuracy and completeness, as the information is derived from official tax and financial records rather than self-reported surveys. This ensures that investment behaviors are measured with a high degree of precision, mitigating common biases in financial decision-making studies. Furthermore, the dataset covers the entire Danish population, providing a unique opportunity to examine financial behavior across different socioeconomic groups and network structures.

The construction of social networks follows a well-defined methodology that allows us to distinguish between different types of peer interactions. Neighborhood ties are determined based on individuals residing in the same postal district, workplace networks are formed by identifying individuals who share the same employer and office building, and family links are derived from official registry data. This classification enables a systematic investigation of how different social environments influence financial decision-making. The combination of high-quality financial data and well-defined social networks makes this dataset particularly well-suited for studying the role of peer effects in investment behavior.

## 2.1 Danish Registry Data

The dataset contains economic, financial, and personal information for the Danish population, focusing on married couples from 2007 to 2015. The dataset is constructed on the basis of several different administrative registers from Statistics Denmark. Individual and household data originate from the official Danish Civil Registration System. These records include the personal identification number (CPR), gender, date of birth, CPR numbers of family members (parents, children, and siblings), and their marital histories (number of marriages, divorces, and widowhoods). In addition to providing individual characteristics, such as age, gender, and marital status, these data enable us to follow the family tree of each individual. The dataset identifies individuals, households, generations, and time. In addition, personal records include address information up to a church parish (shire or sogn) in which the household is registered.

The Danish Tax and Customs Administration (SKAT) provides income, wealth, and portfolio holdings. This dataset contains personal income and wealth information by CPR numbers on the Danish population. SKAT receives this information directly from the relevant sources, as financial institutions supply information to SKAT about their customers' deposits and holdings of security investments. Employers similarly supply statements of wages paid to their employees. Through Statistics Denmark, we obtain access to this information from 2007 to 2015. we also have information about the same period's stock and mutual fund holdings.

Educational records are from the Danish Ministry of Education. All completed (formal and informal) education levels are registered annually and made available through Statistics

Denmark. We use these data to measure education levels and financial education, with an individual with a degree in economics, business, or finance defined as financially sophisticated. The employment records and firm-level information comes from the Integrated Database for Labor Market Research (IDA). This employer-employee dataset includes, among other things, demographics and firm and plant IDs and addresses, which are used to identify co-workers.

The estimation sample includes Danish individuals aged 18–65 who are married, working, and employed rather than self-employed. The final sample is an unbalanced panel of about 5,315,000 observations covering 2007-2015 and about 1,050,000 individuals from about 583,000 households.

All peers are restricted to being above 18 years old. However, there is no age restriction on maximum age. All co-worker peers are employed, and all neighbors stay in one shire. The family and co-worker networks structure rests on employment and marital relation. Thus all first-degree co-workers with peer-instruments are married, and all direct relatives - children, siblings, and parents with peer-instruments, are restricted to being married too.

## 2.2 Individuals and Financial Assets

We categorize individuals in our sample according to their financial behavior at any point in time. There are two assets: stocks and mutual funds. We also observe an individual's portfolio *and* his/her trading activity, i.e. the buying and selling (or doing nothing) of any asset.

We refer to *market participants* as individuals who hold a positive portfolio at period $t$. Among those, there are *entrants* and *investors*. *Entrants* are individuals who buy assets at $t$ and did not hold any assets in the previous period $t-1$ (i.e. had a "zero" portfolio). *Investors* are individuals who have a positive portfolio at $t-1$. They can further be *active*, if they rebalance their portfolio at $t$, either buying or selling assets (including selling all their holdings). Or they can be *inactive* if they do nothing at $t$. The following figure illustrates our categorization.

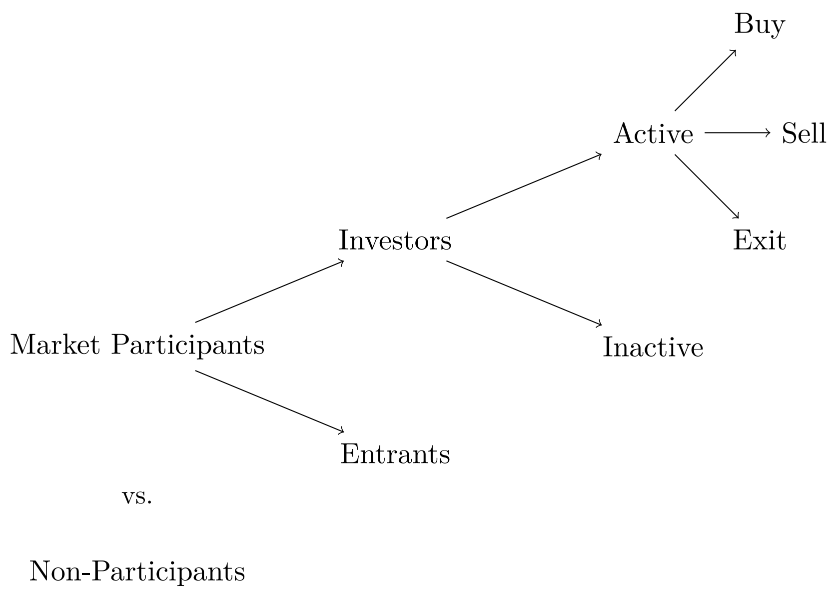


Figure 1: Individual Financial Behavior

## 2.3 Multiplexity of Peer Effects

Our goal is twofold. First, to estimate a causal effect of the stock trading of peers on individual stock trading behavior. Second, to analyze how such effects differ within and across peer groups. The motivation is that people interact in distinct social circles simultaneously - that is, they belong to different social networks or peer groups - and each may affect their stock market decisions in a particular way.

### 2.3.1 Peer Groups

We first need to define and identify peers in our sample. We leverage the granularity of our data to delineate three main peer groups, or networks: co-workers, family, and neighbors[4].

[4]Ideally, we would run a survey with the individuals in our sample, reconstruct the web of interactions they span (family, neighbors and co-workers), and then collect socio-economic information on both ends of each edge. Thanks to the granularity of our data, our peer group definition is the best as it can get without relying on observed network linkages (i.e. survey responses).

**Co-workers** The co-worker network is defined as individuals working in the same firm in the same year[5]. We use a firm identifier and workplace address from the Danish employment register to identify co-workers. In some cases, the address of the place of work allows me to identify colleagues that work on the same floor, making it even more plausible that they communicate with each other.

**Family** The family network encompasses close family members only: spouses, parents, and siblings. We do not include parents' parents (grandmothers and grandfathers) and siblings (aunts and uncles), because this information in our data is generally missing for everyone born before 1965.

**Neighbors** The neighborhood network is defined as individuals living in the same shire of residence, a small geographical location based on historical church districts.[6] There are approximately 3,000 shires in Denmark. Figure **??** and **??** present the shires map in Denmark.

These three social networks (or peer groups) allow us to investigate peer effects within and across them. As we show next, this multiplexity approach provides new insights into how the interaction between social connections and behavior varies across contexts.

### 2.3.2 Identification Strategy

The identification of peer effects has been studied in vast literature (among others Bramoullé et al. (2009); Liu and Lee (2010); Calvó-Armengol et al. (2009); Lin (2010); Ouimet and Tate (2019); Maturana and Nickerson (2019)), and is a challenge because of endogeneity problems (Manski, 1993; Bramoullé et al., 2009; De Paula, 2017). Thus, one cannot simply estimate a causal peer effect by regressing an individual's stock trading on their peers' average stock trading.

[5]In our data, each firm has an identifier and each employee a reported workplace address. In some cases, the workplace address allows us to identify colleagues working on the same floor, enhancing the plausibility of communication among them.

[6]In the Appendix, we use an alternative definition for neighbors, that is more restrictive. We look at an individual's residential address building.

The identification of peer effects relies on the instrumental variable approach. We choose two blocks of variables as instruments[7]. First, to instrument for peers' financial behavior, we use the composition of the network identified as third-degree peers in terms of their gender, age, marital status, and other demographic characteristics. Second, as instruments, we use the sensitivity to the economic shock of the distance 3-peers measured through their employment characteristics. For example, we use measures such as the growth in the number of employees, type of firm, private or public, and occupation.[8]

Third-degree co-workers are defined as the co-worker of the spouse of a co-worker. The definition implies that the direct peer (co-worker) has a spouse. However, direct co-workers include both single and married individuals. Thus, the missing observations for the third-degree co-workers are observations for individuals with only single co-workers. Single versus married close family members partly explain part of the missing observations for the family network. Another explanation for the missing family instruments is the fact that information about parents is, in general, not available for everyone born before 1965. Thus, we can not construct the family instruments for many parents-peers in the data.

In the main empirical analysis, in the subsequent Section 4, we provide and study the IV estimation results. In the Appendix, we provide alternative results with OLS regressions.

