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SOCIAL TIES AND THE DEMAND FOR FINANCIAL SERVICES

by Eleonora Patacchini[$] and Edoardo Rainone*

Abstract

This paper studies the importance of social interactions between young adults for the adoption of financial services. Specifically, we investigate whether, how, and why financial decisions taken by interacting agents are correlated. We exploit a unique dataset of friendship networks in the United States and a novel estimation strategy that accounts for potentially endogenous network formation. We find that not all social contacts are equally important: only long-lasting relationships influence financial decisions. Moreover, this peer influence only exists in cohesive social structures. This evidence underlines the fact that trust plays an important role in financial decisions. When agents consider whether or not to adopt a financial instrument, they face a risk and may place greater value on information coming from agents they trust. These results can help explain the importance of face-to-face social contacts for financial decisions.

JEL Classification: C11, C31, D1, D14, D81, D85, E45, G11, M31.
Keywords: financial market participation, financial literacy, social interactions, trust, network formation, endogeneity, Bayesian estimation.

Contents

[$] Cornell University, EIEF and CEPR. E-mail: ep454@cornell.edu

*Bank of Italy. E-mail: edoardo.rainone@bancaditalia.it.

1 Introduction[1]

What factors drive the demand for financial services? Beginning with Duflo and Saez (2003)'s seminal paper on retirement plans, a number of studies have investigated the role of peers, friends, and social networks in the adoption of financial services. The majority of this literature, however, is based on field experiments in specific settings (see, e.g., Cai et al., 2015; Duflo and Saez, 2003; Beshears et al., 2015; Bursztyn et al., 2014). Notable exceptions include Hong et al. (2004) and Brown et al. (2008). Hong et al. (2004) use the US Health and Retirement survey to examine the relationship between sociability and asset holdings. Their analysis compares "social" and "non-social" households, which are distinguished using questions on interactions with neighbors and church attendance. They find that the impact of sociability is stronger in states where stock market participation rates are higher, which is consistent with a peer effects story. Brown et al. (2008) use a large panel of taxpayer data with geographical identifiers (zip codes) to study the relationship between an individual's decision to own stocks and the average stock market participation of the individual's community. The authors claim causality by combining an instrumental variables approach with community fixed effects. One key disadvantage of these studies is that they lack information on the precise social interactions between individuals (i.e. information about who interacts with whom).

This paper provides a first examination into the role of social interactions in financial decisions using data from a nationally representative survey for the United States that includes information on financial choices and on the links between individuals and their friends. To deal with endogeneity issues stemming from a possible sorting of individuals into friendship groups, we use an instrumental variables (IV) strategy in which the activity of friends is instrumented using the characteristics of friends-of-friends (see, e.g., Bramoullé et al., 2009; Liu and Lee, 2010; Calvó-Armengol et al., 2009; De Giorgi et al., 2010). This instrument, paired with the use of network fixed effects, allows us to credibly control for omitted variables. As a robustness check, we also show the results of our analysis when the formation of friendship groups is explicitly modeled at the dyad level and estimation is conducted using a Bayesian methodology. This exercise helps eliminate concerns about selection on unobservable variables within networks.

Our analysis provides one main novel and important result. We find that not all social contacts are equally important: only long-lasting relationships (strong ties) influence financial decisions. Short, intense friendships (as measured by the frequency of interactions) do not have a strong effect. Moreover, the correlation in agents' behavior only arises among strong ties in cohesive social structures. Borrowing from (Jackson et al., 2012), we consider that two friends are in a cohesive social structure if their link is supported, that is if there is (at least) another agent who is linked to both of them.

Our findings are consistent with the strand of the finance literature which shows that trust is important for individuals making financial decisions (see, most notably Guiso et al., 2008; Guiso et al., 2004; Gennaioli et al., 2014).[2] When individuals are deciding whether or not to adopt a financial instrument, they face a risk and may place higher value on information coming from agents who they trust.

Our paper is also related to the literature on financial literacy. Survey data show that financial literacy is lowest among the young and the old (see Lusardi and Mitchell, 2014). In particular, young adults' limited awareness of financial instruments and investment possibilities is a matter of concern since financial decisions made early in life create habits that are difficult to break. Financial knowledge affects teenagers' ability to become financially secure adults (Martin and Oliva, 2001), their exposure to financial crises (Klapper et al., 2013), their preparedness for retirement (Alessie et al., 2011), and their saving behavior (Bernheim et al., 2001).

[1]We are grateful to Carin van der Cruijsen, and to the participants to the DNB Payment conference 2016-Retail Payments: Mapping out the Road Ahead for helpful comments and discussions.

[2]Butler et al. (2016) highlight financial advice as an important example of a trust-based exchange. In the US, 73% of all retail investors consult a financial advisor before purchasing shares (Hung et al., 2008).

The common consensus in this literature is that individuals who use more financial and payment instruments exhibit, on average, better understanding of core financial concepts.[3] Our analysis contributes to this literature by indicating that social interactions may play an important role in fostering the spread of financial knowledge among high school students.[4] Our analysis is also directly related to Bönte and Filipiak (2012), who find a positive relationship between financial literacy (awareness and adoption of financial instruments) and social interactions (at the caste level) in India.

Our paper is organized as follows. We begin by describing our data in Section 2. In Section 3, we present our empirical model and identification strategy, and, in Section 4, we discuss our main estimation results. We examine the mechanism of peer influence in Section 5. In Section 6, we use simulation experiments to show the implications of social interactions for the adoption of financial services. Section 7 concludes.

2 Data description

Our analysis is based on an unique database on friendship networks from the National Longitudinal Survey of Adolescent to Adult Health (Add Health).[5] The Add Health survey was designed to study the impact of the social environment (i.e. friends, family, neighborhood, and school) on students' behavior in the United States. It collects data on students in grades 7-12 from a nationally representative sample of roughly 130 private and public schools in the years 1994-1995 (Wave I). Every student attending the sampled schools on the interview day was asked to complete a questionnaire (*in-school data*) containing questions on respondents' demographic and behavioral characteristics, education, family background, and friendship. A subset of students selected from the rosters of the sampled schools - about 20,000 individuals - was then asked to complete a longer questionnaire containing more sensitive individual and household information (*in-home and parental data*). Those subjects were interviewed again in 1995–1996 (Wave II), in 2001–2002 (Wave III), and in 2007-2008 (Wave IV).

From a network perspective, the most interesting aspect of the Add Health data is the friendship information, which is based upon actual friend nominations. In the survey, students are asked to identify their best friends from a school roster (up to five males and five females).[6] This information is collected in Wave I and one year after, in Wave II. As a result, one can reconstruct the whole geometric structure of the friendship networks and their evolution, at least in the short run. Let $g_{ij,r,t}$ be equal to 1 if i nominates j at time t in the network r and zero otherwise. About 10% of the nominations in our data are not reciprocal, that is there are cases where agent i nominates agent j as best friend but agent j does not list agent i among her/his best friends. We consider two agents to be connected if at least one has nominated the other as a best friend. Indeed, even if agent j does not nominate i as best friend, it is reasonable to think that social interactions have taken place.[7] Such detailed information on social interaction patterns allows us to measure the peer group more precisely than in previous studies by knowing exactly who nominates whom in a network (i.e. who

[3] See Disney and Gathergood (2013) for consumer credit products, van Rooij et al. (2011) for stock market participation and Lusardi and Mitchell (2007) for checking and savings accounts, among others.

[4] Most high school students in the U.S. receive a failing grade in financial literacy (Mandell, 2008; Markow and Bagnaschi, 2005). Similar findings are reported for financial literacy among college students (Chen and Volpe, 1998; Shim et al., 2010).

[5] This research uses data from Add Health, a program project directed by Kathleen Mullan Harris and designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris at the University of North Carolina at Chapel Hill, and funded by grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 23 other federal agencies and foundations. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Information on how to obtain the Add Health data files is available on the Add Health website (http://www.cpc.unc.edu/addhealth). No direct support was received from grant P01-HD31921 for this analysis.

[6] The limit in the number of nominations is not binding (even by gender). Less than 1% of the students in our sample show a list of ten best friends, both in Wave I and Wave II.

[7] An alternative definition of network link that exploits the direction of the nominations does not substantially change our results.

interacts with whom in a social group).

Moreover, one can distinguish between *strong* and *weak* ties in the data. We define a relationship between two students as a strong tie if the students nominate each other in both waves (i.e. in Wave I in 1994-1995 *and* in Wave II in 1995-1996) and a *weak* tie if they nominate each other in one wave only (Wave I *or* Wave II). More precisely, we define a weak tie as $g_{ij,r}^{W} = 1$ if $\{g_{ij,r,t-1} = 1, g_{ij,r,t} = 0\}$ or $\{g_{ij,r,t-1} = 0, g_{ij,r,t} = 1\}$ and a strong tie as $g_{ij,r}^{S} = 1$ if $\{g_{ij,r,t-1} = 1, g_{ij,r,t} = 1\}$.[8]

The information about financial decisions is collected in Wave III. Unfortunately, friends' nominations are not collected in this wave, as some individuals have left high school. However, more than 80% are still at school and the large majority of the individuals (more than 75%) declare that they are still in contact with at least one friend nominated in the past wave. Of course, new friends can be created at the time of Wave III, and/or friendship relationships between schoolmates may change over time (see Section 3.2). However, the network of social contacts during high school remains a good approximation of face-to-face interactions at present (or in the recent past). The questionnaire of Wave III contains detailed information on the use of financial and payment instruments like savings and checking accounts, credit cards, loans, shares of stock in publicly held corporations, mutual funds, or investment trusts. Table 1 reports summary statistics on the financial activity participation of the agents in our sample. More than 60% of the students have a checking account, a savings account, and a credit card. About 40% have credit card debt and more than 30% have a student loan. Interestingly, 25% of individuals own shares of stock in publicly held corporations, mutual funds, or investment trusts, including stocks in IRAs.[9] For each individual, we construct an index of financial activity participation using a traditional principal component analysis (PCA), where the loadings of these different activities are used to derive a total score. Panel (a) of Figure 1 shows a scree plot documenting how much variation in our data is explained by the different principal components. It plots the eigenvalue of each component, which is a measure of the component's importance in explaining variation in the data, in descending order by eigenvalue. Our measure of financial activity is the first principal component. It explains about a half of the total variance.[10] The last column of Table 1 shows that each financial activity is positively correlated with this variable, meaning that the larger the variety of financial services that an individual uses, the higher the value of our indicator of financial participation. Panel (b) of Figure 1 depicts its distribution. The index ranges between 0 and 2.64, with mean of 1.47. The distribution shows that there is a high concentration of students using financial services more than the average.

A unique feature of our data is that, by matching the identification numbers of the friendship nominations to respondents' identification numbers, one can obtain information on all nominated friends. Such a data structure thus allows us to investigate the impact of peers' adoption of financial instruments on individual decisions.[11]

Before proceeding with the formal analysis, we provide a heuristic description of a social network to illustrate the relationship between financial activity and the network topology. Figure 2 shows a representative network. Each node represents an agent, with the size of the node proportional to her/his level of participation in the financial market. The lines represent the connections between the agents; the thicker they are, the longer the relationship between pairs of agents. As can be seen from the picture, agents in groups characterized by a relatively high density of ties tend to show a higher and more similar levels of financial activity. This stylized

[8] In Section 4.2, we show that the results remain qualitatively unchanged if we use an alternative definition of weak ties.

[9] Unfortunately, information on the precise timing of the financial decisions is not available in our data. The only existing studies using this information are based on ad hoc survey on small samples (see Varcoe et al., 2010; Danes et al., 1999; Bowen, 2002).

[10] PCA uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables (called principal components). This transformation is defined in such a way that the first principal component accounts for the largest portion of variability in the data.

[11] The other existing surveys that report friend nominations are ego-networks. In these surveys, the respondent lists her contacts and some basic characteristics of them (such as gender, education, employment status). Detailed information about nominated contacts is typically not available.

fact motivates our analysis in the following sections.

The sample of individuals that are followed over time and have non-missing information for our target variables in Waves I, II, and III consists of 12,874 individuals. As is common with Add Health data, the network construction procedure further reduces the sample size - roughly 20% of the students do not nominate any friends and another 20% cannot be correctly linked. Also, we do not consider networks at the extremes of the network size distribution (i.e. consisting of 2 or 3 individuals or more than 400) because peer effects can show extreme values (very high or very low) in these edge networks (see Calvó-Armengol et al., 2009). In addition, in this study, we focus on networks of 10-50 agents to cope with the computational burden required by the use of Bayesian estimation procedures. Our final sample consists of 569 individuals distributed over 21 networks.[12] In Table 2, we detail our sample selection procedure. We report the characteristics of four different samples, which correspond to the four steps of our selection procedure. We consider in column 1 the sample of individuals that are followed over time and have non-missing information for our target variables in Waves I, II, and III. In column 2, we further restrict the sample to those with friendship information. In column 3, we display the sample of students that is obtained after the network construction procedure (i.e. when students with no nominations are eliminated) embedded in networks between 4 and 400 members. Finally, in column 4, we use the sample of students in networks of 10-50 agents. Table 2 shows that differences in means between these samples are never statistically significant. Table A.1 in the Appendix provides precise definitions of the variables used in our study as well as details on nomination data. The mean and the standard deviation of network size are roughly 27 and 13 students, respectively. On average, these individuals have 23% strong ties and 76% weak ties.