## 2.4 Dependent Variable: Stock Trading

The main measure of investment behavior is based on observable stock trading. The investment data contains annual snapshots of individual portfolios with assets identified by ISIN codes. Using combined data from Datastream and Morningstar, we classify assets into individual stocks, risky mutual funds, riskless mutual funds, and others. We use the number of stocks and their ISINs to determine the changes in portfolio composition from one year

[7]Not all individuals in the sample have family and co-worker networks large enough to find peers-instruments. That explains the difference in the number of observations.

[8]The full set of instruments includes: demographic variables, such as gender, marital status, age, age squared, number of kids under six years old, number of kids between 7 and 18 years old, education length, employment as a blue or white-collar worker, or managerial position, and workplace-level variables, such as logarithm of the firm size, firm growth, firm sector as in the public or private sector.

to another. The changes in holding of a stock $j$ for each $i$ in year $t$ are the following:

$$N_{Trade,jit} = |N_{jit} - N_{ji(t-1)}|, \tag{1}$$

where $N_{Trade,jit}$ correspond to the number of stocks $j$ traded, either bought or sold, by a individual $i$ from year $(t-1)$ to year $t$, respectively. The left-hand side variable in the regressions is $Trading_{it}$ and equals to one if any of the stocks have been traded by individual $i$ and zero otherwise:

$$Trading_{it} = 1_{\exists N_{Trade,jit} > 0} \tag{2}$$

The peer stock trading is calculated as a simple average among the peer group members. For example, the average stock trading among co-workers is equal to the share of co-workers who traded stocks in year $t$, i.e., $Trading_{it} \neq 0$:

$$Trading_{peer,it} = \frac{1}{Num_{peer}} \sum_{k=1}^{Num_{peer}} Trading_{kt}, \tag{3}$$

where $Num_{peer}$ is the number of peers in the respective group: co-workers $(CW)$, family $(FAM)$, and neighbors $(Neigh)$.

## 2.5 Descriptive Statistics

This section provides an overview of the dataset. The descriptive statistics highlight two key dimensions. First, the differences between the full sample and the sub-sample of active financial market participants, defined as the individuals who either hold or trade stocks or mutual funds. Second, the variation across peer groups—co-workers, family, and neighbors.

The first comparison provides insight into the characteristics associated with financial market engagement, while the second allows for an evaluation of heterogeneity in characteristics across different social networks.

**Individuals and their Peers** Table 3 in the appendix shows descriptive statistics for the full sample of individuals and the co-workers, neighbors, and family networks. Individuals are married and employed rather than self-employed. On average, they are 45 years old and likely to have kids between 7 and 18. They are likely to work a white-collar job (60%), in a workplace with about 75 employees (log firm size is 4.23), or in a private firm in the service sector.[9]

Table 3 also presents averages for characteristics of peer groups. Individuals have, on average, 4,700 neighbors, 350 co-workers, and four close family members. Co-workers are more likely to be married than family and neighbors. The average age of relatives is higher than that of individuals and co-workers but lower than the average age of neighbors. Individuals have more years of schooling on average than their peers (14.55 years). Family and neighbors are the wealthiest groups, consistent with their age. On the other hand, individuals lead concerning income, with co-workers following closely. Co-workers have the highest share of financial assets compared to other peers and individuals.

We define an individual as financially sophisticated if she has a degree in economics or business or works at a financial institution, most likely a bank. 6% of individuals classify as financially sophisticated during the period. At the same time, only 5% of co-workers, 4% of family members, and 3% of neighbors are financially sophisticated. Regarding occupation, neighbors are the least likely to have a managerial job (14%) but the most likely to have a blue-collar occupation (73%).[10] As expected, co-workers resemble individuals of interest the most in terms of occupation and employment.

We now turn to the descriptive financial statistics, displayed in 5 in the appendix. Co-workers exhibit the highest levels of financial market engagement, followed by family members, while neighbors display the lowest participation rates. This ranking is evident in

[9]The sample selection process does not restrict the sample to the same individuals remaining over the sample period, hence an unbalanced panel. As a result, the occupation and firm characteristics, such as type and sector, do not add up to 100%.

[10]Because peer group composition is likely to change over a 9-years period, the values of firm characteristics, such as type and sector, as well as occupational variables, do not sum up to 100%

both the full and restricted samples (6), suggesting that social interactions in the workplace are more relevant for financial decision-making than those occurring within households or neighborhoods. Among co-workers, the proportion of individuals participating in financial markets increases from 34%in the full sample to 39%in the restricted sample. The corresponding increase for family members is from 35%to 46%, while for neighbors, the change is more modest, rising from 35%to 36%. This suggests that peer effects may be stronger in professional and familial contexts, where financial discussions are more likely to take place, compared to geographically proximate relationships.

Asset composition also varies across peer groups. Co-workers are disproportionately engaged in stock trading, while family members are more likely to hold mutual funds. This is consistent with the idea that financial discussions in professional settings are more likely to focus on high-risk, high-reward assets such as individual stocks, whereas within families, investment decisions may be more conservative and geared toward long-term financial planning. Neighbors exhibit lower levels of participation across both asset classes, reinforcing the idea that financial market engagement is less likely to be influenced by social interactions in residential settings.

**Individuals versus Investors** A comparison between the full sample (Table 3, Table 5) and the sub-sample of investors (Table 4, Table 6) reveals systematic differences in demographic characteristics and financial behavior. As expected, in the full sample, only 40% of individuals hold or trade financial assets, whereas this figure rises to 89% in the restricted sample. This increase is observed across both stocks and mutual funds, with a particularly pronounced rise in stock market participation.

Investors are, on average, older and more educated, with an age gap of approximately two years and a higher likelihood of having completed tertiary education. A particularly pronounced difference is the share of individuals with an economics or business-related degree, which rises from 4%in the full sample to 6%among market participants. Given the established relationship between financial literacy and investment activity, this suggests that education plays a key role in determining stock market entry.

Income and wealth disparities between the two groups are substantial. The log of income increases from 13.57 in the full sample to 13.65 among market participants, while the log of wealth rises from 8.76 to 10.92, reflecting a considerable difference in financial resources. A similar pattern emerges for financial assets, where market participants report a significantly higher mean level than non-participants. These patterns are consistent with the well-documented positive correlation between income, wealth, and financial market participation, reinforcing the notion that liquidity constraints and risk tolerance play an important role in shaping investment decisions.

Overall, the descriptive statistics for individuals and their peers provide useful insights. They lay a strong empirical foundation for the upcoming econometric analysis, where we formally estimate the magnitude of peer effects in investment decisions.

The composition of peer groups suggests distinct mechanisms through which they may influence financial decision-making. Co-workers, given their relatively high levels of financial sophistication and income, are likely to serve as conduits for investment-related information, particularly in professional settings where financial discussions are common. Family members, while slightly less financially sophisticated, may exert influence through direct financial ties and shared household decision-making. Neighbors, despite having higher wealth levels, appear to be the least financially sophisticated and most occupationally diverse, suggesting that any financial influence they exert may operate more through observational learning or community norms rather than direct financial discussions.

These characteristics highlight the need to consider heterogeneity in peer effects, as different social networks are likely to shape financial behavior through distinct channels. Co-workers are likely to play a role in informational spillovers, family members in joint decision-making, and neighbors in norm-based or observational influences. These patterns will be further explored in the empirical analysis, where the magnitude and significance of peer effects can be formally estimated.

## 3 Empirical Strategy

In this section, we present our empirical framework. In the following Section 4, we present and discuss our results. Our empirical model estimates how the financial behavior of different peer groups — co-workers, family members, and neighbors — simultaneously influences an individual's own trading decisions.

We analyze peer effects on different individual financial trading behavior metrics. We estimate how peers influence portfolio adjustments, as well as asset-specific decisions (stocks vs. mutual funds). We further distinguish between buying and selling activities to uncover differences in the direction of peer influence. Finally, we restrict the sample to investors to examine how peer effects vary among individuals with prior market exposure.

The multi-peer model is given by Eq. (4). We jointly regress an individual dummy variable for trading behavior $Behavior_{it}$ on the average behavior of each peer group, controlling for individual characteristics, peer attributes, and fixed effects at multiple levels.

$$\begin{aligned} Behavior_{it} =& \alpha + \beta_{cw} Behavior_{(cw,it)} + \beta_{fam} Behavior_{(fam,it)} + \beta_{neigh} Behavior_{(neigh,it)} \\ & + \gamma \Delta X_{it} + \delta_{cw} \Delta \overline{Z_{cw,it}} + \delta_{fam} \Delta \overline{Z_{fam,it}} + \delta_{neigh} \Delta \overline{Z_{neigh,it}} \\ & + Year_t + Municipality_k + Year \times Municipality_{kt} + Bank_b \\ & + u_i, \end{aligned} \tag{4}$$

where the set of fixed effects are: year ($Year_t$), municipality ($Municipality_k$), year-municipality ($Year \times Municipality_{kt}$), and main bank ($Bank_b$). Year fixed effects control for the time trend in stock trading. Municipality and year-municipality fixed effects control for within municipality stock trading patterns constant and time-varying, respectively. Bank fixed effects are constructed based on unique identifiers of the primary bank of the individual and control for the effect of financial advice for stock trading.[11]

We run regressions under nine specifications of the dummy $Behavior_{it}$. This allows us to examine various dimensions of trading activity. Specifically, the definitions of $Behavior_{it}$ differ in two dimensions: asset type and trading activity. On the asset dimension, we look into the overall portfolio (which may include stocks and/or mutual funds), and then restrict to only stocks and only mutual funds. On the activity dimension, we look into any change in asset holdings, and then restrict to only buying and only selling asset(s) shares. For the sake of exposition, we present these regression equations in the Appendix.