Figures A.1 - A.6 report the distribution of individual characteristics conditional on engaging in a given financial activity and conditional on not engaging in that activity. Perhaps unsurprisingly, students adopting financial services have higher income and higher parental income than those not adopting them (with the exception of student loans) (Figures A.1 and A.3). Consistent with Stavins (2016), our data indicate that education is a strong predictor of payment instrument adoption. Less-educated students are significantly less likely to adopt all payment instruments (Figure A.2). In addition, those with credit cards, shares, and credit card debt are relatively old (Figure A.4). Looking at racial differences, non-white students are less likely to have shares and hold a checking account (Figure A.5 and A.6). This is in line with the findings of (as in Stavins, 2016). Perhaps interestingly, our data also reveal that Latinos are overrepresented among non-adopters of student loans (while Blacks are not).

3 Empirical model and estimation strategy

3.1 The network model

Consider a population of n individuals partitioned into $\bar{r}$ networks. For the n_r individuals in the rth network, their connections with each other are represented by an $n_r \times n_r$ adjacency matrix $\mathbf{G}_r = [g_{ij,r}]$ where $g_{ij,r} = 1$ if individuals i and j are friends and $g_{ij,r} = 0$ otherwise. The diagonal elements $g_{ii,r}$ are set to zero by convention. Let $\mathbf{G}_r^* = [g_{ij,r}^*]$ be the row-normalized $\mathbf{G}_r$ such that $g_{ij,r}^* = g_{ij,r} / \sum_{k=1}^{n_r} g_{ik,r}$.

[12] Our results do not depend crucially on these network size thresholds. They remain qualitatively unchanged when changing the network size window slightly. Also, although the computational complexity of the Bayesian analysis prevents us from working with large networks, the IV estimation results remain qualitatively unchanged when using the larger sample of networks between 4 and 400 students (see Section 4.1, and Appendix 2, Table A.2-A.3).

The financial activity of individual i in network r, $y_{i,r}$, is given by

$$y_{i,r} = \phi \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} + \sum_{k=1}^{p} x_{ik,r} \beta_k + \sum_{k=1}^{p} (\sum_{j=1}^{n_r} g^*_{ij,r} x_{jk,r}) \delta_k + \eta_r + \epsilon_{i,r}. \tag{1}$$

In this model, $\sum_{j=1}^{n_r} g_{ij,r} y_{j,r}$ denotes the aggregate financial activity of i's direct contacts with its coefficient ϕ representing *the endogenous effect*, wherein an individual's choices may depend on those of his/her contacts about the same activity.[13] $x_{ik,r}$ indicates the k_{th} exogenous variable accounting for observable differences in individual characteristics (e.g., gender, race, education, income, family background, etc.). $\sum_{j=1}^{n_r} g^*_{ij,r} x_{jk,r}$ is the average value of the exogenous variables over i's direct contacts, with its coefficient δ_k representing *the contextual effect*, wherein an individual's financial activity may depend on the exogenous characteristics of his/her contacts. η_r is a network-specific parameter representing *the correlated effect*, wherein individuals in the same group tend to behave similarly because they face a common environment. $\epsilon_{i,r}$ is an i.i.d. error term with zero mean and finite variance σ^2.

Model (1) can be extended to the case of heterogeneous peer effects. If we consider that each ego-network (i.e. the social contacts of a specific agent) can be split into two different pieces (weak and strong ties), then Model (1) becomes

$$\begin{aligned} y_{i,r} \quad = \quad & \phi^S \sum_{j=1}^{n_r} g^S_{ij,r} y_{j,r} + \phi^W \sum_{j=1}^{n_r} g^W_{ij,r} y_{j,r} + \boldsymbol{x}'_{i,r} \beta \\ & + \frac{1}{g^S_{i,r}} \sum_{j=1}^{n_r} g^S_{ij,r} x'_{j,r} \delta^S + \frac{1}{g^W_{i,r}} \sum_{j=1}^{n_r} g^W_{ij,r} x'_{j,r} \delta^W + \eta_r + \epsilon_{i,r}, \end{aligned} \tag{2}$$

where $g^S_{i,r} = \sum_{j=1}^{n} g^S_{ij,r}$ and $g^W_{i,r} = \sum_{j=1}^{n} g^W_{ij,r}$ are the total number of strong and weak ties each individual i has in network r. In this model, ϕ^S and ϕ^W represent *the endogenous effects* (i.e. the effect of strong and weak ties' financial activities on one's own financial choices), while δ^S and δ^W capture the impact of the exogenous characteristics of the peers (which are allowed vary by peer type).

3.2 Identification and estimation

A number of papers address the identification and estimation of peer effects with network data (see, e.g., Bramoullé et al., 2009; Liu and Lee, 2010; Calvó-Armengol et al., 2009; Lin, 2010; Lee et al., 2010; Patacchini et al., 2017). Below, we review the crucial issues and explain how we address them.

Reflection problem In linear-in-means models, simultaneity in the behavior of interacting agents introduces a perfect collinearity between the expected mean outcome of the group and its mean characteristics. Therefore, it is difficult to differentiate between the effect of peers' choices (*endogenous effects*) and peers' characteristics (*contextual effects*) that do have an impact on their choices (the so-called reflection problem; see Manski, 1993). Basically, the reflection problem arises because, in the standard approach, individuals interact in groups - individuals are affected by all individuals belonging to their group and by nobody outside the group. In the case of social networks, instead, this is almost never true since the reference group is individual specific. For example, take individuals i and k such that $g_{ik,r} = 1$. Then, individual i is directly influenced by $\overline{y}_i = \sum_{j=1}^{n_r} g_{ij,r} y_j$ while individual k is directly influenced by $\overline{y}_k = \sum_{j=1}^{n_r} g_{kj} y_j$, and there is little chance for these two values to be the same unless the network is complete (i.e. everybody is linked with everybody).

Correlated effects While a network approach allows us to distinguish endogenous effects from correlated

[13] Peer effects are modeled as the sum of other's outcome (and not the mean), because adoption can also depend on the number of peers using a specific service instead of just the average adoption rate.

effects, it does not necessarily estimate the causal effect of peers' influence on individual behavior. The estimation results might be flawed because of the presence of peer-group specific *unobservable* factors affecting both individual and peer behavior. For example, a correlation between the individual and peer school performance may be due to an exposure to common factors (e.g., having good teachers) rather than to social interactions. The way in which this has been addressed in the literature is to exploit the architecture of network contacts to construct valid IVs for the endogenous effect. Since peer groups are individual-specific in social networks, the characteristics of indirect friends are natural candidates. Consider the network in Figure 3. Individual k affects the behavior of individual i only through her/his common friend j, and she/he is not exposed to the factors affecting the peer group consisting of individual i and individual j. As a result, the characteristics x_k of individual k are valid instruments for y_j, the endogenous outcome of j. Details on the IV estimation procedure are contained in Appendix 1.

Sorting In most cases, individuals sort into groups non-randomly. For example, students with less-educated parents may be more likely to sort with low human capital peers. If the variables that drive this process of selection are not fully observable, potential correlations between (unobserved) group-specific factors and the target regressors are major sources of bias. The richness of social network data (where we observe individuals over networks) provides a possible solution through the use of *network fixed effects*. If the unobservable characteristics driving selection into groups are common to the individuals within each network, then the possible correlation between the regressors and the error term is eliminated. One way to check the validity of this approach is to look at selection patterns on observable variables. It has been noted that the degree of selection on observables can provide a good indicator of the degree of selection on unobservables (Altonji et al., 2005). Thus, failure to find a correlation between individual and peer-group observables (after adding network fixed effects and other controls) would support the assumption of no sorting within networks based on unobservables. Unfortunately, we do find correlations in observables in our data. Table 3 reports the estimated correlations between individual and peer-group averages (i.e. averages over best friends) of observable variables with alternative sets of controls. Without controls (column 1), there is strong evidence that friends are not randomly chosen. The inclusion of network fixed effects (column 2) and further individual and friend characteristics (column 3) explains the correlation in linking decisions for most variables. However, a few significant correlations remain, and we cannot rule out also the presence of sorting along unobservable characteristics within networks. For example, one can envision the existence of individual-level unobservable (or unmeasurable) factors, such as risk aversion or optimism, which are plausibly related to both friendship formation and financial decision making.

To eliminate this suspected source of bias, we test the robustness of our analysis to explicitly modeling the network formation and integrating the outcome equation in a Bayesian analysis.

Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016) propose two slightly different Bayesian methodologies to estimate peer effects with unobservables driving both link formation and outcomes.[14] In Goldsmith-Pinkham and Imbens (2013), unobservables are dichotomous and only one network is considered. As we have multiple networks in our data, we follow Hsieh and Lee (2016). They present a model with one peer type, which corresponds to Model (1). We implement an extension of their method for heterogeneous peer effects. If there is an unobservable characteristic that drives the choice of, say, strong ties and is correlated with $\epsilon_{i,r}$ then $g^S_{ij,r}$ is endogenous and estimates of Model (2) are biased. By failing to account for similarities in (unobserved) characteristics, similar behaviors might mistakenly be attributed to peer influence when they simply result from similar characteristics. Let $z_{i,r}$ denote such an *unobserved characteristic* which influence

[14]The Bayesian approach allows us to model couple-specific unobserved heterogeneity for each possible couple in the sample. A traditional selection model is configured to capture individual-specific unobserved heterogeneity. The inclusion of heterogeneity would imply the computation of high-dimensional multivariate normal integrals, which is unfeasible using standard methods. Pereda-Fernández (2016) shows how to approximate this type of integrals when the correlation has a particular structure.

the link formation process. Let us also assume that $z_{i,r}$ is correlated with $\epsilon_{i,r}$ in Model (2) according to a bivariate normal distribution

$$(z_{i,r}, \epsilon_{i,r}) \sim N\left(\left(\begin{array}{c} 0 \\ 0 \end{array}\right), \left(\begin{array}{cc} \sigma_z^2 & \sigma_{\varepsilon z} \\ \sigma_{\varepsilon z} & \sigma_\varepsilon^2 \end{array}\right)\right). \tag{3}$$

Agents choose social contacts at two points in time, t-1 and t. At each time, agent i chooses to be friends with j according to a vector of observed and unobserved characteristics in a standard link formation probabilistic model

$$P(g_{ij,r,t-1} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}) = \Lambda(\gamma_{0,t-1} + \sum_k |x_{i,r} - x_{j,r}|\gamma_{k,t-1} + |z_{i,r} - z_{j,r}|\theta_{t-1}), \tag{4}$$

and

$$P(g_{ij,r,t} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, g_{ij,r,t-1}, \gamma_t, \theta_t, \lambda) = \Lambda(\gamma_{0,t} + \lambda g_{ij,r,t-1} + \sum_k |x_{i,r} - x_{j,r}|\gamma_{k,t} + |z_{i,r} - z_{j,r}|\theta_t), \tag{5}$$

where $\Lambda(\cdot)$ is a logistic function. Homophily behavior in the unobserved characteristics implies that $\theta_\tau < 0$, where $\tau = t-1, t$, this meaning that the closer two individuals are in terms of unobservable characteristics, the higher the probability that they are friends. The same argument holds for observables. If $\sigma_{\varepsilon z}$ and θ_τ are different from zero, then networks $g^S_{ij,r}$ and $g^W_{ij,r}$ in model (1) are endogenous. Joint normality in (3) implies $E(\epsilon_{i,r}|z_{i,r}) = \frac{\sigma_{\varepsilon z}}{\sigma_z^2} z_{i,r}$, when conditioning on $z_{i,r}$. Hence, the outcome equation is

$$\begin{aligned} y_{i,r} \quad = \quad & \phi^S \sum_{j=1}^{n_r} g^S_{ij,r} y_{j,r} + \phi^W \sum_{j=1}^{n_r} g^W_{ij,r} y_{j,r} + \boldsymbol{x}'_{i,r}\beta + \frac{1}{g^S_{i,r}} \sum_{j=1}^{n_r} g^S_{ij,r} x'_{j,r} \delta^S \\ & + \frac{1}{g^W_{i,r}} \sum_{j=1}^{n_r} g^W_{ij,r,t} x'_{j,r} \delta^W + \eta_r + \frac{\sigma_{\varepsilon z}}{\sigma_z^2} z_{i,r} + u_{i,r}, \end{aligned} \tag{6}$$

where $u_{i,r} \sim N(0, \sigma_z^2 - \frac{\sigma^2_{\varepsilon z}}{\sigma_z^2})$. Note that if no correlation is at work ($\sigma_{\varepsilon z} = 0$), then estimating equation (6) or (2) is equivalent. Given the complexity of this framework, it is convenient to simultaneously estimate the parameters of equations (4), (5) and (6) with a Bayesian approach. Details on the Bayesian estimation procedure are contained in Appendix 1.[15]

4 Estimation results

The aim of our empirical analysis is twofold: (*i*) to assess the presence of peer effects in the adoption of financial services, (*ii*) to differentiate between the impact of weak and strong social ties.

[15]The extended model (4)-(6) is more demanding than model (2) in terms of identification conditions. Identification in the baseline model (2) rests on the exogeneity of the X variables and on the presence of intransitivities in the exogenous network topology as captured by the matrix G. Identification in the extended model (4)-(6) requires an additional source of exogenous variation through absolute values of differences. Indeed, in the extended model (4)-(6), the dyad-specific regressorsused in the network formation model are naturally excluded from the outcome equation. As a consequence, covariates affect links through absolute values of differences, while they affect outcomes directly. This constitutes a form of exclusion restriction that relies on nonlinearities.