All our estimates results, presented in the Section 4, are obtained using an instrumental variable (IV) approach to address the endogeneity concerns inherent in estimating peer effects. As discussed in the identification strategy, a naive regression of an individual's trading behavior on their peers' trading behavior would suffer from reflection bias and omitted variable concerns (Manski, 1993; Bramoullé et al., 2009; De Paula, 2017).

The IV estimation approach ensures that these estimates reflect causal peer effects rather than spurious correlations, strengthening the validity of our conclusions. In the Appendix, we further investigate the robustness of these findings and explore alternative specifications to assess the sensitivity of our results.

# 4 Results

In this section, we present our results, depicted in Table 1 and Table 2. Each table displays the peer effects of co-workers, family, and neighbors in three asset categories: overall portfolio, stock holdings only, and mutual fund holdings only. Moreover, estimate results are specific to three different trading activities. The first panel *"A. Trading"* shows peer effects for any changes in an individual's holdings[12]. The next two panels, *"B. Buy"* and *"C. Sell"*,

[11] Primary bank is a bank where an individual has a salary account or primary account (Nem Konto).

[12] By adjustment we mean: buying or selling asset(s); entering the market by buying asset(s) for the first time; and exiting the market by selling all the portfolio or asset-specific holdings.

provide the peer effects for the specific buying activity and selling activity, respectively.

Our main findings can be summarized as follows. First, neighbors consistently exert the strongest influence on individual trading decisions. The second-strongest peer group effect depends on the asset type. Co-workers are more influential for stocks and family for mutual funds. Second, peer influence is generally more pronounced for stock trading than for mutual funds, consistent with the idea that more visible or salient assets are more likely to be influenced by one's social environment. Third, when we distinguish between buying and selling, we find that peer groups tend to have stronger effects on buying decisions, with a notable exception: neighbors' influence on mutual fund trading is pronounced for both buying and selling. Finally, restricting our sample to experienced investors reveals that peer effects intensify among those with prior market exposure, suggesting that social networks are not merely guiding novices into the market, but also affecting the decisions of seasoned participants.

The findings reveal significant heterogeneity across peer groups and asset types, highlighting the multifaceted nature of social influences in financial decision-making.

## 4.1 Full Sample

Table 1 provides our main set of estimates in the full sample of individuals. A first striking pattern to observe is that all significant coefficients are positive. Meaning that individuals are positively affected by any behavior of any peer group.

**General Trading Activity** We start by looking into any changes in asset holdings (i.e holding adjustments), which we refer as trading. Table 1 Panel A provides the main set of estimates.

Neighbors display a stark influence in all three categories of trading, with the largest coefficients. Interestingly, this peer effect is similar across stocks and mutual funds. This indicates the importance of community-level interactions, such as those occurring in public

Table 1: Investors: Full Sample Peer Effects

| | Trading | | | Buy | | | Sell | | |
|---|---|---|---|---|---|---|---|---|---|
| Peer Group | **Portfolio** | **Stocks** | **Mutual Funds** | **Portfolio** | **Stocks** | **Mutual Funds** | **Portfolio** | **Stocks** | **Mutual Funds** |
| **Co-workers** | 0.0615*** | 0.0967*** | -0.00253 | 0.0988*** | 0.130*** | 0.0280*** | 0.0317*** | 0.0636*** | 0.00427 |
| | (0.00692) | (0.00831) | (0.00495) | (0.00703) | (0.00782) | (0.00740) | (0.00596) | (0.00772) | (0.00515) |
| **Family** | 0.0497*** | 0.0693*** | 0.0179*** | 0.0524*** | 0.0664*** | 0.0511*** | 0.0411*** | 0.0521*** | 0.0272*** |
| | (0.00365) | (0.00425) | (0.00321) | (0.00342) | (0.00389) | (0.00378) | (0.00337) | (0.00387) | (0.00358) |
| **Neighbors** | 0.542*** | 0.619*** | 0.607*** | 0.601*** | 0.612*** | 0.712*** | 0.707*** | 0.721*** | 0.746*** |
| | (0.0447) | (0.0513) | (0.0492) | (0.0417) | (0.0453) | (0.0483) | (0.0493) | (0.0521) | (0.0548) |
| Observations | 475,141 | 475,141 | 475,141 | 475,141 | 475,141 | 475,141 | 475,141 | 475,141 | 475,141 |

In all regressions, we control for: Individual Characteristics, Peer Characteristics, Year FE, Municipality FE, Year-Municipality FE, Year-Bank FE, Individual FE.

spaces, schools, or places of worship, as conduits for financial behavior. These results suggest that shared norms and regional socio-economic conditions at the community level play a critical role in shaping individual investment decisions.

Co-workers also significantly influence portfolio and stock trading, though the magnitudes are much smaller than those observed for neighbors. This suggests that individuals are moderately responsive to the trading behavior of their colleagues. Interestingly, this effect intensifies when isolating stock trading decisions, where the coefficient increases from 0.163 to 0.0967. This finding aligns with the hypothesis that workplace interactions provide a fertile environment for the exchange of information about high-visibility financial instruments like individual stocks. By contrast, the influence of co-workers on mutual fund trading is statistically insignificant, suggesting that mutual funds may be less salient in workplace discussions.

Family members have a weaker but still statistically significant effect. This effect is strong for stock trading (0.0897) and smaller for mutual fund holdings (0.0264). This highlights the heterogeneity across asset classes.

We also find that how geographically close neighbors are is crucial for this peer group effect. In the Appendix, we use a narrower definition of neighbors as those living in the same building. In this case, neighbors exhibit negligible or no significant influence at all. This suggests that casual or incidental interactions among geographically close neighbors are insufficient to generate meaningful peer effects, reinforcing the idea of that the scope of the social network matters.

This first set of results has two main take-aways. First, neighbors have the largest peer effect. Second, peer effects are generally stronger for stock trading than for mutual fund trading across all peer groups. This pattern could reflect the greater visibility and social relevance of stock investments, which may be more frequently discussed or mimicked within peer networks. In contrast, the comparatively weaker effects observed for mutual funds suggest that these assets may be less socially salient or involve more private decision-making processes.

**Buy versus Sell** To better understand the dynamics of peer influence, we distinguish between buying and selling decisions, as shown in Table 1 Panel B and Table 1 Panel C . The patterns observed in the general trading activity persist, but new insights emerge.

For buying decisions, neighbors continue to exhibit the largest effect across the three categories, followed by co-workers and family peer effects. For mutual funds, in particular, the influence of co-workers is now significant but comparatively small.

On the sell side, there is an interesting contrast. Co-workers and family peer effects are comparatively smaller. Meanwhile, neighbors peer effects are the greatest, particularly for mutual funds.

Co-workers play a particular strong role in encouraging stock purchases, with a coefficient of 0.130, which is notably larger than the effect observed for portfolio and mutual funds, and for trading and selling.

Focusing on the influence of family on mutual funds, we notice that it is the largest on the buying side. In a similar vein, co-workers influence in mutual funds only comes in the buying decisions.

There seems to be a substitution effect of advice when thinking about stock versus mutual funds. An interpretation of the estimates in Table 1 Panel B and Table 1 Panel C is that individuals rely more on workplace to gather information for stock trading, and explore neighborhood interactions for mutual funds trading.

Altogether, Table 1 Panel B and Table 1 Panel C show that peer effects are consistently stronger for stock trading than for mutual fund trading across all peer groups. This pattern likely reflects the greater visibility and social relevance of stock investments, which may be more frequently discussed or mimicked within peer networks. In contrast, the comparatively weaker effects observed for mutual funds suggest that these assets may be less socially salient or involve more private decision-making processes, perhaps because they are considered as safer investments. Additionally, neighbors are the only peer group that have a more pronounced effect for selling activist than for buying decisions.

## 4.2 Sub-sample of Investors

To explore whether prior market participation amplifies peer effects, we restrict the sample to investors — individuals who already hold financial assets in their portfolios in the previous period[13]. This allows us to assess whether financial experience amplifies the influence of social networks on trading decisions.

The results, presented in Table 2, reveal that peer effects are significantly stronger for this subgroup across all networks and asset types.

The influence of neighbors becomes particularly pronounced among experienced investors, with an effect reaching 0.691 for portfolio adjustments and 0.965 for stock trading. These magnitudes are considerably larger than those observed in the full sample, suggesting that investors are more attuned to community-level signals and norms. Family effects, while smaller, remain significant and consistent across asset types. Notably, co-workers exert a stronger influence on stock trading, with a coefficient of 0.234, but becomes irrelevant for

[13] The full sample, with results in Table 1, includes market entrants and exits.