4.1 Peer effects

Table 4 collects the estimation results for the financial activity index using model (1), that is without distinguishing between strong and weak ties. Columns (1) to (6) report the results when network exogeneity is assumed, with different estimation methods. Column (7) shows the Bayesian estimation results, which account for possible network endogenity. Columns (1) to (3) report OLS estimates with increasing sets of controls. Column (1) includes individual socio-demographic characteristics (age, race, gender, education, employment status, occupation, parental education, marital status, family background variables, etc.), while column (2) extends the number of control variables to include peers' characteristics. This specification addresses the concern that a correlation between own and peers' behavior is simply driven by similar (observable) characteristics between peers. Finally, column (3) adds network fixed effects, thus accounting for any further unobserved factors common to all individuals in a social group. The issue addressed here is that correlated actions between connected agents may simply be driven by common shocks or sorting into groups according to network-specific unobserved characteristics. Column (4) presents the estimation results using ML, when we account for the simultaneity endemic in spatial models.[16] Columns (5) and (6) are devoted to the IV estimates. As explained in Section 3.2, the IV strategy that is now standard in network model estimation consists of exploiting network architecture and uses peers of peers' characteristics as instruments for peers' behavior. Table 5 reports the first stage results. The F-statistic confirms the relevance of the IVs. Because of the many-IVs bias that may arise in estimating spatial models with IVs, we follow Liu and Lee (2010) and also use a bias-corrected IV.[17] Finally, column (7) reports means and standard deviations of the posterior distributions of the parameters of Model (4) - (5) - (6), that is with correlated unobservables, estimated by Bayesian methods. We let our Markov Chain run for 80,000 iterations, discarding the first 7,000, even though ergodicity of the Markov Chain is achieved quite quickly. It appears that the Bayesian estimates (column (7)) are remarkably similar to the ones that are obtained using the IV bias-corrected (column (6)). This suggests that unobservable factors influencing the link formation are not relevant in the financial decisions of agents. Indeed, the estimated correlation between unobservables in the outcome and link formation equations ($\sigma_{\varepsilon z}$) is not significantly different from zero. For completeness, Figures 4 and 5 show the kernel density estimates of the posterior distributions (left panel) and the Markov chain (right panel) of ϕ and $\sigma_{\varepsilon z}$. The time-series of the values of the chains (right panel) reveals that stationarity has been achieved.[18]

Table 4 shows that the effect of peers' financial activity on own activity is significant and positive, i.e. there are *peer effects in financial activity*. These are non-negligible effects, especially given our long list of individual and peers' controls. Although the computational burden required by the Bayesian procedure prevents us from performing this type of estimation on the entire sample, we report in the Appendix Table A.2 the OLS, ML and IV results for the a larger sample of students (column 4, of Table 2). The results remain qualitatively unchanged.

4.2 Peer effects by peer type

Table 6 collects the estimation results of model (2). It has a structure similar to Table 4.[19] Column (4) shows the Bayesian estimation results, which account for possible endogeneity of strong and weak tie networks. The

[16] Spatial models are simultaneous equation models where peers' behavior depends on own behavior. This implies that $\sum_{j=1}^{n_r} g_{ij,r}y_{j,r}$ is correlated with the error term $\varepsilon_{i,r}$ in equation (1). ML accounts for this simultaneity as it is based on the reduced form. Network fixed effects cannot be included in the model because the group mean $\overline{y}_r$ is not a sufficient statistic for η_r when the adjacency matrix is not row-normalized (see Lee et al., 2010).

[17] See Appendix 1 for more details. For the sake of brevity, the appendix focuses on the case with weak and strong ties. The case with one peer effect is just a special case, that is when $\phi^S = \phi^W$.

[18] The kernel densities and the time-series of the values of the chain for the parameters of the control variables are reported in Appendix 2, Figures A.7 - A.10.

[19] For brevity, we do not report the ML estimation results. They are similar to the IV bias-corrected estimation results.

results in Table 6 do not change qualitatively across columns and reveal that the financial choices of weak ties have no significant impact on individual financial activity, while the financial choices of strong ties do have a positive and significant effect on own ones.[20] OLS and IV estimates seem to overestimate the effects. The IV bias-corrected and Bayesian estimates are very close to each other. This means that unobservable factors influencing the *strength* of a tie are not relevant in the demand for financial services ($\sigma_{\varepsilon z}$ is not significantly different from zero).[21] Given that our networks are quite small in size, it is likely that any correlated unobserved factor is already captured by the network fixed effects. The upper panel of Figure 6 shows the kernel density estimates of the posterior distributions of ϕ^S and ϕ^W. Two features of note are: *(i)* the distribution of ϕ^W is centered on zero; *(ii)* the distribution of ϕ^S is shifted towards the right.[22] This confirms that the effect of weak ties is virtually zero and that of strong ties is different from zero and positive. The lower panels depict the time-series of the values of the chain, which reveal that stationarity has been achieved.[23]

In terms of magnitude, in an average group of four strong ties, a standard deviation increase in the financial activity of each of the peers translates into a 27% increase of a standard deviation in the individual's financial activity. This yields increases of about 26% in the probability of getting a credit card, 7% in the probability of opening a checking or savings account, 5% in the probability of buying shares, 4% in the probability of getting a loan, and 10% in the probability of having credit card debt.

To check whether our results are robust to alternative definitions of weak ties we re-estimate model (2) using a different definition of weak ties. One could expect that there are different social interactions between two people when they are "recent friends" (if $\{g_{ij,r,t-1} = 0, g_{ij,r,t} = 1\}$) and when they were "once friends" (if $\{g_{ij,r,t-1} = 1, g_{ij,r,t} = 0\}$) but no longer consider themselves to be friends. To differentiate between the timing of changes in friendship status, we thus re-estimate model (2) distinguishing weak ties between "recent friends" and "once friends". Table 7 reports the results. Weak ties are never significantly different from zero even if they are defined as "recent friends", while the estimated coefficient for strong ties remains close to the estimates in Table 6.

The important observation related to the policy relevance of our results is that policy makers can rarely manipulate peer outcomes. Peer effects should be seen as a mechanism through which an exogenous shock (i.e. a change in the exogenous variables) could spread through the networks. Our evidence on the existence of peer effects in financial activity thus indicates that the marginal effects of the control variables in a network model would be different than in a model without network effects. Indeed, if $\phi^S \neq 0$ or $\phi^W \neq 0$ (in model (2)), then the marginal effect of the k-th covariate would be $(I_{n_r} - \phi^S G_r^S - \phi^W G_r^W)^{-1}(I_{n_r}\beta_k + G_r\gamma_k)$, which is an $n_r \times n_r$ matrix with its (i,j)-th element representing the effect of a change in $x_{jk,r}$ on $y_{i,r}$. The important observation is that the marginal effects are now heterogeneous across individuals, since they depend on the individual's position in the network. In Section 6 we use Monte Carlo simulations to mimic the effect of a change in the exogenous variables in presence of network effects.

4.3 Network Formation

For completeness, Table 8 reports on the factors driving link formation in Wave I and II. It shows the complete list of estimation results of model (4)-(5)-(6), that is when network formation and behavior over the network

[20]When estimating model (2) including only strong ties (i.e. $g^W_{ij,r} = 0$), we obtain comparable results.

[21]Observe that we model unobserved factors at the individual level. This means that the unobserved factors affecting weak and strong tie formation may be different.

[22]Borrowing from decision theory, we can say that ϕ^S stochastically dominates ϕ^W, that is $P(\phi^S \geq x) \geq P(\phi^W \geq x), \forall x \in \mathbb{R}$ (first-order stochastic dominance). Figure 6 also shows that the distribution of ϕ^S is negatively (left) skewed. This is due to the condition on the autoregressive parameter in spatial models (peer effect parameter) that guarantees matrix inversion in Model (2). More specifically, the parameter space is (-0.10,0.10) for our network. While this is never binding for ϕ^W, ϕ^S is constrained to be below the upper bound. See Appendix 1 for model details.

[23]We show Appendix 2, Table A.3 that the results remain qualitatively unchanged if we perform our IV analysis on a larger sample (column 4, Table 2).

are simultaneously estimated. The estimates of the outcome equation (first column) are the ones in column (4) of Table 6. Looking at the estimates of the network formation model in the last two columns, one can see that all the significant coefficients are negative. This evidence reveals homophily behavior -the closer two agents are in terms of observable characteristics, the higher the likelihood of a link between them. Interestingly, the factors predicting the existence of a link change slightly between Wave I and Wave II. While family background characteristics (such as parental education and income) are important in Wave I, individual characteristics (such as own income and employment status) acquire more importance in Wave II. Importantly, it appears that there are unobserved factors that are relevant in network formation both for Wave I and II. Those factors, however, are not correlated with the error term in the outcome equation. Indeed, the estimate of $\sigma_{\varepsilon z}$ is not statistically significant. In our case where networks are quite small, the inclusion of network fixed effects is likely to control for correlated unobservables. As a result, the use of traditional estimation strategies with network fixed effects that treat network formation as exogenous are not likely to produce biased coefficient estimates. This is why our estimates in columns (6) and (7) of Table 4 and in columns (3) and (4) in Table 6 are similar.

4.4 Peer effects by financial service

Table 9 reports the estimates of peer effects for each financial instrument separately. We computed OLS, IV and IV bias-corrected estimators. The results consistently indicate that financial service dissemination is most relevant when initiated by individuals with whom a person has long-lasting relationships irrespective of the financial service. In terms of magnitude, the effect of strong ties is particularly high for student loans, shares, and credit card utilization, while it is lower for both checking and savings accounts. Observe that for the diffusion of student loans weak ties are important too. This finding is perhaps not surprising in light of the evidence reported in Avery and Turner (2012). Figure 1 in Avery and Turner (2012) documents that the increase in the debts is particularly marked after 1993-1994. The years of the Add Health survey 1994-1995 (Wave I)- 2001-2002 (Wave III) are thus the years in which this debt is booming. The evidence that weak ties are also important in shaping decisions to take out student loans is consistent with the idea that the bubble is generated by herd behavior. Table 10 reports OLS and IV bias-corrected estimates of the effects of the control variables on each outcome separately. Most notably, we find a significant effect of father's education on the probability of having a checking account or a credit card. Perhaps unsurprisingly, higher parental income decreases the probability of borrowing money through a student loan.[24]

5 Inspecting the mechanism

By exploiting the recent advances in the econometrics of social networks, our estimation strategy accounts for a possible sorting of agents into networks and controls for unobserved individual characteristics. These unobserved factors possibly capture characteristics such as risk aversion and optimism. Having thus ruled out possible effects of confounding factors, we should believe in a causal effect of peers' behavior on individual behavior which depends on the length of the friendship relationship. Thus, the relevant question is why strong ties are important whereas weak ties are not.

One possibility is that when agents have to decide whether to adopt a financial instrument, they face a risk and place higher value on information from (or the behavior of) agents they trust more. Trust has been widely studied as an important driver of financial decisions (Guiso et al., 2004; Guiso et al., 2008). Repeated interactions play an important role in determining the level of trust. Several theoretical papers

[24] The information on parental background in our data is not detailed enough to dig further into the importance of family inputs. For example, information on parental financial literacy or financial decisions are not available.

explore the role of information transmission and trust formation in communities and networks. Balmaceda and Escobar (2013) model cohesive communities as complete social networks emerging from optimal agents' choices. Agents maximize common knowledge and consequently minimize the temptation to defect. In their conceptual framework where investors observe whether their direct neighbors invest or not, complete networks are optimal. Their repeated game model with community-based information flow lets trust emerge among agents. The repeated interactions horizon generates a bilateral incentive to let relationships with more trusted agents survive over time. Karlan et al. (2009) view network connections as "social collateral" and argue that the level of trust is determined by the structure of the entire network. In the context of informal contract enforcement, they focus on borrowing and lending choices. The utility derived from links prevents agents from acting unfairly and lets them repay the borrowed value. Kandori (1992) focuses on the role of "social pressure" and "reputation" in informal contracts. Rewarded honesty and punished defection incentivize agents to behave correctly. This incentive is created by repeated interactions among agents.[25] In his model, enforcement mechanisms work best in long-term relationships. Strong correlation patterns in the behavior of connected agents is driven by the presence and circulation of private information among agents.[26,27] Lippert and Spagnolo (2011) explore scenarios characterized by *Word-of-Mouth Communication.* Their game design lets "network closure" be particularly relevant for sustainability of agents relationships, providing a microfoundation for the idea of "embeddedness" from Granovetter (1985).

If our data is consistent with these theories and strong ties indicate significant trust, we should see an effect of strong ties on individual financial decisions in cohesive social structures only. Jackson et al. (2012) use the concept of "supported" links to characterize cohesive social structures. They provide an analysis of repeated interactions in which individuals' decisions are influenced by the network pattern of behavior in a community. Bilateral interactions may not provide natural self-enforcement of cooperation. Any robust equilibrium network must exhibit a specific trait: each of its links (bilateral connection) must be "supported". That is, if some agent i is linked to an agent j, then there must be some agent k linked to both of them. Agents with "supported" links tend to form tightly knit groups characterized by a relatively high density of ties.[28]

Table 11 reports the estimation results of Model (2) when strong and weak ties are split according to their level of *support.* The results confirm our conjecture. It indeed appears that the significant correlation between agents' financial decisions arises among strong ties in highly cohesive social structures. Observe that the network structure per se is not a relevant driver of behavior correlation. Indeed, weak ties in highly cohesive social structures do not show any similar behavior. Significant correlation arises only when agents have long-lasting friendships. This evidence is thus in line with the idea that a trust-based mechanism is driving our results.

[25] The Folk Theorem in the repeated game literature (Rubinstein, 1979; Fudenberg and Maskin, 1986) provides a formal model of personal enforcement, showing that any mutually beneficial outcome can be sustained as a subgame-perfect equilibrium if the same set of agents frequently play the same stage game ad infinitum.

[26] The role of private information in a community of buyers with word-of-mouth communication is also highlighted by Ahn and Suominen (2001). In this model, buyers receive signals from other agents and adapt their willingness to buy a seller's product. This mechanism incentivizes the seller to produce high quality output.

[27] See also Greif et al. (1994) for an analysis of the role of *bilateral* and *multilateral* reputation mechanisms in the organization of economic transactions.