Table 2: Investors: Restricted Sample Peer Effects

| | Trading | | | Buy | | | Sell | | |
|---|---|---|---|---|---|---|---|---|---|
| Peer Group | **Portfolio** | **Stocks** | **Mutual Funds** | **Portfolio** | **Stocks** | **Mutual Funds** | **Portfolio** | **Stocks** | **Mutual Funds** |
| **Co-workers** | 0.163*** | 0.234*** | 0.00610 | 0.230*** | 0.301*** | 0.0129 | 0.0722*** | 0.138*** | 0.0209 |
| | (0.0153) | (0.0174) | (0.0137) | (0.0177) | (0.0189) | (0.0212) | (0.0160) | (0.0206) | (0.0139) |
| **Family** | 0.0641*** | 0.0897*** | 0.0264*** | 0.0699*** | 0.0808*** | 0.0838*** | 0.0498*** | 0.0745*** | 0.0409*** |
| | (0.00741) | (0.00771) | (0.00903) | (0.00751) | (0.00828) | (0.00838) | (0.00741) | (0.00857) | (0.00771) |
| **Neighbors** | 0.691*** | 0.965*** | 0.937*** | 1.094*** | 0.982*** | 1.286*** | 1.083*** | 1.127*** | 1.448*** |
| | (0.0999) | (0.105) | (0.168) | (0.108) | (0.114) | (0.138) | (0.123) | (0.126) | (0.149) |
| Observations | 127,319 | 127,319 | 127,319 | 127,319 | 127,319 | 127,319 | 127,319 | 127,319 | 127,319 |

In all regressions, we control for: Individual Characteristics, Peer Characteristics, Year FE, Municipality FE, Year-Municipality FE, Year-Bank FE, Individual FE.

mutual funds trading.

**Buy versus Sell** When breaking the results into buying and selling decisions, we observe that peer effects remain particularly strong for buying. For instance, the influence of co-workers and neighbors on stock purchases among experienced investors increases to 0.301 and 0.982, respectively. Interestingly, family effects on mutual fund purchases rise to 0.0838 while the co-worker effect becomes insignificant. Selling decisions, on the other hand, are dominated by neighbors, where mutual fund sales exhibit the largest effect (1.448).

**Comparison with the Full Sample** The contrast of the full-sample results (Table 1) with those of the experienced investors subsample (Table 2) highlights the relative importance of each peer group across trading activities, asset types, and trading directions (buying vs. selling). Notably, peer effects are stronger among experienced investors, suggesting that market participants with prior trading exposure are more attuned to social influences. Below, we discuss these results in detail, focusing on the magnitude differences across peer groups and asset types.

An intriguing finding from Table 2 is the contrasting roles of different peer groups in mutual funds holdings among experienced investors. While neighbors remain the dominant channel, with a substantial effect of 1.286 on mutual fund purchases, the family effect increases significantly to 0.0838, and the co-worker effect becomes statistically insignificant.

The pronounced influence of neighbors on mutual fund purchases aligns with the broader pattern observed across asset types and samples. As mutual funds are often associated with long-term, community-aligned investment strategies, neighbors may provide critical cues regarding local economic conditions, community norms, and collective financial behavior. These findings underscore that community-level interactions continue to play a primary role in shaping decisions around mutual funds, even among more financially experienced investors.

The rise of family effects for mutual fund purchases among experienced investors, however, suggests an additional layer of influence. Mutual funds, being perceived as safer and more stable, may align more closely with long-term financial planning within families. For instance, discussions about retirement, college savings, or other collective financial goals are likely to amplify the role of family in these decisions. This is particularly evident for experienced investors, who may already possess sufficient financial knowledge and are thus less reliant on external sources like co-workers for guidance on mutual funds. Instead, such decisions may become more insular, centering around trusted familial relationships.

The insignificance of co-worker effects in mutual fund purchases is noteworthy and contrasts sharply with their strong role in stock trading. This may be due to the different characteristics of the two asset types: stocks are dynamic and prone to short-term trading opportunities, which are commonly discussed in professional settings, while mutual funds are passive investments requiring less frequent or immediate decision-making. As a result, mutual fund choices may fall outside the scope of workplace discussions, especially for experienced investors who may already have predefined strategies for these investments.

In summary, neighbors remain the primary channel for mutual fund purchases, but the increased significance of family among experienced investors highlights the differentiated roles that peer groups play across asset types. These results emphasize the importance of both community-level signals and familial advice in shaping long-term investment decisions, while also underscoring the limited relevance of workplace interactions in this domain.

## 4.3 Summary of the Key Findings

Our empirical analysis provides strong evidence that peer effects play a significant role in shaping individual financial behavior. Across different social networks—co-workers, family members, and neighbors—we observe consistent and robust peer influence on trading decisions, reinforcing the idea that investment behavior is not made in isolation but is instead influenced by social interactions.

The results from Table 1 and Table 2 highlight the nuanced and heterogeneous nature of peer effects across different social networks, trading behaviors, and asset types.

A key insight from our findings is that peer effects vary significantly depending on both the type of social network and the nature of the trading decision. Neighbors consistently exhibit the strongest influence across all specifications, affecting both buying and selling behavior, suggesting that geographical proximity facilitates information sharing, imitation, or exposure to similar economic conditions. Co-workers primarily affect buying decisions, particularly for stocks, reinforcing the idea that workplace discussions tend to be biased towards investment opportunities rather than exit strategies. Family members exert a weaker, but still statistically significant, influence, indicating that financial habits may be partially transmitted within families, but to a lesser extent than in workplace or neighborhood settings.

Moreover, when restricting the sample to experienced investors—those who already held financial assets in the previous period—peer effects become even stronger. This suggests that prior market participation amplifies peer influence, rather than diminishing it. While peer effects in the full sample were more pronounced for buying than selling, experienced investors also exhibit strong peer effects in their selling decisions, indicating that once individuals are actively engaged in financial markets, they become more responsive to peer signals not only when entering the market but also when adjusting their portfolios.

The results also reveal a systematic asymmetry in peer influence between stocks and mutual funds. Peer effects on stock trading are consistently larger, likely reflecting the fact that stock investments are more actively managed, more visible in social interactions, and more prone to sentiment-driven decision-making. In contrast, mutual fund investments, typically more passive and long-term, are less susceptible to peer influence—though among experienced investors, we observe an increase in mutual fund peer effects, particularly in neighborhood networks.

These findings contribute to the broader literature on social interactions and financial decision-making, providing causal evidence that peer influence is a powerful force in financial markets. The results suggest that financial contagion within social networks could be a key driver of market participation and trading intensity, with implications for understanding herding behavior, the diffusion of financial information, and the role of social norms in investment choices.

# 5 Theoretical Framework

Our empirical results demonstrate that individual financial decisions are significantly influenced by peer behavior, with distinct patterns across social networks, asset types, and investor experience levels. The strong peer effects observed, particularly among neighbors and co-workers, suggest that social interactions play a crucial role in shaping trading behavior—either through information diffusion, social learning, or imitation mechanisms. However, the empirical analysis alone does not fully capture the strategic nature of these interactions, nor does it formalize how individuals optimize their trading decisions in response to peer behavior.

To provide a structural interpretation of these findings, we now introduce a simple model of investment behavior in a multilayer network that resonates with our empirical framework.

Agents in the model are interpreted as the individuals (investors) we observe in our data.

In the multilayer network, each layer represents a peer group - Neighbors, Family, and Co-workers - and their collection is the investors' social circle. Each investor optimally chooses his demand for the asset (for example, a stock) taking into account all his social interactions. That is, his connections in each and every layer. Importantly, each layer has an intrinsic *influence* level on investors. This represents the peer effect of each social group - our main empirical interest.

This theoretical framework allows us to derive equilibrium conditions for trading behavior, explore the mechanisms driving peer influence, and examine how network structure shapes financial market participation and trading intensity.

This section outlines the structure of the model, key assumptions, and the derivation of equilibrium conditions.

**Model Specification** The economy consists of a set of individuals $N = \{1, 2, \ldots, n\}$ who have[14] three social circles $K = \{1, 2, 3\}$. Let $G^k = (g^k_{ij}) = \{0, 1\}$ for all $i, j \in N$ be the (unweighted) adjacency matrix of the network layer $k$ . We assume that $g_{ii} = 0$ for all $i \in N$, that is, there are no self-loops. Further assume that $G^k$ represents an undirected network, so that $G$ is symmetric, i.e., $g^k_{ij} = g^k_{ji}$ for all $i, j \in N$. The collection of all layers form the multi-layer network $G$ such that $G = \cup_{k \in K} G^k$.