[28] An alternative measure of network connectivity is the clustering coefficient. While clustering is a node-specific measure, support considers pairs of nodes (link-specific measure). Thus, support is more appropriate in our analysis, which is based on bilateral interaction-types (weak or strong). Observe that networks with an high level of clustering will necessarily display a high fraction of supported links, whereas the converse is not true.

6 Policy experiments

Using our data and the estimates of the parameters in Model (2),[29] we perform Monte Carlo simulations to asses the extent to which the presence of social interactions can alter the effect of exogenous shocks on the financial activity of agents.[30] The simulated shocks are variations in income, which is one of the most important determinants of financial activity. In a simplistic view, an increase in income can be interpreted as a decrease in participation cost, ceteris paribus. Our goal is to provide evidence about the individual and aggregate effects of strong and weak ties.

Four exercises are implemented. The first three exercises evaluate aggregate effects (i.e. the change in the sum of agents' financial activity after a given intervention). In the first exercise, the intervention is a changing income shock for a fixed number of agents (intensive margin) who have different numbers of strong ties. In the second, the intervention is a fixed income shock for an increasing number of agents (extensive margin) who have a different number of strong ties. In the third exercise, we increase the income of a fixed number of agents who have no strong ties while decreasing the income of agents who have strong ties and look at the final aggregate financial activity. The fourth exercise describes the individual effects; we increase the income of a given agent while decreasing the income of her/his peers and look at the consequences on her/his individual financial activity.

Figure 7 depicts the results for the first two exercises. The surfaces represent the variation of aggregate financial activity in our sample after the simulated shocks. Panel (a) depicts the effect of an increasing positive shock of income (h, x-axis) on aggregate financial activity for agents who have different number of strong ties (n_s, y-axis), holding constant the number of shocked agents. The shock intensity is administered in terms of the estimated standard deviation in our sample (std points). Each point of the surface is an average coming from 500 replications, where in each replication we shock a random sample of nodes of the same numerosity.[31] It appears that the higher the number of strong ties the shocked agents have, the higher the aggregate effect of the income shocks. The amplification effects of strong ties is sizable. Indeed, the aggregate effect of an income shock of 10 std points administered to agents that have 4 strong ties is the same that of 20 std points administered to agents without strong ties. In panel (b), we increase the number of shocked agents (n_h, y-axis), holding constant the shock intensity.[32] It appears that the aggregate financial activity is higher if the shock is administered to agents with an higher number of strong ties. Indeed, shocking 10 agents who have 4 strong ties produces the same aggregate result as shocking 20 agents who have no strong ties. Peer effects can in fact act as a mechanism through which a shock is propagated (and amplified) throughout the network.

Figure 8 shows how the network structure of social ties matters when negative and positive income shocks hit the population. The surface again represents the variation of aggregate financial activity. In this numerical experiment, we increase the income of a fixed number of agents who have no strong ties (i.e. with no network diffusion of their shocks),[33] and decrease the income of an increasing number of agents who have different numbers of strong ties (i.e. with network diffusion of their shock).[34] We observe that the higher the number of strong ties each shocked agent has, the smaller the number of shocked agents needed to render null the positive shock at the aggregate level. This evidence helps explain why some policies targeting a large number of agents

[29] The IV estimates in column (3) of Table 6 are used.

[30] The experiments have also been performed using each outcome separately. The results remain qualitatively unchanged and are available upon request.

[31] The number of shocked agents is chosen in a way such that for each category of strong ties we use a numerosity not larger than the real one. In our case, the minimum number of agents for each category of strong ties is 13 (when the number of strong ties is equal to 4). We then shock 13 randomly chosen nodes for each category at each replication. The results, however, remain qualitatively unchanged when changing the number of shocked nodes.

[32] The shock intensity is 2 std points. The results remain qualitatively the same when changing the shock intensity.

[33] We set this number equal to 13, as in our previous exercise. The qualitative results, however, do not depend on this number.

[34] The shocks are symmetrical and equal to +2 std points for agents who have no strong ties and equal to -2 std points for those who do have strong ties.

do not achieve the desired effects. Even if the observable costs of using, say, a new digital credit card are lower than the costs of using a traditional product, the social equilibrium may fail to predict the expected rate of adoption of the new credit card. Social interaction effects amplify whatever aggregate local preferences are induced by exogenous cross-product differences in participation costs. Many agents may be discouraged from adopting the new product largely because no one they trust has adopted the product. From Figure 8 one can see that if highly connected agents have a negative shock, then the aggregate financial activity decreases. This is true even if a large number of agents experience positive shocks (provided that these agents have relatively weak social ties). For example, Figure 8 reveals that if 11 agents who have 4 strong ties are negatively shocked and 13 agents who have not strong ties are positively shocked, then the aggregate financial activity decreases. Social interactions may be responsible for this (seemingly) paradoxical result.

We perform one final simulation to consider the effects at the individual level of individual and peers' shocks in our last simulation exercise. Each point of the surface represented in Figure 9 depicts the variation of individual financial activity after the simulated shocks averaged over 500 replications. In each replication, we randomly extract an individual i who has a certain number of strong ties, increase her/his income by a fixed amount, and decrease each of her/his peer's income by an increasing amount.[35] The exercise is implemented for agents who have different numbers of strong ties. We find that the higher the number of strong ties the agent has, the lower the magnitude of the negative shock given to the peers that is needed to cancel the effect of the individual positive shock. For example, Figure 9 shows that if an agent has 1 strong tie, then she/he needs the peer's negative shock to be double in absolute value to counterbalance the effect of her/his positive one. However, if the agent has 4 strong ties, it is enough a negative shock equal to one fifth of one's own of each of them .

7 Concluding remarks

Despite the widespread belief about the importance of word-of-mouth on financial service utilization, the finance literature provides little evidence on the role of peer-to-peer communications. This study is among the first to investigate the influence of social interactions on the demand for financial services using detailed data on each individual and friends' financial decisions. Our analysis examines the existence and extent of heterogeneous peer effects in financial decisions. We find that peers do influence each others' financial decisions, but that these peer effects exist only within relatively long-term friendships. Our evidence is consistent with the hypothesis that, when agents have to decide whether or not to adopt a financial instrument, they face a risk and may most highly value the information coming from trustworthy agents. Finally, we find large aggregate effects of increasing financial participation among well-connected individuals. If social interactions help to increase financial services participation, then the effectiveness of a policy may be magnified by the network effects it engenders.

[35] We set the individual income shock equal to 10 std points, while the shock given to the peers varies from -1 to -20 std points. The qualitative results remain qualitatively unchanged when changing such intensities.

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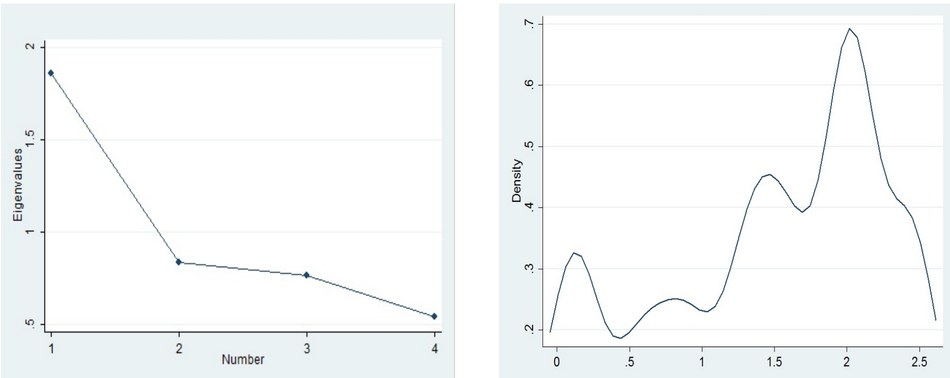
Table 1: Financial Activity Participation

	Percentage of agents possessing	Contribution to the Financial Activity Index
Checking Account	76%	0.40
Credit Card	61%	0.57
Savings Account	63%	0.73
Shares	25%	0.80
Student Loan	33%	0.53
Credit Card Debt	41%	0.47

Notes. The Financial Activity Index is obtained using a principal component analysis on the listed variables.

Figure 1: Principal component analysis of financial services

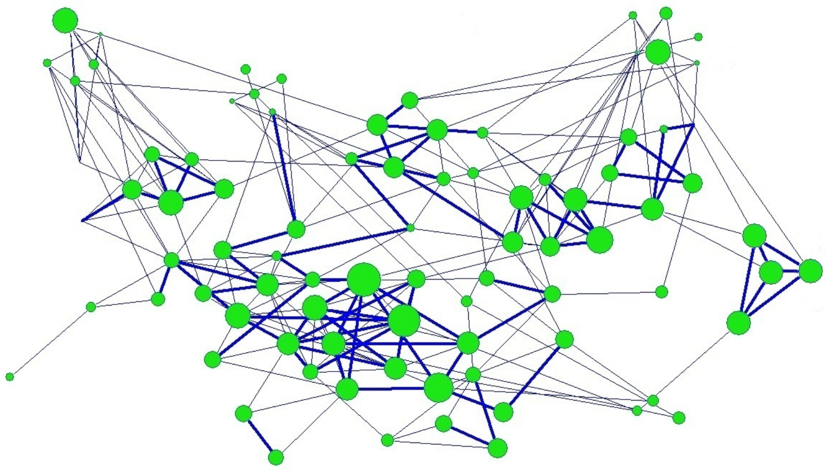


(a) Scree plot

(b) First principal component

Notes. Panel (a): 47 % of the total inertia is explained by the first component, 20 % of the total inertia is explained by the second and third component, the remaining 13 % is explained by the second and fourth components. Panel (b): a normal distribution is used for the kernel density.

Figure 2: Social Ties and Financial Activity



Notes. A network of 49 agents (nodes) is represented. The size of the node is proportional to the agent's financial activity; the thickness of the line is proportional to the length of the relationship between agents. Thicker lines represent strong ties, while thinner ones represent weak ties.

Table 2: Sample representativeness

Sample	Original sample	Sample in the nomination roster		Sample in networks between 4-400		Sample in networks between 10-50	
	Mean	Mean	Difference [p-value]	Mean	Difference [p-value]	Mean	Difference [p-value]
Financial Activity Index	1.43	1.41	[0.49]	1.47	[0.52]	1.49	[0.51]
Checking Account	0.73	0.72	[0.50]	0.76	[0.53]	0.80	[0.52]
Credit Card	0.60	0.59	[0.49]	0.61	[0.52]	0.57	[0.47]
Savings Account	0.63	0.63	[0.50]	0.63	[0.50]	0.66	[0.52]
Shares	0.24	0.23	[0.49]	0.24	[0.51]	0.27	[0.52]
Student Loan	0.31	0.31	[0.50]	0.33	[0.51]	0.25	[0.45]
Credit Card Debt	0.42	0.40	[0.49]	0.40	[0.50]	0.32	[0.45]
Male	0.46	0.45	[0.50]	0.47	[0.51]	0.44	[0.49]
Latino	0.14	0.14	[0.50]	0.12	[0.48]	0.05	[0.43]
Black	0.22	0.21	[0.50]	0.16	[0.46]	0.08	[0.43]
Age	21.92	21.61	[0.45]	21.65	[0.51]	20.83	[0.36]
Education	14.17	14.11	[0.49]	14.26	[0.52]	14.31	[0.51]
Income	13.88	13.21	[0.49]	14.07	[0.52]	12.03	[0.46]
Employed	0.70	0.69	[0.49]	0.70	[0.51]	0.70	[0.50]
Occ. Manager	0.07	0.06	[0.49]	0.05	[0.49]	0.06	[0.50]
Occ. Prof. Tech.	0.16	0.16	[0.50]	0.17	[0.51]	0.15	[0.49]
Occ. Manual	0.25	0.25	[0.50]	0.25	[0.50]	0.25	[0.50]
Occ. Sales	0.19	0.19	[0.50]	0.20	[0.50]	0.20	[0.51]
Married	0.17	0.15	[0.49]	0.16	[0.50]	0.16	[0.50]
Family Size	3.25	3.28	[0.50]	3.36	[0.51]	3.04	[0.45]
Father Education	9.78	9.84	[0.50]	10.73	[0.54]	12.13	[0.56]
Parental Income	47.33	48.21	[0.49]	49.40	[0.52]	58.50	[0.46]
Observations	12,874	9,918		1,497		569	

Notes. T-tests for differences in means are performed. P-values are reported in squared brackets. Differences are computed with respect to the larger sample.

Figure 3: Identification with Network Data

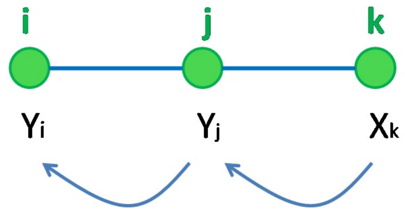


Table 3: Correlations between Individual and Peer-group Averages

Variable			
	(1)	(2)	(3)
Male	0.1700***	0.0557***	0.0968***
	(0.0102)	(0.0161)	(0.0371)
Latino	0.1485***	0.0990***	0.1195***
	(0.0149)	(0.0205)	(0.0250)
Black	0.3077***	0.1236***	0.1224***
	(0.0138)	(0.0173)	(0.0311)
Age	0.1937***	-0.0032***	0.0361
	(0.0056)	(0.0013)	(0.2503)
Education	0.1902***	0.0030	0.0387
	(0.0054)	(0.0022)	(0.2777)
Income	0.1550***	-0.0173	-0.0555
	(0.0142)	(0.0224)	(0.0445)
Employed	0.1743***	0.0040	0.0006
	(0.0078)	(0.0112)	(0.1106)
Occ. Manager	0.0517***	-0.0260	-0.0571**
	(0.0219)	(0.0242)	(0.0300)
Occ. Prof. Tech	0.1026***	0.0144	-0.0313
	(0.0151)	(0.0186)	(0.0369)
Occ. Manual	0.1498***	0.0521***	-0.0514
	(0.0124)	(0.0181)	(0.0497)
Occ. Sales	0.1291***	0.0041	-0.0496
	(0.0142)	(0.0198)	(0.0439)
Married	0.1477***	0.0092	-0.0135
	(0.0131)	(0.0194)	(0.0290)
Family size	0.1811***	-0.0014	-0.0295
	(0.0077)	(0.0110)	(0.0626)
Father Education	0.1787***	0.0018	-0.0146
	(0.0067)	(0.0090)	(0.1559)
Parental Income	0.1770***	0.0029	0.0163
	(0.0105)	(0.0159)	(0.0417)
Contextual Effects	No	No	Yes
Network Fixed Effects	No	Yes	Yes
Number of Observations	569	569	569
Number of Networks	21	21	21

Notes. OLS estimation results, standard errors in parentheses.*** p<0.01,** p<0.05,* p<0.1. Dummy variables for missing Income, Family Size, Father Education, Parental Income and GPA are included. Maximum network size 50, minimum 10.

Table 4: Peer Effects in Financial Decisions

Dependent variable: Financial Activity Index

	OLS (1)	OLS (2)	OLS (3)	ML (4)	IV (5)	IV bias-corrected (6)	Bayesian (7)
Peer Effects(ϕ)	**0.0783*** **	**0.0861*** **	**0.0696*** **	**0.0524*** **	**0.0873*** **	**0.0538***	**0.0518*** **
	(0.0215)	**(0.0282)**	**(0.0279)**	**(0.0189)**	**(0.0322)**	**(0.0322)**	**(0.0162)**
Male	-0.0952*	-0.1009*	-0.0989*	-0.1155*	-0.1110*	-0.1095*	-0.0605*
	(0.0585)	(0.0615)	(0.0594)	(0.0668)	(0.0582)	(0.0582)	(0.0330)
Latino	0.0895	0.1502	0.1771	0.0842	0.1686	0.1644	0.0254
	(0.1241)	(0.1318)	(0.1294)	(0.1441)	(0.1312)	(0.1312)	(0.0393)
Black	-0.1486	-0.1913	0.1789	-0.2338	0.2193	0.2210	0.0385
	(0.1052)	(0.1325)	(0.1519)	(0.1445)	(0.1522)	(0.1522)	(0.0502)
Age	0.0068	0.0074	0.0122	-0.0758***	0.0323	0.0342	0.0358*
	(0.0205)	(0.0232)	(0.0256)	(0.0163)	(0.0248)	(0.0248)	(0.0214)
Education	0.1192***	0.1204***	0.1010***	0.1116***	0.0919***	0.0947***	0.1286***
	(0.0196)	(0.0202)	(0.0199)	(0.0217)	(0.0198)	(0.0198)	(0.0170)
Income	3.72E-06*	4.31E-06**	4.04E-06**	8.74E-06***	4.01E-06**	4.13E-06**	4.44E-06***
	(2.10E-06)	(2.13E-06)	(2.07E-06)	(3.53E-06)	(2.04E-06)	(2.03E-06)	(1.87E-06)
Employed	0.0729	0.1247	0.1118	0.1163	0.0517	0.0460	0.0310
	(0.1487)	(0.1511)	(0.1465)	(0.1603)	(0.1433)	(0.1433)	(0.0745)
Occ. Manager	0.2322	0.2430	0.2378	0.2616	0.3355**	0.3407**	0.1056**
	(0.1802)	(0.1830)	(0.1757)	(0.1942)	(0.1719)	(0.1718)	(0.0510)
Occ. Prof. Tech.	0.1408	0.1107	0.1146	0.1136	0.1804	0.1787	0.1217*
	(0.1570)	(0.1592)	(0.1537)	(0.1690)	(0.1509)	(0.1508)	(0.0658)
Occ. Manual	0.0025	-0.0548	-0.0652	-0.1013	0.0117	0.0204	-0.0243
	(0.1488)	(0.1514)	(0.1465)	(0.1611)	(0.1437)	(0.1436)	(0.0719)
Occ. Sales	0.0830	0.0529	0.0460	0.0652	0.1058	0.1118	0.0679
	(0.1521)	(0.1543)	(0.1511)	(0.1634)	(0.1484)	(0.1483)	(0.0705)
Married	0.3018***	0.3112***	0.3618***	0.3353***	0.3521***	0.3521***	0.2159***
	(0.0778)	(0.0799)	(0.0792)	(0.0843)	(0.0779)	(0.0779)	(0.0375)
Family Size	-0.0147	-0.0152	-0.0170	-0.0305	-0.0088	-0.0126	-0.0229
	(0.0192)	(0.0196)	(0.0190)	(0.0204)	(0.0188)	(0.0188)	(0.0155)
Father Education	0.0215*	0.0272**	0.0028	0.0101	0.0053	0.0068	0.0032
	(0.0132)	(0.0136)	(0.0143)	(0.0140)	(0.0140)	(0.0140)	(0.0052)
Parental Income	0.0006	0.0004	-0.0006	0.0003	-0.0006	-0.0006	-0.0006
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Constant	-2.1339***	-2.2749***		-2.3442***			
	(0.4887)	(0.5312)		(0.4912)			
$\sigma_{\epsilon \mathbf{z}}$							**-0.0860**
							(0.0534)
School Performance Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	No	No	Yes	No	Yes	Yes	Yes
Number of Observations	569	569	569	569	569	569	569
Number of Networks	21	21	21	21	21	21	21

Notes. See Table 3.

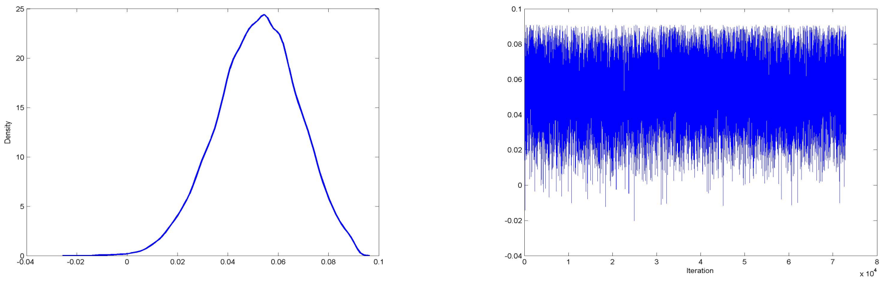
Table 5: 2SLS First Stage Results

Dependent variable: Peers' outcome

Variables:	Own characteristics	Peers' characteristics	Peers of peers' characteristics (exclusion restrictions)
Male	-0.1113	-0.0694	0.0159
	(0.0830)	(0.0655)	(0.0341)
Latino	0.3363**	0.1356	-0.4939***
	(0.1731)	(0.1441)	(0.0674)
Black	-0.0420	0.4622***	0.1238
	(0.2032)	(0.1874)	(0.0968)
Age	-0.0294	0.0143	0.0231***
	(0.0350)	(0.0282)	(0.0078)
Education	0.0700***	0.1323***	-0.0031
	(0.0277)	(0.0223)	(0.0111)
Income	3.61E-07	8.24E-06***	-8.19E-07
	(2.68E-06)	(3.50E-06)	(1.69E-06)
Employed	0.2556	-0.1312	-0.2035***
	(0.2114)	(0.1583)	(0.0842)
Occ. Manager	0.0877	0.3160	-0.1892
	(0.2548)	(0.2038)	(0.1171)
Occ. Prof. Tech.	-0.1222	0.1921	-0.0868
	(0.2256)	(0.1682)	(0.0922)
Occ. Manual	-0.0747	0.0374	0.0247
	(0.2102)	(0.1639)	(0.0848)
Occ. Sales	-0.1370	0.1682	0.0263
	(0.2171)	(0.1671)	(0.0863)
Married	-0.2654***	0.4318***	0.1468***
	(0.1168)	(0.0796)	(0.0444)
Family Size	0.0359	-0.0389*	-0.0423***
	(0.0266)	(0.0211)	(0.0116)
Father Education	0.0317	-0.0065	-0.0051
	(0.0202)	(0.0146)	(0.0073)
Parental Income	0.0006	-0.0021***	-0.0004
	(0.0010)	(0.0006)	(0.0004)
F-stat			**10.8892**
School Performance Variables		Yes	
Network Fixed Effects		Yes	
Number of Observations		569	
Number of Networks		21	

Notes. See Table 3.

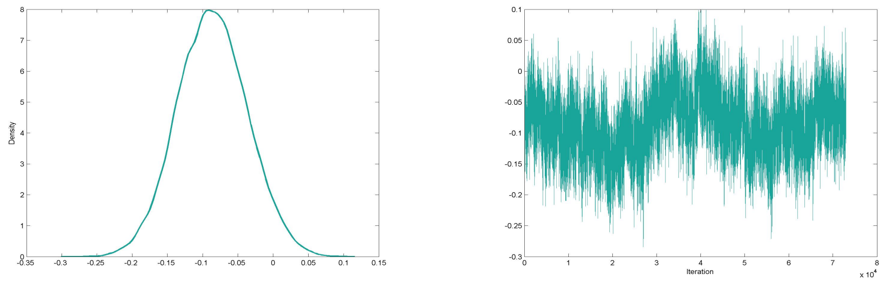
Figure 4: Bayesian Estimation Results
Peer Effects (ϕ)



(a) Posterior Distribution (b) Markov Chain

Notes. Panel (a) shows the kernel density estimate of the posterior distribution. Panel (b) shows the Markov chain draws.

Figure 5: Bayesian Estimation Results
Covariance between Unobservables ($\sigma_{\epsilon,z}$)



(a) Posterior Distribution (b) Markov Chain

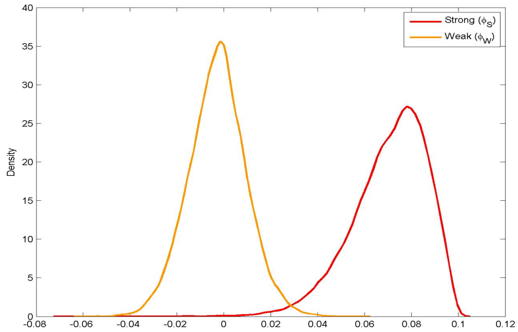
Notes. See 4.

Table 6: Weak and Strong Ties in Financial Decisions

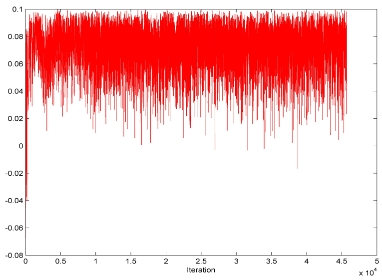
Dependent variable: Financial Activity Index	OLS	IV	IV bias-corrected	Bayesian
	(1)	(2)	(3)	(4)
Strong Ties (ϕ^S)	**0.2225*** **	**0.1755*** **	**0.0671***	**0.0707*** **
	(0.0463)	**(0.0398)**	**(0.0402)**	**(0.0158)**
Weak Ties (ϕ^W)	**0.0162**	**-0.0295**	**0.0128**	**-0.0027**
	(0.0251)	**(0.0206)**	**(0.0208)**	**(0.0123)**
Male	-0.0769	-0.0720	-0.0670	-0.0257
	(0.0702)	(0.0604)	(0.0603)	(0.0340)
Latino	0.1292	0.1356	0.1580	0.0138
	(0.1516)	(0.1297)	(0.1295)	(0.0392)
Black	0.2346	0.2584*	0.3204**	0.0653
	(0.1786)	(0.1573)	(0.1570)	(0.0540)
Age	0.0089	0.0104	0.0165	0.0205
	(0.0296)	(0.0262)	(0.0262)	(0.0220)
Education	0.1077***	0.0913***	0.0996***	0.1327***
	(0.0223)	(0.0198)	(0.0198)	(0.0169)
Income	3.17E-06	2.63E-06	2.91E-06	3.54E-06**
	(2.40E-06)	(2.00E-06)	(1.99E-06)	(1.82E-06)
Employed	-0.0372	-0.0313	-0.0131	0.0334
	(0.1698)	(0.1447)	(0.1445)	(0.0752)
Occ. Manager	0.3421*	0.3662**	0.3461**	0.0935*
	(0.2066)	(0.1761)	(0.1757)	(0.0527)
Occ. Prof. Tech.	0.2852	0.2689*	0.2363	0.1332**
	(0.1809)	(0.1558)	(0.1556)	(0.0678)
Occ. Manual	0.0733	0.0783	0.0731	-0.0099
	(0.1703)	(0.1452)	(0.1449)	(0.0729)
Occ. Sales	0.1784	0.1755	0.1762	0.0760
	(0.1752)	(0.1501)	(0.1498)	(0.0717)
Married	0.4283***	0.4404***	0.4097***	0.2248***
	(0.0960)	(0.0807)	(0.0806)	(0.0389)
Family Size	-0.0144	-0.0116	-0.0143	-0.0200
	(0.0221)	(0.0189)	(0.0188)	(0.0153)
Father Education	0.0064	0.0016	0.0062	0.0021
	(0.0166)	(0.0141)	(0.0141)	(0.0050)
Parental Income	-0.0002	-0.0002	-0.0006	-0.0004
	(0.0007)	(0.0006)	(0.0006)	(0.0005)
$\sigma_{\epsilon z}$				**-0.0338**
				(0.0643)
School Performance Variables	Yes	Yes	Yes	Yes
Contextual Effects	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	569	569	569	569
Number of Networks	21	21	21	21

Notes. See Table 3.