We consider a multilayer network model where each node $i$ represents an individual (investor to map into our empirical setup) embedded in multiple social layers. We refer to the individuals as investors, mapping to our empirical investigation. Let $x_i$ denote the (trading) activity chosen by investor $i$, which is influenced by its neighbors in different network layers. Her utility can be expressed as:

$$U_i = \alpha x_i - \frac{1}{2} x_i^2 + \sum_j \left( \beta^1 g^1_{ij} + \beta^2 g^2_{ij} + \beta^3 g^3_{ij} \right) x_j x_i, \tag{5}$$

Thus, the activity $x_i$ is determined by maximizing $U_i$, considering the influence from the

[14]The model is general and it holds for any number $k > 0$ layers. With a single layer, we are back at the canonical single-layer network model.

connections in each and every layer *jointly*.

The utility function 5 has two parts. The first part, $\alpha x_i - \frac{1}{2}x_i^2$, corresponds to the utility of the activity (for eg. buying a certain amount of the asset), independently of activity choice of the other investors in the network. The parameter $\alpha$ is an individual's intrinsic marginal utility from the activity, and the quadratic term captures its decreasing marginal returns.

The second part of 5, $\sum_j \left(\beta^1 g_{ij}^1 + \beta^2 g_{ij}^2 + \beta^3 g_{ij}^3\right) x_j x_i$, captures the multi-layer network externalities. Parameters $\beta^1, \beta^2$, and $\beta^3$ describe the influence of each layer, that is, the *layer-specific peer effects*. We allow for $\beta^k$ to differ and do not impose a sign restriction. Indeed, if $\beta_1 = \beta_2 = \beta_3$ all layers exert the same effect and we're are back to the stand peer effect model. If $\beta^k = 0 \quad \forall k$, each investor's utility depends entirely on her own trading decision. As we discuss later on, we will impose some regularity condition on these coefficients to guarantee convexity of the utility function.

**Remarks on the model** Before solving the model, we briefly discuss several features of our setup.

For each layer $k$, we assume that the set of investors $N$ is the same. This is without loss of generality since we allow for heterogeneous social networks. In addition, we assume that $\beta^k$ is layer-specific and not individual-specific; that is, each agent has the same preference weight for the same layer. This also implies that agents care about all layers.

Agents make an *single* decision that is influenced *by all layers, jointly*. This means that agents behave in the same way in all layers[15]. Also, since $x_i$ is continuous, the model looks at the intensive margin of trade. That is, whether to buy $(x_i > 0)$ or sell $(x_i < 0)$ and how much[16].

Note that in our setting, the network effects aggregate over different layers. Whether the parameter $\beta^k$ is positive or negative depends on the social context. For each investor $i$ and

[15] This is different from the recent economic literature multilayer networks. As in Zenou and Zhou (2024); Chen et al. (2018); Kor and Zhou (2023).

[16] In our empirical analysis, we also investigate the extensive margin: whether to trade or not. The model can encompass this scenario by restricting to $x_i$ to be binary. We discuss this version in the Appendix.

$j$,

$$\frac{\partial U_i}{\partial x_i \partial x_j} = \sum_k \beta^k g_{ij}^k$$

This means that the sign *and* the magnitude of each parameter $\beta^k$ determines the strategic interaction between agents. For example, when all $\beta^k$ are positive corresponds to the case where the activities are complements, while when they are all negative corresponds to the case where the activities are substitutes. It is interesting to look when these parameters have different signs, so that their magnitude and the layer-specific connections determine the nature of strategic interaction.

**Notation and Assumptions** We first define some useful matrices. Let $\mathbf{x}$ be the vector of actions for all investors, $I$ be the $N \times N$ identity matrix, and $\mathbf{1}$ be the $N$-dimensional vector of ones. Let $\mathbf{G^s}$ be the matrix sum of the individual network-layer adjacency matrices $\mathbf{G^k}$, $\mathbf{G^s} = \mathbf{G^1} + \mathbf{G^2} + \mathbf{G^2}$.

Define the strategic interdependence matrix, $\Phi$

$$\Phi = \beta^1 \mathbf{G}^1 + \beta^2 \mathbf{G}^2 + \beta^3 \mathbf{G}^3 \tag{6}$$

Also define $\lambda_1(G^k)$ as the largest eigenvalue of $G^k$.[17] Throughout the paper, we impose the following assumption:

**Assumption 1:** $\lambda_{\max}(\beta^1 G^1 + \beta^2 G^2 + \beta^3 G^3) < 1$.

This assumption specifies a sufficient and necessary condition so that the underlying multi-layer network game among individuals has a unique and interior Nash equilibrium (in

[17]It is also equal to its spectral radius by the Perrron-Frobenius Theorem since $G^k$ is a nonnegative symmetric matrix.

pure strategies) for any $\mathbf{x}$ (Proposition 1).[18] Intuitively, it guarantees that the aggregate network effect of all layers is not "too intense".

For each fixed layer $k$, Assumption 1 is the standard in the monolayer network literature. TIt is equivalent to the condition $1 - \lambda_{\max}(\beta^k G^k) > 0$. For instance, when $\beta^k > 0$, it reduces to $\beta^k < \frac{1}{\lambda_{\max}(G^k)}$ (Ballester et al. (2006)), while when $\beta^k < 0$ it reduces to $|\beta^k| < -\frac{1}{\lambda_{\min}(G^k)}$ (Bramoullé and Kranton (2007); Bramoullé et al. (2014)).

# Equilibrium Computation

To determine investors' optimal actions in the multi-layer network, we derive the equilibrium by solving the individual optimization problem.

Each investor optimally chooses their action $x_i$, balancing their intrinsic utility ($\alpha$) against the network externalities from peers in all layers. Taking the first-order condition of Eq. (5) with respect to $x_i$ gives:

$$x_i = \alpha + \sum_j \left(\beta^1 g_{ij}^1 + \beta^2 g_{ij}^2 + \beta^3 g_{ij}^3\right) x_j. \tag{7}$$

**Proposition 1.** ***Existence and Uniqueness of Equilibrium***

*Suppose that Assumption 1 holds. There exists a unique equilibrium in which investors choose trading activity levels*

$$\mathbf{x}^* = \left[\mathbf{I} - (\beta^1 \mathbf{G^1} + \beta^2 \mathbf{G^2} + \beta^3 \mathbf{G^3})\right]^{-1} \alpha \mathbf{1} \tag{8}$$

This follows from the fact that the matrix $I - (\beta^1 G^1 + \beta^2 G^2 + \beta^3 G^3)$ is invertible under Assumption 1. The equilibrium action of each investor is a linear function of their intrinsic preference $\alpha$, modulated by the multi-layer peer effects.

To capture cross-layer linkages, we introduce a new multi-layer influence measure, defined

[18] A sufficient but not necessary (and stronger) condition is: $|\beta^1|\lambda_1(G^1) + |\beta^2|\lambda_1(G^2) + |\beta^3|\lambda_1(G^3) < 1$.

as follows:

**Definition 1:** Define $\mathbf{c} \equiv \mathbf{c}(\mathbf{G}, K)$, the multi-layer centrality, with

$$\mathbf{c}(\mathbf{G}, K) = \left[\mathbf{I} - (\beta^1\mathbf{G^1} + \beta^2\mathbf{G^2} + \beta^3\mathbf{G^3})\right]^{-1}\mathbf{1} \tag{9}$$

The term $\mathbf{c}(\mathbf{G}, K)$ represents each investor's influence in the network, incorporating peer effects from all social layers. When peer effects are strong (i.e., large $\beta^1, \beta^2, \beta^3$), the matrix inverse amplifies network effects, making central nodes even more influential.

The following corollary shows that, in addition to the expression in Proposition 1, the equilibrium activity levels can be compactly expressed in terms of investors' centrality.

**Corollary 1.** *Suppose Assumtpion 1 holds. Then, the unique equilibrium can be written as*

$$\mathbf{x}^* = \alpha\mathbf{c}(\mathbf{G}, K) \tag{10}$$

Investors with higher multi-layer centrality exhibit greater equilibrium trading activity because their actions are more influenced by network interactions. Importantly, this centrality measure does not depend merely on the number of direct connections but also on indirect influences across all layers of the network.

Since $\beta^1, \beta^2, \beta^3$ are identical across investors, an investor's equilibrium trading activity is determined not just by how many peers they are directly connected to, but by how their position amplifies the peer effects throughout the network.

Corollary 1 illustrates how the individual influence of investors, determined by their multi-layer centralities, shapes the equilibrium. Importantly, this centrality measure encompasses the heterogenous peer effects investors face. It is also useful for the subsequent comparative statics results as it simplifies the analysis of the equilibrium.

# 6 Conclusion

This paper provides new evidence on the multi-layered nature of peer effects in financial decision-making, demonstrating that individuals' trading behavior is shaped by simultaneous influences from multiple social networks—co-workers, family, and neighbors. Unlike previous studies that analyze a single peer group in isolation, our results show that these different social ties exert distinct, yet concurrent, effects on financial decisions.