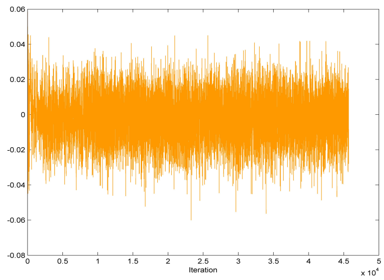
Figure 6: Bayesian Estimation Results.
Strong (ϕ_S) vs Weak (ϕ_W) Tie Effects



(a) Posterior Distributions



(b) Markov Chain



(c) Markov Chain

Notes. See 4.

Table 7: Robustness Check - Alternative Definition of Weak Ties

Dependent variable: Financial Activity Index

	Once Friends			Recent Friends		
	OLS	IV	IV bias-corrected	OLS	IV	IV bias-corrected
Strong Ties (ϕ^S)	0.1732 ***	0.2003 ***	0.0684 *	0.1497 ***	0.1838 ***	0.0676 *
	(0.0520)	(0.0405)	(0.0410)	(0.0523)	(0.0405)	(0.0406)
Weak Ties (ϕ^W)	-0.0616	-0.0431	0.0039	-0.0207	-0.0068	0.0181
	(0.0400)	(0.0306)	(0.0310)	(0.0413)	(0.0291)	(0.0292)
Male	-0.0933	-0.0811	-0.0880	-0.0760	-0.0858	-0.0914
	(0.0707)	(0.0599)	(0.0606)	(0.0704)	(0.0593)	(0.0596)
Latino	0.1091	0.0691	0.0922	0.0974	0.0737	0.0674
	(0.1510)	(0.1244)	(0.1260)	(0.1511)	(0.1288)	(0.1297)
Black	0.2774	0.2888 **	0.3002 **	0.2274	0.2740 *	0.3034 *
	(0.1702)	(0.1450)	(0.1469)	(0.1816)	(0.1550)	(0.1560)
Age	0.0219	0.0242	0.0240	0.0080	0.0095	0.0181
	(0.0289)	(0.0244)	(0.0248)	(0.0289)	(0.0242)	(0.0244)
Education	0.1070 ***	0.1074 ***	0.1147 ***	0.1105 ***	0.1128 ***	0.1184 ***
	(0.0223)	(0.0187)	(0.0189)	(0.0222)	(0.0186)	(0.0187)
Income	0.0000	0.0000	0.0000 *	0.0000	0.0000 *	0.0000 *
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Employed	-0.0606	-0.1166	-0.0981	0.0342	0.0054	0.0158
	(0.1717)	(0.1443)	(0.1462)	(0.1719)	(0.1415)	(0.1424)
Occ. Manager	0.4049 *	0.4482 ***	0.4153 **	0.2572	0.3258 *	0.3245 *
	(0.2083)	(0.1737)	(0.1759)	(0.2079)	(0.1719)	(0.1730)
Occ. Prof. Tech.	0.3142 *	0.3350 **	0.2974 *	0.1983	0.2255	0.2113
	(0.1826)	(0.1537)	(0.1557)	(0.1815)	(0.1505)	(0.1515)
Occ. Manual	0.0889	0.1171	0.1159	-0.0241	0.0269	0.0255
	(0.1709)	(0.1435)	(0.1454)	(0.1737)	(0.1423)	(0.1433)
Occ. Sales	0.1963	0.2271	0.2170	0.0938	0.1209	0.1198
	(0.1764)	(0.1485)	(0.1504)	(0.1778)	(0.1465)	(0.1474)
Married	0.4194 ***	0.4239 ***	0.3954 ***	0.3994 ***	0.3904 ***	0.3649 ***
	(0.0967)	(0.0793)	(0.0804)	(0.0955)	(0.0784)	(0.0789)
Family Size	-0.0114	-0.0152	-0.0191	-0.0121	-0.0100	-0.0104
	(0.0221)	(0.0186)	(0.0188)	(0.0223)	(0.0184)	(0.0185)
Father Education	0.0056	0.0048	0.0083	0.0039	0.0069	0.0114
	(0.0167)	(0.0139)	(0.0141)	(0.0167)	(0.0138)	(0.0139)
Parental Income	-0.0003	-0.0002	-0.0004	-0.0005	-0.0006	-0.0009
	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
Constant	-2.1201***			-2.1416***		
	(0.5402)			(0.5425)		
School Performance Variables	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	Yes	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	569	569	569	569	569	569
Number of Networks	21	21	21	21	21	21

Notes. See Table 3.

Table 8: Network Formation and Financial Activity
Bayesian Estimation

	Outcome	Link Formation	
		$t-1$	t
	(1)	(2)	(3)
Strong Ties	0.0707***		
	(0.0158)		
Weak Ties	-0.0027		
	(0.0123)		
Male	-0.0257	-0.0831***	-0.1667***
	(0.0340)	(0.0212)	(0.0244)
Age	0.0205	-1.0166***	-1.1772***
	(0.0220)	(0.0604)	(0.0820)
Latino	0.0138	-0.0579***	-0.1441***
	(0.0392)	(0.0215)	(0.0296)
Black	0.0653	-0.1783***	-0.2340***
	(0.0540)	(0.0408)	(0.0578)
Education	0.1327***	-0.1493***	-0.1968***
	(0.0169)	(0.0266)	(0.0317)
Income	3.54E-06**	-0.0487	-0.1770***
	(1.82E-06)	(0.0308)	(0.0386)
Employed	0.0334	-0.0290	-0.0647***
	(0.0752)	(0.0214)	(0.0242)
Occ. Manager	0.0935*	-0.0069	-0.0418*
	(0.0527)	(0.0180)	(0.0237)
Occ. Prof. Tech.	0.1332**	-0.0367*	0.0376
	(0.0678)	(0.0203)	(0.0242)
Occ. Manual	-0.0099	-0.0641***	-0.0560**
	(0.0729)	(0.0220)	(0.0259)
Occ. Sales	0.0760	-0.0580***	-0.0051
	(0.0717)	(0.0183)	(0.0241)
Married	0.2248***	0.0043	0.0008
	(0.0389)	(0.0195)	(0.0237)
Family Size	-0.0200	0.0391	0.0548
	(0.0153)	(0.0255)	(0.0343)
Father Education	0.0021	-0.1797***	-0.0658
	(0.0050)	(0.0587)	(0.0910)
Parental Income	-0.0004	-0.0379	-0.0453
	(0.0005)	(0.0294)	(0.0354)
Constant		-0.7269***	-1.2700***
		(0.0712)	(0.1028)
Link at t-1 ($g_{ij,t-1}$)			1.4096***
			(0.0704)
Unobservables (z)		0.6891***	0.9642***
		(0.0549)	(0.0698)
$\sigma_{\epsilon z}$	-0.0338		
	(0.0643)		
σ_{ϵ}	0.7062		
	(0.3235)		
School Performance Variables	Yes	Yes	Yes
Contextual Effects	Yes	Yes	Yes
Network Fixed Effects	Yes	Yes	Yes
Number of Observations	569	18985	18985
Number of Networks	21	21	21

Notes. See Table 3. We report peer effects estimates when network formation and behavior over network are jointly considered. Column (1) reports on the results for Model (6), columns (2)-(3) report on the results for Model (4)-(5).

Table 9: Weak and Strong Ties in Financial Decisions - Disaggregated Outcomes
main variables

Dependent variable:	Shares		Checking Account		Credit Card		Savings Account		Student Loan		Credit Card Debt	
	ϕ^S	ϕ^W	ϕ^S	ϕ^W	ϕ^S	ϕ^W	ϕ^S	ϕ^W	ϕ^S	ϕ^W	ϕ^S	ϕ^W
OLS	0.1101***	-0.0381	0.0340**	0.0155	0.0677***	0.0042	0.0366*	0.0010	0.0744***	0.0960***	0.0496*	0.0030
	(0.0307)	(0.0235)	(0.0158)	(0.0110)	(0.0218)	(0.0157)	(0.0210)	(0.0140)	(0.0263)	(0.0177)	(0.0271)	(0.0201)
IV	0.0857**	-0.0084	0.0407***	0.0142	0.0615***	0.0069	0.0446*	-0.0162	0.0698***	0.0450**	0.0176	0.0150
	(0.0371)	(0.0287)	(0.0174)	(0.0119)	(0.0246)	(0.0171)	(0.0232)	(0.0154)	(0.0299)	(0.0200)	(0.0322)	(0.0230)
IV bias-corrected	0.0565*	-0.0036	0.0378**	0.0145	0.0525**	0.0082	0.0384*	-0.0144	0.0559*	0.0456**	0.0167	0.0150
	(0.0331)	(0.0287)	(0.0173)	(0.0119)	(0.0245)	(0.0171)	(0.0232)	(0.0154)	(0.0299)	(0.0200)	(0.0322)	(0.0230)
Race Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Occupation and Income	Yes		Yes		Yes		Yes		Yes		Yes	
Family Characteristics	Yes		Yes		Yes		Yes		Yes		Yes	
Other Demographics	Yes		Yes		Yes		Yes		Yes		Yes	
School Performance Variables	Yes		Yes		Yes		Yes		Yes		Yes	
Contextual Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Network Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Number of Observations	569		569		569		569		569		569	
Number of Networks	21		21		21		21		21		21	

Notes. See Table 3.

Table 10: Weak and Strong Ties in Financial Decisions - Disaggregated Outcomes
Control Variables

Dependent variable:	Shares		Checking Account		Credit Card		Savings Account		Student Loan		Credit Card Debt	
	OLS	IV b-c	OLS	IV b-c	OLS	IV b-c	OLS	IV b-c	OLS	IV b-c	OLS	IV b-c
Male	0.0035	-0.0083	-0.0791 **	-0.1012 ***	-0.1202 ***	-0.1243 ***	0.0021	-0.0025	0.0021	-0.0035	-0.1142 ***	-0.0936 ***
	(0.0332)	(0.0337)	(0.0343)	(0.0350)	(0.0339)	(0.0353)	(0.0339)	(0.0348)	(0.0321)	(0.0334)	(0.0335)	(0.0350)
Latino	-0.0480	-0.0508	-0.0180	-0.0498	0.0361	0.0548	0.1023	-0.0271	-0.0023	0.0188	0.0462	0.1085
	(0.0688)	(0.0770)	(0.0682)	(0.0762)	(0.0794)	(0.0888)	(0.0794)	(0.0868)	(0.0698)	(0.0767)	(0.0791)	(0.0880)
Black	-0.0876	0.0112	-0.1733 ***	-0.1219 *	-0.0049	0.0797	-0.0434	0.1398 *	0.1400 ***	0.1881 ***	0.0611	-0.0593
	(0.0543)	(0.0847)	(0.0419)	(0.0725)	(0.0446)	(0.0787)	(0.0446)	(0.0771)	(0.0412)	(0.0714)	(0.0446)	(0.0798)
Age	0.0133	0.0048	-0.0110	0.0119	0.0088	0.0196	-0.0213 *	-0.0213	0.0408 ***	0.0519 ***	0.0187 *	0.0244 *
	(0.0111)	(0.0139)	(0.0114)	(0.0139)	(0.0113)	(0.0140)	(0.0114)	(0.0139)	(0.0107)	(0.0130)	(0.0113)	(0.0141)
Education	0.0299 ***	0.0228 **	0.0579 ***	0.0429 ***	0.0649 ***	0.0541 ***	0.0608 ***	0.0521 ***	0.0831 ***	0.0871 ***	0.0251 **	0.0252 **
	(0.0105)	(0.0110)	(0.0103)	(0.0107)	(0.0104)	(0.0109)	(0.0104)	(0.0108)	(0.0097)	(0.0101)	(0.0102)	(0.0108)
Income	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000	0.0000	0.0000	0.0000	-0.0000 *	-0.0000 **	0.0000 ***	0.0000 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Employed	0.0989	0.0687	0.0231	-0.0055	0.0362	0.0355	0.1300	0.0997	-0.0534	-0.0326	0.0499	0.0551
	(0.0889)	(0.0880)	(0.0938)	(0.0943)	(0.0923)	(0.0929)	(0.0928)	(0.0923)	(0.0979)	(0.0968)	(0.0908)	(0.0918)
Occ. Manager	-0.0983	-0.0514	0.1208	0.1592	0.1106	0.1416	-0.0965	-0.1027	0.0343	0.0116	0.1102	0.1360
	(0.1072)	(0.1050)	(0.1125)	(0.1122)	(0.1115)	(0.1117)	(0.1122)	(0.1111)	(0.1148)	(0.1136)	(0.1106)	(0.1110)
Occ. Prof. Tech	-0.1162	-0.0722	0.0709	0.1035	0.1061	0.1212	-0.0307	0.0107	-0.0321	-0.0429	-0.0144	-0.0251
	(0.0947)	(0.0939)	(0.0996)	(0.0997)	(0.0980)	(0.0986)	(0.0983)	(0.0976)	(0.1027)	(0.1016)	(0.0962)	(0.0972)
Occ. Manual	-0.1057	-0.0700	0.0379	0.0610	0.0354	0.0287	-0.1221	-0.0819	0.0162	-0.0269	-0.0649	-0.0727
	(0.0888)	(0.0878)	(0.0930)	(0.0931)	(0.0922)	(0.0927)	(0.0928)	(0.0922)	(0.0980)	(0.0974)	(0.0906)	(0.0915)
Occ. Sales	-0.0738	-0.0198	0.0240	0.0523	0.0481	0.0551	-0.0687	-0.0330	-0.0277	-0.0652	0.0895	0.0849
	(0.0925)	(0.0921)	(0.0970)	(0.0978)	(0.0957)	(0.0972)	(0.0963)	(0.0964)	(0.1013)	(0.1009)	(0.0942)	(0.0958)
Married	0.0711 *	0.0834 *	0.0928 **	0.0921 **	0.1525 ***	0.1681 ***	0.1158 ***	0.1352 ***	0.0236	0.0420	0.1737 ***	0.1806 ***
	(0.0425)	(0.0430)	(0.0443)	(0.0449)	(0.0447)	(0.0460)	(0.0447)	(0.0458)	(0.0417)	(0.0429)	(0.0439)	(0.0455)
Family size	-0.0143	-0.0126	-0.0076	-0.0055	-0.0186 *	-0.0176	0.0096	0.0064	-0.0085	-0.0093	-0.0176	-0.0135
	(0.0110)	(0.0107)	(0.0109)	(0.0108)	(0.0110)	(0.0110)	(0.0110)	(0.0108)	(0.0106)	(0.0105)	(0.0109)	(0.0110)
Father Education	0.0186 **	0.0116	0.0197 **	0.0189 **	0.0170 **	0.0163 *	0.0105	0.0060	-0.0025	-0.0006	-0.0087	-0.0065
	(0.0075)	(0.0080)	(0.0080)	(0.0084)	(0.0078)	(0.0085)	(0.0078)	(0.0083)	(0.0074)	(0.0081)	(0.0076)	(0.0083)
Parental Income	0.0012 ***	0.0005	0.0002	-0.0002	0.0007	0.0001	0.0004	-0.0000	-0.0008 **	-0.0006 **	0.0001	0.0000
	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Peer effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Network fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	569	569	569	569	569	569	569	569	569	569	569	569
Number ofnetworks	21	21	21	21	21	21	21	21	21	21	21	21

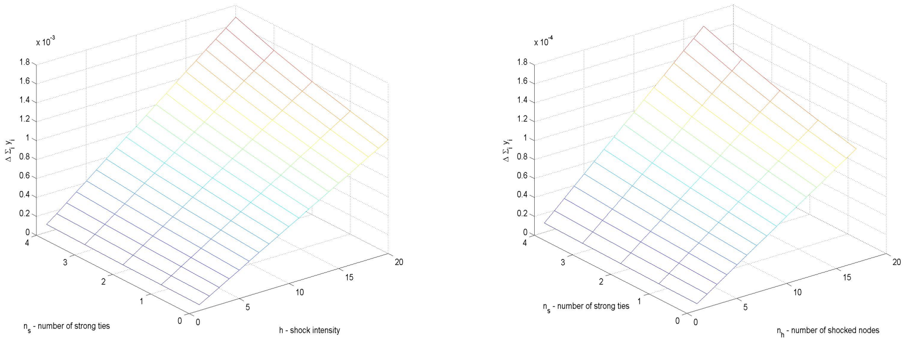
Notes. See Table 3. IV b-c: IV bias corrected.

Table 11: Mechanisms of Peer Effects in Financial Decisions

Dependent variable: Financial Activity Index			
	% of links	OLS	IV bias-corrected
Strong Ties Supported	72%	0.1646***	0.0691**
		(0.0316)	(0.0318)
Strong Ties not Supported	28%	0.1923***	0.0409
		(0.0347)	(0.0357)
Weak Ties Supported	58%	-0.0037	0.0266
		(0.0276)	(0.0274)
Weak Ties not Supported	42%	-0.0575	-0.0053
		(0.0318)	(0.0314)
Male		-0.0657	-0.0703
		(0.0610)	(0.0604)
Latino		0.1756	0.1876
		(0.1313)	(0.1293)
Black		0.2567*	0.3269**
		(0.1548)	(0.1575)
Age		0.0102	0.0146
		(0.0266)	(0.0261)
Education		0.0935***	0.0991***
		(0.0201)	(0.0197)
Income		0.0000	0.0000
		(0.0000)	(0.0000)
Employed		0.0210	0.0061
		(0.1476)	(0.1449)
Occ. Manager		0.3036*	0.3164*
		(0.1786)	(0.1757)
Occ. Prof. Tech		0.2472	0.2187
		(0.1571)	(0.1555)
Occ. Manual		0.0408	0.0589
		(0.1478)	(0.1455)
Occ. Sales		0.1546	0.1633
		(0.1515)	(0.1504)
Married		0.4169***	0.3943***
		(0.0830)	(0.0797)
Family Size		-0.0088	-0.0116
		(0.0193)	(0.0188)
Father Education		0.0042	0.0058
		(0.0144)	(0.0140)
Parental Income		-0.0002	-0.0007
		(0.0006)	(0.0006)
School Performance Variables		Yes	Yes
Contextual Effects		Yes	Yes
Network Fixed Effects		Yes	Yes
Number of Observations		569	569
Number of Networks		21	21

Notes. See Table 3. The percentage of links is calculated with respect to the total number of links of the same type (strong or weak).

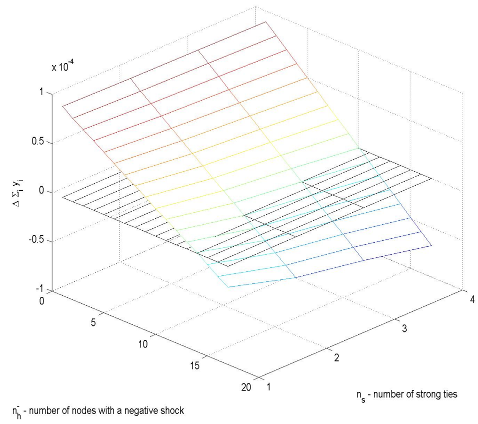
Figure 7: Simulation Results
Income Shocks and Strong Tie Effects



(a) Intensive Margin (b) Extensive Margin

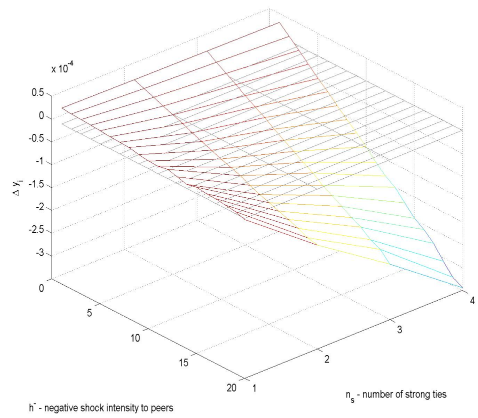
Notes. The surfaces represent $\sum_i \Delta y_i$, which is the variation of the financial activity of agent i, y_i, after the shock. n_s is the number of strong ties of the shocked agents. In Panel (a) shock intensity (h) goes from 1 to 20 income std points, while the number of shocked agents is constant and equal to 13. For each combination of (n_s, h) the income of a random sample of agents which have a n_s strong ties is increased by h. In Panel (b) the shock intensity is constant and equal to 2 income std points, while the number of shocked agents (n_h) goes from 1 to 13. For each combination of (n_s, n_h) the income of n_h agents, which have n_s strong ties, is increased by 2 income std points. Each point of the surfaces is the average of 500 replications, in which agents are randomly sampled. The results remain basically unchanged if we use a different number of shocked agents in panel (a) or a different shock intensity in panel (b).

Figure 8: Simulation Results
Heterogeneous Income Shocks and Strong Tie Effects



Notes. See Figure 7. The income of 13 agents with no strong ties is increased by 2 income std points. The surface represents $\Delta \sum_i y_i$ when the income of n_h^- agents, who have n_s strong ties, is decreased by 2 income std points.

Figure 9: Simulation Results
Individual vs Peer Income Shocks



Notes. The surface represents Δy_i, which is the variation of the financial activity of agent i, y_i, after the shock. Each point of the surface is the average of 500 replications in which an agent i is randomly sampled. In each replication, agent i's income is increased by 10 income std points and the income of all of peers of i is decreased by h^- income std points.

Appendix 1: Methodological Details

1.1 IV Estimation

We use the 2SLS estimation strategy from Liu and Lee (2010), and extend it to the case of two different network structures. Let $\mathbf{Y}_r = (y_{1,r}, \cdots, y_{n_r,r})'$, $\mathbf{X}_r = (x_{1,r}, \cdots, x_{n_r,r})'$, and $\epsilon_r = (\epsilon_{1,r}, \cdots, \epsilon_{n_r,r})'$. Denote the $n_r \times n_r$ adjacency matrix by $\mathbf{G}_r = [g_{ij,r}]$, the row-normalized of $\mathbf{G}_r$ by $\mathbf{G}_r^*$, and the n_r-dimensional vector of ones by $\mathbf{l}_{n_r}$. Let us split the adjacency matrix into two submatrices $\mathbf{G}_r^S$ and $\mathbf{G}_r^W$, which keep track of strong and weak ties, respectively. Then, model (2) can be written in matrix form as

$$\mathbf{Y}_r = \phi^S \mathbf{G}_r^S \mathbf{Y}_r + \phi^W \mathbf{G}_r^W \mathbf{Y}_r + \mathbf{X}_r^* \beta^* + \eta_r \mathbf{l}_{n_r} + \epsilon_r, \tag{7}$$

For a sample with $\bar{r}$ networks, stack up the data by defining $\mathbf{Y} = (\mathbf{Y}_1', \cdots, \mathbf{Y}_{\bar{r}}')'$, $\mathbf{X}^* = (\mathbf{X}_1^{*\prime}, \cdots, \mathbf{X}_{\bar{r}}^{*\prime})'$, $\epsilon = (\epsilon_1', \cdots, \epsilon_{\bar{r}}')'$, $\mathbf{G} = \mathrm{D}(\mathbf{G}_1, \cdots, \mathbf{G}_{\bar{r}})$, $\mathbf{G}^* = \mathrm{D}(\mathbf{G}_1^*, \cdots, \mathbf{G}_{\bar{r}}^*)$, $\iota = \mathrm{D}(\mathbf{l}_{n_1}, \cdots, \mathbf{l}_{n_{\bar{r}}})$ and $\eta = (\eta_1, \cdots, \eta_{\bar{r}})'$, where $\mathrm{D}(\mathbf{A}_1, \cdots, \mathbf{A}_K)$ is a block diagonal matrix in which the diagonal blocks are $n_k \times n_k$ matrices $\mathbf{A}_k$'s. For the entire sample, the model is thus

$$\mathbf{Y} = \phi^S \mathbf{G}^S \mathbf{Y} + \phi^W \mathbf{G}^W \mathbf{Y} + \mathbf{X}^* \beta + \iota \cdot \eta + \epsilon. \tag{8}$$

Model (8) can be written as

$$\mathbf{Y} = \mathbf{Z}\theta + \iota \cdot \eta + \epsilon, \tag{9}$$

where $\mathbf{Z} = (\mathbf{G^S Y}, \mathbf{G^W Y}, \mathbf{X}^*)$, $\theta = (\phi^S, \phi^W, \beta')'$, and $\iota = \mathrm{D}(\mathbf{l}_{n_1}, \cdots, \mathbf{l}_{n_{\bar{r}}})$.

We treat η as a vector of unknown parameters. When the number of networks $\bar{r}$ is large, we have the incidental parameter problem. Let $\mathbf{J} = \mathrm{D}(\mathbf{J}_1, \cdots, \mathbf{J}_{\bar{r}})$, where $\mathbf{J}_r = \mathbf{I}_{n_r} - \frac{1}{n_r}\mathbf{l}_{n_r}'\mathbf{l}_{n_r}$. The network fixed effect can be eliminated by a transformation with $\mathbf{J}$ such that

$$\mathbf{JY} = \mathbf{JZ}\theta + \mathbf{J}\epsilon. \tag{10}$$

Let $\mathbf{M} = (\mathbf{I} - \phi^S \mathbf{G}^S - \phi^W \mathbf{G}^W)^{-1}$. The equilibrium outcome vector $\mathbf{Y}$ in (9) is then given by the reduced form equation

$$\mathbf{Y} = \mathbf{M}(\mathbf{X}^* \beta + \iota \cdot \eta) + \mathbf{M}\epsilon. \tag{11}$$

It follows that $\mathbf{G}^S\mathbf{Y} = \mathbf{G}^S\mathbf{M}\mathbf{X}^*\beta + \mathbf{G}^S\mathbf{M}\iota\eta + \mathbf{G}^S\mathbf{M}\epsilon$ and $\mathbf{G}^W\mathbf{Y} = \mathbf{G}^W\mathbf{M}\mathbf{X}^*\beta + \mathbf{G}^W\mathbf{M}\iota\eta + \mathbf{G}^W\mathbf{M}\epsilon$. $\mathbf{G}^S\mathbf{Y}$ and $\mathbf{G}^W\mathbf{Y}$ are correlated with ϵ because $\mathrm{E}[(\mathbf{G}^S\mathbf{M}\epsilon)'\epsilon] = \sigma^2 \mathrm{tr}(\mathbf{G}^S\mathbf{M}) \neq 0$ and $\mathrm{E}[(\mathbf{G}^W\mathbf{M}\epsilon)'\epsilon] = \sigma^2 \mathrm{tr}(\mathbf{G}^W\mathbf{M}) \neq 0$. Hence, in general, (10) cannot be consistently estimated by OLS. If $\mathbf{G}$ is row-normalized such that $\mathbf{G} \cdot \mathbf{l}_n = \mathbf{l}_n$, where $\mathbf{l}_n$ is a n-dimensional vector of ones, the endogenous social interaction effect can be interpreted as an average effect.

Liu and Lee (2010) use an instrumental variable approach and propose different estimators based on different instrumental matrices, here denoted by $\mathbf{Q}_1$ and $\mathbf{Q}_2$. In particular, besides the conventional instrumental matrix ($\mathbf{Q}_1 = \mathbf{J}(\mathbf{GX}^*, \mathbf{X}^*)$) for the estimation of (10), they propose to use additional instruments (IVs) $JG\iota$ and enlarge the instrumental matrix $\mathbf{Q}_2 = (\mathbf{Q}_1, JG\iota)$. The additional IVs of $JG\iota$ are simply the row sums of G (i.e. the number of links of each agent). Liu and Lee (2010) show that those additional IVs could help model identification when the conventional IVs are weak and improve on the estimation efficiency of the conventional 2SLS estimator based on $\mathbf{Q}_1$. As a result, an IV based on $\mathbf{Q}_2$ (rather than $\mathbf{Q}_1$) should be preferred. However, the number of such additional instruments depends on the number of networks. If the number of networks grows with the sample size, so does the number of IVs. The 2SLS could be asymptotically biased when the number of IVs increases too quickly relative to the sample size, i.e. when there are many networks. Liu and Lee (2010) thus propose a bias-correction procedure based on the estimated leading-order many-IV bias (*IV bias-corrected*). The bias-corrected IV estimator is properly centered, asymptotically normally distributed, and efficient when the average network size is sufficiently large.[36] The (more efficient) IV estimator (based on $\mathbf{Q}_2$) and its bias-corrected version are the IV estimators used in our analysis.