Using Danish registry data and an instrumental variable approach, we establish that neighbors exert the strongest influence, followed by co-workers and family members, with peer effects being more pronounced for stocks than for mutual funds. We also find that peer influence is asymmetric, with co-workers primarily affecting buying decisions, while neighbors impact both buying and selling behavior. Furthermore, we show that peer effects are amplified among experienced investors, suggesting that prior market participation enhances social responsiveness rather than diminishing it.

Our findings highlight that an individual's financial behavior cannot be fully understood through a single-layer network approach—social influence is inherently multi-faceted, and failing to account for simultaneous peer effects across multiple social groups leads to an incomplete picture of financial decision-making.

To provide a structural interpretation of these findings, we develop a multi-layer network model that demonstrates how an investor's trading activity depends on their centrality across and within the social layers. The model captures heterogeneous peer effects and strategic behavior, offering insights into the mechanisms driving social learning and coordinated trading behavior.

These findings contribute to the literature on behavioral finance, network economics, and household finance, emphasizing that peer effects are not merely present but must be studied as simultaneous and interacting forces. If peer effects drive herding and correlated trading patterns, they may amplify market volatility and asset mispricing. However, they also suggest that social networks can facilitate financial learning, potentially improving market participation and financial literacy. Moving beyond single-layer network approach allows us to fully capture the complexity of social influence, with significant implications for market dynamics, investment behavior and policy interventions.

To conclude, we want to highlight that this paper lays the ground to better understand what *drives* peer effects in financial decision-making. For instance, is it social learning? Or a mimicking behavior rising from (di)similarity within a social group? Our data and theoretical framework possibilitate evolution in this direction, which we have as a companion work in progress. Importantly, we believe that unveiling and dissecting the channels giving rising to peer effects are the crucial next steps in this literature.

The concept of multi-layer networks and concurrent peer effects extrapolate from finance. It is intrinsic to individual decision-making. For example, this concept is relevant for research on labor markets and inflation expectations. Futhermore, the literature still lacks a unified framework on multi-layer networks. Important recent advances have been made (Zenou and Zhou (2024), Chen et al. (2018)). However, the common assumption so far has been that individuals make a separate decision in each layer which is reasonable under certain scenarios. This paper argues that it is also important to consider a single decision spanning all layers.

# References

Arrondel, L., Calvo Pardo, H.F., Giannitsarou, C., Haliassos, M., 2020. Informative social interactions. Available at SSRN 3171564 .

Ballester, C., Calvó-Armengol, A., Zenou, Y., 2006. Who's who in networks. wanted: the key player. Econometrica 74, 1403–1417.

Bramoullé, Y., Djebbari, H., Fortin, B., 2009. Identification of peer effects through social networks. Journal of econometrics 150, 41–55.

Bramoullé, Y., Kranton, R., 2007. Public goods in networks. Journal of Economic Theory 135, 478–494. doi:10.1016/j.jet.2006.06.006.

Bramoullé, Y., Kranton, R., D'Amours, M., 2014. Strategic Interaction and Networks. American Economic Review 104, 898–930. doi:10.1257/aer.104.3.898.

Calvó-Armengol, A., Patacchini, E., Zenou, Y., 2009. Peer effects and social networks in education. The Review of Economic Studies 76, 1239–1267.

Chen, Y.J., Zenou, Y., Zhou, J., 2018. Multiple Activities in Networks. American Economic Journal: Microeconomics 10, 34–85. arXiv:26528492.

De Paula, A., 2017. Econometrics of network models, in: Advances in Economics and Econometrics: Theory and Applications: Eleventh World Congress, Cambridge University Press Cambridge. pp. 268–323.

Georgarakos, D., Haliassos, M., Pasini, G., 2013. Household Debt and Social Interactions. SSRN Electronic Journal URL: http://www.ssrn.com/abstract=2208516, doi:10.2139/ssrn.2208516. 00000.

Haliassos, M., Jansson, T., Karabulut, Y., 2020. Financial literacy externalities. The Review of Financial Studies 33, 950–989.

Han, B., Hirshleifer, D., Walden, J., 2022. Social transmission bias and investor behavior. Journal of Financial and Quantitative Analysis 57, 390–412.

Heimer, R.Z., 2016. Peer pressure: Social interaction and the disposition effect. The Review of Financial Studies 29, 3177–3209.

Hong, H., Kubik, J.D., Stein, J.C., 2004. Social interaction and stock-market participation. The journal of finance 59, 137–163.

Hvide, H.K., Östberg, P., 2015. Social interaction at work. Journal of Financial Economics 117, 628–652.

Kaustia, M., Knüpfer, S., 2012. Peer performance and stock market entry. Journal of Financial Economics 104, 321–338.

Knüpfer, S., Rantapuska, E., Sarvimäki, M., 2022. Social Interaction in the Family: Evidence from Investors' Security Holdings*. Review of Finance URL: https://doi.org/10.1093/rof/rfac060, doi:10.1093/rof/rfac060, arXiv:https://academic.oup.com/rof/advance-article-pdf/doi/10.1093/rof/rfac060/45983227/rfac060.pdf. rfac060.

Kor, R., Zhou, J., 2023. Multi-activity influence and intervention. Games and Economic Behavior 137, 91–115. doi:10.1016/j.geb.2022.11.007.

Lin, X., 2010. Identifying peer effects in student academic achievement by spatial autoregressive models with group unobservables. Journal of Labor Economics 28, 825–860.

Liu, X., Lee, L.f., 2010. Gmm estimation of social interaction models with centrality. Journal of Econometrics 159, 99–115.

Manski, C.F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60, 531–542.

Maturana, G., Nickerson, J., 2019. Teachers teaching teachers: The role of workplace peer effects in financial decisions. The Review of Financial Studies 32, 3920–3957.

Ouimet, P., Tate, G., 2019. Learning from coworkers: Peer effects on individual investment decisions. The Journal of Finance .

Pedersen, L.H., 2022. Game on: Social networks and markets. Journal of Financial Economics 146, 1097–1119.

Shiller, R.J., 2017. Narrative economics. American economic review 107, 967–1004.

Zenou, Y., Zhou, J., 2024. Games on Multiplex Networks. doi:10.2139/ssrn.4772575, arXiv:4772575.

Zhang, A.C., Fang, J., Jacobsen, B., Marshall, B.R., 2018. Peer effects, personal characteristics and asset allocation. Journal of Banking & Finance 90, 76–95.

# Appendix A Data

In this section, we provide descriptive demographic and financial statistics for individuals and their social networks. We discuss these tables in Section 2.5 .

## A.1 Descriptive Tables

**Demographic Information** Table 3 provides information on the characteristics of individuals and their peers in the whole sample. Table 4 provides similar information for the restricted sample of investors.

**Financial Information** Table 5 provides information on the financial state of individuals and their peers in the whole sample. Table 6 provides similar information for the restricted sample of investors.

Table 3: Demographic Descriptive Statistics

| | Individuals mean/sd | Coworkers mean/sd | Family mean/sd | Neighbours, Address mean/sd | Neighbours, Shire mean/sd |
|---|---|---|---|---|---|
| Gender | 0.50 | 0.49 | 0.48 | 0.45 | 0.49 |
| | (0.50) | (0.30) | (0.27) | (0.33) | (0.02) |
| Married | 1.00 | 0.68 | 0.51 | 0.72 | 0.56 |
| | (0.00) | (0.16) | (0.34) | (0.36) | (0.09) |
| Age | 45.69 | 42.90 | 46.74 | 43.66 | 49.66 |
| | (9.38) | (5.16) | (11.75) | (9.32) | (2.77) |
| # of Kids 0-6 | 0.42 | 0.36 | 0.23 | 0.35 | 0.21 |
| | (0.73) | (0.22) | (0.37) | (0.55) | (0.05) |
| # of Kids 7-18 | 0.74 | 0.62 | 0.31 | 0.67 | 0.37 |
| | (0.92) | (0.27) | (0.41) | (0.73) | (0.09) |
| Years of Schooling | 14.36 | 14.12 | 13.30 | 13.86 | 12.72 |
| | (2.78) | (1.55) | (2.16) | (2.19) | (0.70) |
| Education in Economics | 0.04 | 0.03 | 0.03 | 0.02 | 0.02 |
| | (0.19) | (0.08) | (0.10) | (0.11) | (0.02) |
| Employed in Finance | 0.02 | 0.02 | 0.01 | 0.02 | 0.01 |
| | (0.13) | (0.08) | (0.07) | (0.09) | (0.01) |
| Finanially Sophisticated | 0.05 | 0.05 | 0.04 | 0.04 | 0.03 |
| | (0.23) | (0.12) | (0.12) | (0.14) | (0.02) |
| Log of Wealth | 8.76 | 2.61 | 8.46 | 3.71 | 8.76 |
| | (6.56) | (4.26) | (4.54) | (9.40) | (1.31) |
| Log of Income | 13.57 | 12.77 | 12.32 | 12.68 | 12.25 |
| | (0.35) | (0.31) | (0.73) | (0.47) | (0.14) |
| Log of Financial Assets | 11.34 | 10.24 | 11.08 | 10.23 | 11.03 |
| | (1.88) | (0.88) | (1.59) | (1.90) | (0.38) |
| LTV | 0.59 | 0.48 | 0.31 | 0.50 | 0.32 |
| | (0.48) | (0.18) | (0.29) | (0.39) | (0.09) |
| Leverage | 1.65 | 1.31 | 1.08 | 1.50 | 1.16 |
| | (1.60) | (0.57) | (1.17) | (1.29) | (0.34) |
| Occupation: Blue | 0.50 | 0.53 | 0.71 | 0.61 | 0.73 |
| | (0.50) | (0.32) | (0.29) | (0.37) | (0.08) |
| Occupation: White | 0.59 | 0.59 | 0.37 | 0.52 | 0.33 |
| | (0.49) | (0.34) | (0.31) | (0.38) | (0.09) |
| Occupation: Manager | 0.30 | 0.31 | 0.16 | 0.26 | 0.14 |
| | (0.46) | (0.29) | (0.24) | (0.34) | (0.06) |
| Log Firm Size | 4.22 | 4.36 | 2.61 | 3.86 | 2.42 |
| | (1.88) | (1.77) | (1.54) | (1.37) | (0.36) |
| Firm Growth | 0.10 | 0.10 | 0.07 | 0.11 | 0.07 |
| | (0.51) | (0.48) | (0.27) | (0.37) | (0.03) |
| Type: Public Sector | 0.31 | 0.32 | 0.18 | 0.34 | 0.17 |
| | (0.46) | (0.47) | (0.24) | (0.35) | (0.03) |
| Type: Limited Liability | 0.40 | 0.41 | 0.25 | 0.34 | 0.24 |
| | (0.49) | (0.49) | (0.27) | (0.35) | (0.05) |
| Manufacturing | 0.10 | 0.10 | 0.06 | 0.10 | 0.06 |
| | (0.30) | (0.30) | (0.15) | (0.22) | (0.03) |
| Construction | 0.05 | 0.05 | 0.04 | 0.06 | 0.04 |
| | (0.23) | (0.22) | (0.13) | (0.18) | (0.02) |
| Services | 0.56 | 0.56 | 0.36 | 0.54 | 0.33 |
| | (0.50) | (0.48) | (0.30) | (0.37) | (0.06) |
| Other | 0.29 | 0.28 | 0.54 | 0.30 | 0.56 |
| | (0.45) | (0.44) | (0.31) | (0.34) | (0.05) |
| size | | 296.79 | 3.41 | 2.77 | 4,726.42 |
| | | (769.48) | (1.53) | (1.87) | (3,666.41) |
| Observations | 731473 | 668667 | 698528 | 562015 | 731473 |

Table 4: Demographic Descriptive Statistics of Participants

| | Individuals mean/sd | Coworkers mean/sd | Family mean/sd | Neighbours, Address mean/sd | Neighbours, Shire mean/sd |
|---|---|---|---|---|---|
| Gender | 0.57 | 0.52 | 0.49 | 0.45 | 0.49 |
| | (0.50) | (0.28) | (0.28) | (0.32) | (0.02) |
| Married | 1.00 | 0.70 | 0.50 | 0.73 | 0.56 |
| | (0.00) | (0.15) | (0.35) | (0.35) | (0.09) |
| Age | 47.81 | 43.26 | 46.65 | 44.04 | 49.75 |
| | (9.12) | (4.87) | (12.58) | (9.27) | (2.70) |
| # of Kids 0-6 | 0.36 | 0.37 | 0.24 | 0.34 | 0.21 |
| | (0.70) | (0.21) | (0.40) | (0.54) | (0.05) |
| # of Kids 7-18 | 0.72 | 0.62 | 0.31 | 0.68 | 0.37 |
| | (0.92) | (0.26) | (0.42) | (0.72) | (0.09) |
| Years of Schooling | 14.74 | 14.29 | 13.60 | 13.98 | 12.79 |
| | (2.50) | (1.45) | (2.18) | (2.18) | (0.72) |
| Education in Economics | 0.06 | 0.05 | 0.04 | 0.03 | 0.02 |
| | (0.24) | (0.09) | (0.12) | (0.12) | (0.02) |
| Employed in Finance | 0.05 | 0.04 | 0.02 | 0.02 | 0.01 |
| | (0.21) | (0.13) | (0.08) | (0.09) | (0.01) |
| Finanially Sophisticated | 0.11 | 0.09 | 0.05 | 0.04 | 0.03 |
| | (0.31) | (0.17) | (0.15) | (0.15) | (0.02) |
| Log of Wealth | 10.92 | 3.24 | 9.24 | 4.28 | 8.86 |
| | (5.82) | (4.18) | (4.51) | (9.25) | (1.32) |
| Log of Income | 13.65 | 12.84 | 12.34 | 12.70 | 12.26 |
| | (0.39) | (0.31) | (0.75) | (0.48) | (0.14) |
| Log of Financial Assets | 11.89 | 10.39 | 11.34 | 10.30 | 11.06 |
| | (1.76) | (0.86) | (1.60) | (1.90) | (0.38) |
| LTV | 0.54 | 0.50 | 0.32 | 0.51 | 0.32 |
| | (0.46) | (0.17) | (0.30) | (0.38) | (0.09) |
| Leverage | 1.60 | 1.33 | 1.12 | 1.57 | 1.17 |
| | (1.66) | (0.54) | (1.22) | (1.34) | (0.34) |
| Occupation: Blue | 0.42 | 0.48 | 0.68 | 0.59 | 0.73 |
| | (0.49) | (0.32) | (0.31) | (0.38) | (0.08) |
| Occupation: White | 0.63 | 0.63 | 0.39 | 0.54 | 0.34 |
| | (0.48) | (0.33) | (0.32) | (0.37) | (0.09) |
| Occupation: Manager | 0.36 | 0.33 | 0.18 | 0.28 | 0.14 |
| | (0.48) | (0.29) | (0.26) | (0.34) | (0.06) |
| Log Firm Size | 4.39 | 4.53 | 2.69 | 3.85 | 2.44 |
| | (1.94) | (1.84) | (1.62) | (1.40) | (0.36) |
| Firm Growth | 0.09 | 0.09 | 0.07 | 0.11 | 0.07 |
| | (0.49) | (0.47) | (0.28) | (0.37) | (0.03) |
| Type: Public Sector | 0.24 | 0.25 | 0.17 | 0.33 | 0.17 |
| | (0.43) | (0.43) | (0.24) | (0.35) | (0.03) |
| Type: Limited Liability | 0.50 | 0.51 | 0.26 | 0.35 | 0.24 |
| | (0.50) | (0.50) | (0.28) | (0.35) | (0.05) |
| Manufacturing | 0.10 | 0.11 | 0.05 | 0.10 | 0.06 |
| | (0.30) | (0.30) | (0.15) | (0.22) | (0.03) |
| Construction | 0.05 | 0.05 | 0.04 | 0.06 | 0.04 |
| | (0.22) | (0.21) | (0.13) | (0.18) | (0.02) |
| Services | 0.56 | 0.57 | 0.37 | 0.55 | 0.34 |
| | (0.50) | (0.48) | (0.31) | (0.37) | (0.07) |
| Other | 0.28 | 0.28 | 0.53 | 0.29 | 0.56 |
| | (0.45) | (0.43) | (0.32) | (0.34) | (0.05) |
| size | | 340.76 | 3.25 | 2.80 | 4,911.87 |
| | | (766.31) | (1.48) | (1.83) | (3,640.17) |
| Observations | 197457 | 181767 | 190578 | 152218 | 197457 |

Table 5: Financial Descriptive Statistics

| | Individuals mean/sd | Coworkers mean/sd | Family mean/sd | Neighbours, Address mean/sd | Neighbours, Shire mean/sd |
|---|---|---|---|---|---|
| Stock Market Participation | 0.40 | 0.34 | 0.35 | 0.36 | 0.35 |
| | (0.49) | (0.17) | (0.35) | (0.38) | (0.08) |
| Change all | 0.20 | 0.18 | 0.18 | 0.18 | 0.18 |
| | (0.40) | (0.13) | (0.28) | (0.30) | (0.05) |
| Buy all | 0.13 | 0.11 | 0.10 | 0.11 | 0.10 |
| | (0.33) | (0.10) | (0.22) | (0.25) | (0.04) |
| Sell all | 0.13 | 0.12 | 0.13 | 0.12 | 0.13 |
| | (0.34) | (0.10) | (0.24) | (0.26) | (0.04) |
| Change stocks | 0.13 | 0.11 | 0.10 | 0.11 | 0.10 |
| | (0.34) | (0.11) | (0.21) | (0.25) | (0.04) |
| Buy stocks | 0.09 | 0.08 | 0.07 | 0.08 | 0.06 |
| | (0.29) | (0.09) | (0.17) | (0.21) | (0.03) |
| Sell stocks | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 |
| | (0.24) | (0.07) | (0.16) | (0.18) | (0.03) |
| Change funds | 0.11 | 0.09 | 0.11 | 0.10 | 0.11 |
| | (0.31) | (0.09) | (0.23) | (0.24) | (0.03) |
| Buy funds | 0.04 | 0.04 | 0.05 | 0.04 | 0.05 |
| | (0.21) | (0.06) | (0.15) | (0.16) | (0.03) |
| Sell funds | 0.09 | 0.08 | 0.09 | 0.08 | 0.09 |
| | (0.28) | (0.08) | (0.21) | (0.22) | (0.03) |
| Enter, Stocks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.06) | (0.01) | (0.04) | (0.04) | (0.00) |
| Enter, Funds | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.07) | (0.02) | (0.05) | (0.05) | (0.00) |
| Exit, Stocks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.05) | (0.01) | (0.04) | (0.04) | (0.00) |
| Exit, Funds | 0.01 | 0.00 | 0.01 | 0.00 | 0.01 |
| | (0.07) | (0.02) | (0.05) | (0.05) | (0.00) |
| Active Buy Stocks | 0.09 | 0.08 | 0.06 | 0.07 | 0.06 |
| | (0.29) | (0.09) | (0.17) | (0.21) | (0.03) |
| Active Buy Funds | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |
| | (0.20) | (0.06) | (0.15) | (0.15) | (0.03) |
| Active Sell Stocks | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 |
| | (0.24) | (0.07) | (0.15) | (0.17) | (0.03) |
| Active Sell Funds | 0.09 | 0.07 | 0.09 | 0.08 | 0.09 |
| | (0.28) | (0.08) | (0.21) | (0.21) | (0.03) |
| Has only Stocks | 0.75 | 0.25 | 0.23 | 0.26 | 0.22 |
| | (0.43) | (0.15) | (0.30) | (0.35) | (0.07) |
| Has only Funds | 0.18 | 0.06 | 0.08 | 0.07 | 0.08 |
| | (0.39) | (0.07) | (0.19) | (0.20) | (0.02) |
| Both Funds and Stocks | 0.07 | 0.03 | 0.05 | 0.03 | 0.05 |
| | (0.25) | (0.05) | (0.16) | (0.14) | (0.02) |
| size | | 296.79 | 3.41 | 2.77 | 4,726.42 |
| | | (769.48) | (1.53) | (1.87) | (3,666.41) |
| Observations | 731473 | 668667 | 698528 | 562015 | 731473 |

Table 6: Financial Descriptive Statistics of Participants

| | Individuals mean/sd | Coworkers mean/sd | Family mean/sd | Neighbours, Address mean/sd | Neighbours, Shire mean/sd |
|---|---|---|---|---|---|
| Stock Market Participation | 0.89 | 0.39 | 0.46 | 0.39 | 0.36 |
| | (0.31) | (0.17) | (0.37) | (0.39) | (0.09) |
| Change all | 0.45 | 0.21 | 0.24 | 0.19 | 0.19 |
| | (0.50) | (0.14) | (0.32) | (0.31) | (0.05) |
| Buy all | 0.27 | 0.13 | 0.14 | 0.12 | 0.10 |
| | (0.44) | (0.12) | (0.25) | (0.25) | (0.04) |
| Sell all | 0.33 | 0.14 | 0.18 | 0.13 | 0.13 |
| | (0.47) | (0.11) | (0.28) | (0.27) | (0.05) |
| Change stocks | 0.28 | 0.14 | 0.13 | 0.12 | 0.10 |
| | (0.45) | (0.13) | (0.24) | (0.26) | (0.04) |
| Buy stocks | 0.19 | 0.10 | 0.09 | 0.08 | 0.07 |
| | (0.39) | (0.11) | (0.20) | (0.22) | (0.03) |
| Sell stocks | 0.15 | 0.07 | 0.07 | 0.06 | 0.05 |
| | (0.36) | (0.08) | (0.19) | (0.19) | (0.03) |
| Change funds | 0.26 | 0.11 | 0.16 | 0.11 | 0.12 |
| | (0.44) | (0.09) | (0.27) | (0.25) | (0.04) |
| Buy funds | 0.11 | 0.04 | 0.06 | 0.04 | 0.05 |
| | (0.31) | (0.06) | (0.18) | (0.16) | (0.03) |
| Sell funds | 0.22 | 0.09 | 0.13 | 0.09 | 0.10 |
| | (0.42) | (0.09) | (0.25) | (0.22) | (0.03) |
| Enter, Stocks | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.07) | (0.02) | (0.04) | (0.04) | (0.00) |
| Enter, Funds | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 |
| | (0.11) | (0.02) | (0.05) | (0.06) | (0.00) |
| Exit, Stocks | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.07) | (0.01) | (0.05) | (0.04) | (0.00) |
| Exit, Funds | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.11) | (0.02) | (0.06) | (0.06) | (0.00) |
| Active Buy Stocks | 0.19 | 0.10 | 0.08 | 0.08 | 0.06 |
| | (0.39) | (0.11) | (0.20) | (0.22) | (0.03) |
| Active Buy Funds | 0.10 | 0.04 | 0.06 | 0.04 | 0.04 |
| | (0.30) | (0.06) | (0.18) | (0.16) | (0.03) |
| Active Sell Stocks | 0.15 | 0.06 | 0.07 | 0.06 | 0.05 |
| | (0.36) | (0.08) | (0.18) | (0.18) | (0.03) |
| Active Sell Funds | 0.22 | 0.08 | 0.13 | 0.08 | 0.09 |
| | (0.42) | (0.08) | (0.25) | (0.22) | (0.03) |
| Has only Stocks | 0.75 | 0.28 | 0.29 | 0.28 | 0.23 |
| | (0.43) | (0.15) | (0.33) | (0.36) | (0.07) |
| Has only Funds | 0.16 | 0.07 | 0.09 | 0.07 | 0.08 |
| | (0.36) | (0.07) | (0.21) | (0.20) | (0.02) |
| Both Funds and Stocks | 0.09 | 0.04 | 0.08 | 0.04 | 0.05 |
| | (0.29) | (0.05) | (0.19) | (0.14) | (0.02) |
| size | | 340.76 | 3.25 | 2.80 | 4,911.87 |
| | | (766.31) | (1.48) | (1.83) | (3,640.17) |
| Observations | 197457 | 181767 | 190578 | 152218 | 197457 |

# Appendix B Empirical Strategy

In this section, we specify the IV regressions for the results in Table 3 Table 4, Table 5, Table 6.

Regarding the type of trading activity, Eq. (B.1) specifies the model for changes in holdings, which we refer as trading.

$$
\begin{aligned}
Trading_{it} =& \alpha + \beta_{cw} Trading_{(cw,it)} + \beta_{fam} Trading_{(fam,it)} + \beta_{neigh} Trade_{(neigh,it)} \\
& + \gamma \Delta X_{it} + \delta_{cw} \Delta \overline{Z_{cw,it}} + \delta_{fam} \Delta \overline{Z_{fam,it}} + \delta_{neigh} \Delta \overline{Z_{neigh,it}} \\
& + Year_t + Municipality_k + Year \times Municipality_{kt} + Bank_b \\
& + u_i,
\end{aligned}
\tag{B.1}
$$

For buying and selling decisions, we run similar regressions with the dependent variable being a dummy for buying and selling stocks or mutual funds in a given period,

$$
\begin{aligned}
Buying_{it} =& \alpha + \beta_{cw} Buying_{(cw,it)} + \beta_{fam} Buying_{(fam,it)} + \beta_{neigh} Buying_{(neigh,it)} \\
& + \gamma \Delta X_{it} + \delta_{cw} \Delta \overline{Z_{cw,it}} + \delta_{fam} \Delta \overline{Z_{fam,it}} + \delta_{neigh} \Delta \overline{Z_{neigh,it}} \\
& + Year_t + Municipality_k + Year \times Municipality_{kt} + Bank_b \\
& + u_i,
\end{aligned}
\tag{B.2}
$$

where $Buying_{it} = 1$ if individual $i$ buys shares of stocks or mutual funds in period $t$, and

$$
\begin{aligned}
Selling_{it} =& \alpha + \beta_{cw} Selling_{(cw,it)} + \beta_{fam} Selling_{(fam,it)} + \beta_{neigh} Selling_{(neigh,it)} \\
& + \gamma \Delta X_{it} + \delta_{cw} \Delta \overline{Z_{cw,it}} + \delta_{fam} \Delta \overline{Z_{fam,it}} + \delta_{neigh} \Delta \overline{Z_{neigh,it}} \\
& + Year_t + Municipality_k + Year \times Municipality_{kt} + Bank_b \\
& + u_i,
\end{aligned}
\tag{B.3}
$$

where $Selling_{it} = 1$ if individual $i$ sells shares of stocks or mutual funds in period $t$.

The asset class determines the sample we run the regression above. For portfolio, we include both stocks and mutual funds holds. Then, we discriminate among stock holdings only and mutual funds holdings only.