Let us derive those estimators for equation (10), i.e. for the model where agents are heterogeneous and allowed to interact according to different network structures. From the reduced form equation (9), we have $E(\mathbf{Z}) = [\mathbf{G}^S\mathbf{M}(\mathbf{X}^*\beta + \iota \cdot \eta), \mathbf{G}^W\mathbf{M}(\mathbf{X}^*\beta + \iota \cdot \eta), \mathbf{X}^*]$. The best IV matrix for $\mathbf{JZ}$ is given by

$$\mathbf{J}f = \mathbf{JE}(\mathbf{Z}) = J[\mathbf{G}^S\mathbf{M}(\mathbf{X}^*\beta + \iota \cdot \eta), \mathbf{G}^W\mathbf{M}(\mathbf{X}^*\beta + \iota \cdot \eta), \mathbf{X}^*] \tag{12}$$

which is an $n \times (3m+2)$ matrix. However, this matrix is unfeasible as it involves unknown parameters. Note that f can be considered as a linear combination of the vectors in $\mathbf{Q_0} = J[\mathbf{G}^S\mathbf{M}(\mathbf{X}^* + \iota), \mathbf{G}^W\mathbf{M}(\mathbf{X}^* + \iota), \mathbf{X}^*]$. As ι has $\bar{r}$ columns the number of IVs in $\mathbf{Q_0}$ increases as the number of groups increases. Furthermore, as $\mathbf{M} = (\mathbf{I} - \phi^S\mathbf{G}^S - \phi^W\mathbf{G}^W)^{-1} = \sum_{j=0}^{\infty}(\phi^S\mathbf{G}^S + \phi^W\mathbf{G}^W)^j$ when $\sup ||\phi^S\mathbf{G}^S + \phi^W\mathbf{G}^W||_\infty < 1$, $\mathbf{MX}^*$ and $\mathbf{M}\iota$ can be approximated by linear combinations of

$$\left(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \left(\mathbf{G}^S\right)^2\mathbf{X}^*, \left(\mathbf{G}^W\right)^2\mathbf{X}^*, \left(\mathbf{G}^W\right)^2\mathbf{G}^S\mathbf{X}^*, \left(\mathbf{G}^W\right)^2\left(\mathbf{G}^S\right)^2\mathbf{X}^*, \cdots\right)$$

and

$$\left(\mathbf{G}^S\iota, \mathbf{G}^W\iota, \mathbf{G}^W\mathbf{G}^S\iota, \left(\mathbf{G}^S\right)^2\iota, \left(\mathbf{G}^W\right)^2\iota, \left(\mathbf{G}^W\right)^2\mathbf{G}^S\iota, \left(\mathbf{G}^W\right)^2\left(\mathbf{G}^S\right)^2\iota, \cdots\right),$$

respectively. Hence, $\mathbf{Q}_0$ can be approximated by a linear combination of

$$\begin{aligned} \mathbf{Q}_\infty \;=\; & \mathbf{J}(\mathbf{G}^S(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\iota, \mathbf{G}^W\iota, \mathbf{G}^W\mathbf{G}^S\iota, \cdots), \\ & \mathbf{G}^W(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\iota, \mathbf{G}^W\iota, \mathbf{G}^W\mathbf{G}^S\iota, \cdots), \mathbf{X}^*). \end{aligned} \tag{13}$$

Let $\mathbf{Q_K}$ be an $n \times K$ submatrix of $\mathbf{Q}_\infty$ (with $K \geq 3m+2$) including $\mathbf{X}^*$. Let $\mathbf{Q}_S$ be an $n \times K_S$ submatrix of $\mathbf{Q}_{S\infty} = \mathbf{G}^S(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\iota, \mathbf{G}^W\iota, \mathbf{G}^W\mathbf{G}^S\iota, \cdots)$ and $\mathbf{Q}_W$ an $n \times K_W$ submatrix of $\mathbf{Q}_{W\infty} = \mathbf{G}^W(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\iota, \mathbf{G}^W\iota, \mathbf{G}^W\mathbf{G}^S\iota, \cdots)$. We assume that $\frac{K_W}{K_S} = 1$. Let $\mathbf{P_K} = \mathbf{Q_K}(\mathbf{Q_K}'\mathbf{Q_K})^{-1}\mathbf{Q_K}'$ be the projector of $\mathbf{Q_K}$. The resulting 2SLS estimator is given by[37]

$$\widehat{\theta}_{2sls} = \left(\mathbf{Z}'\mathbf{P_K}\mathbf{Z}\right)^{-1}\mathbf{Z}'\mathbf{P_K}\mathbf{y}. \tag{14}$$

The 2SLS estimators of $\theta = (\phi^S, \phi^W, \beta')'$ considered in this paper are

(i) *IV* : $\widehat{\theta}_{2sls} = (\mathbf{Z}'\mathbf{P}_2\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{P}_2\mathbf{y}$, where $\mathbf{P}_2 = \mathbf{Q}_2(\mathbf{Q}_2'\mathbf{Q}_2)_2^{-1}\mathbf{Q}_2'$ and $\mathbf{Q}_2$ contains the linearly independent columns of $[\mathbf{Q}_1, \mathbf{JG}^S\,\iota, \mathbf{JG}^W\iota]$.

(ii) *IV Bias-corrected*: $\widehat{\theta}_{c2sls} = (\mathbf{Z}'\mathbf{P}_2\mathbf{Z})^{-1}\{\mathbf{Z}'\mathbf{P}_2\boldsymbol{y} - \widetilde{\sigma}^2_{2sls}[\mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^S\widetilde{\mathbf{M}}\right), \mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^W\widetilde{\mathbf{M}}\right),\ \mathbf{0}_{3m\times 1}]'\}$, where $\tilde{\mathbf{M}} = (\mathbf{I} - \widetilde{\phi}^S_{2sls}\mathbf{G}^S - \widetilde{\phi}^W_{2sls}\mathbf{G}^W)^{-1}$, $\widetilde{\sigma}^2_{2sls}, \widetilde{\phi}^S_{2sls}$ and $\widetilde{\phi}^W_{2sls}$ are $\sqrt{n}$-consistent initial estimators of σ^2, ϕ^S, and ϕ^W obtained by *Finite-IV*. $\widetilde{\sigma}^2_{2sls}[\mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^S\widetilde{\mathbf{M}}\right), \mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^W\widetilde{\mathbf{M}}\right), \mathbf{0}_{3m\times 1}]$ is the empirical counterpart of the theoretical many-IV bias $b_{2sls} = \sigma^2\left(\mathbf{Z}'\mathbf{P_K}\mathbf{Z}\right)^{-1}\left[\mathrm{tr}\left(\mathbf{\Psi}_{K,S}\right), \mathrm{tr}\left(\mathbf{\Psi}_{K,W}\right), \mathbf{0}_{3m\times 1}\right]'$, where $\mathbf{\Psi}_{K,S} = \mathbf{P_K}\mathbf{G}^S\mathbf{M}$ and $\mathbf{\Psi}_{K,W} = \mathbf{P_K}\mathbf{G}^W\mathbf{M}$.

[36] Liu and Lee (2010) also generalize this 2SLS approach to the GMM using additional quadratic moment conditions.

[37] Under some conditions, this 2SLS estimator is robust to the presence of network topology misspecification (see Patacchini and Rainone, 2014).

1.2 Bayesian Estimation

The parameters of equations (4), (5) and (6) are simultaneously estimated with a Bayesian methodology. Bayesian inference requires the computation of marginal distribution for all parameters. Since this requires integration of complicated distributions over several variables, a closed form solution is not readily available and Markov Chain Monte Carlo (MCMC) techniques are employed to obtain random draws from posterior distributions. The unobservable variable ($z_{i,r}$) is thus generated according to the joint likelihood of link formation and outcome; it is drawn in each MCMC step together with the parameters of the model. The Gibbs sampling algorithm allows us to draw random values for each parameter from their posterior marginal distribution, given previous values of other parameters. Once stationarity of the Markov Chain has been achieved, the random draws can be used to study the empirical distributions of the posterior. We details the different steps below.

Prior and Posterior Distributions

In order to draw random values from the marginal posterior distributions of parameters in Model (4)-(5)-(6) we need to set prior distributions of those parameters. Once priors and likelihoods are specified, we can derive marginal posterior distributions of parameters and draw values from them. Given the link formation Model (4)-(5), the probability of observing a network r at time t-1 and t, $\mathbf{G}_r^{t-1}$ and $\mathbf{G}_r^t$ is

$$\begin{aligned} P(\mathbf{G}_r^{t-1}|x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}) &= \prod_{i \neq j} P(g_{ij,r,t-1}|x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}), \\ P(\mathbf{G}_r^{t}|x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}) &= \prod_{i \neq j} P(g_{ij,r,t}|x_{ij,r}, z_{i,r}, z_{j,r}, g_{ij,r,t-1}, \gamma_{t}, \theta_{t}, \lambda). \end{aligned}$$

Let $\beta^* = (\beta, \delta^S, \delta^W)$, following Hsieh and Lee (2016) our prior distributions are

$$\begin{aligned} z_{i,r} &\sim N(0,1) \\ \omega &\sim N_{2K+3}(\omega_0, \Omega_0) \\ \phi^S &\sim U[-\kappa_L, \kappa_L] \\ \phi^W &\sim U[-\kappa_S, \kappa_S] \\ \beta^* &\sim N_{3K+1}(\beta_0, B_0) \\ (\sigma_\varepsilon^2, \sigma_{\varepsilon z}) &\sim TN_2(\sigma_0, \Sigma_0) \\ \eta_r|\sigma_\eta &\sim N(0, \sigma_\eta) \\ \sigma_\eta &\sim IG(\frac{\varsigma_0}{2}, \frac{\zeta_0}{2}) \end{aligned}$$

where $\omega = (\gamma_T, \theta_T, \lambda, \gamma_{T-1}, \theta_{T-1})$, $\kappa_L = \frac{1}{\kappa} - |\phi^W|$, $\kappa_S = \frac{1}{\kappa} - |\phi^S|$ and $\kappa = 1/\max(\min(\max_i(\sum_j g_{ij}^S), \max_j(\sum_i g_{ij}^S)), \min(\max_i(\sum_j g_{ij}^W), \max_j(\sum_i g_{ij}^W)))$ from Gershgorin Theorem, $U[\cdot]$, $TN_2(\cdot)$ and $IG(\cdot)$ are respectively the uniform, bivariate truncated normal, and inverse gamma distributions. Those distributions depend on hyper-parameters (like β_0) that are set by the econometrician. It follows that the marginal posteriors are

$$
\begin{aligned}
P(\mathbf{Z}_r|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\rho) &\propto \prod_{r=1}^{\bar{r}}\prod_{i}^{n_r}\phi(z_{i,r})P(\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S|\mathbf{Z}_r,\rho)\\
P(\omega|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S) &\propto \phi^{2K+3}(\omega,\omega_0,\Omega_0)\prod_{r=1}^{\bar{r}}P(\mathbf{G}_r^W,\mathbf{G}_r^S|\mathbf{Z}_r,\omega)\\
P(\phi^S,\phi^W|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\beta,\sigma_\varepsilon^2,\sigma_{\varepsilon z}) &\propto \prod_{r=1}^{\bar{r}}P(\mathbf{Y}_r|\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\beta^*,\sigma_\varepsilon^2,\sigma_{\varepsilon z})\\
P(\beta^*|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\sigma_\varepsilon^2,\sigma_{\varepsilon z},\phi^S,\phi^W) &\propto \phi^{3K+2}(\widetilde{\beta},\widetilde{\mathbf{B}})\\
P(\sigma_\varepsilon^2,\sigma_{\varepsilon z}|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\phi^S,\phi^W) &\propto \phi_T^2((\sigma_\varepsilon^2,\sigma_{\varepsilon z}),\sigma_0,\Sigma_0)\prod_{r=1}^{\bar{r}}P(\mathbf{Y}_r|\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\beta^*,\sigma_\varepsilon^2,\sigma_{\varepsilon z},\sigma_\eta)\\
P(\eta_r|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\phi^S,\phi^W,\sigma_\varepsilon^2,\sigma_{\varepsilon z},\sigma_\eta) &\propto \phi(\eta_r,\widetilde{\eta_r},\widetilde{M}_r)\\
P(\sigma_\eta|\mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\mathbf{Z}_r,\phi^S,\phi^W,\sigma_\varepsilon^2,\sigma_{\varepsilon z}) &\propto \iota\gamma(\frac{\varsigma_0+\bar{r}}{2},\frac{\zeta_0+\sum_{r=1}^{\bar{r}}\eta_r^2}{2})
\end{aligned}
$$

where $\rho=(\omega,\phi^S,\phi^W,\beta^*,\sigma_\varepsilon^2,\sigma_{\varepsilon z},\sigma_\eta,\eta)$, $\phi^l(\cdot)$ is the multivariate $l-$ dimensional normal density function, $\phi_T^l(\cdot)$ is the truncated counterpart, $\iota\gamma(\cdot)$ is the inverse gamma density function. $\widetilde{\beta}=\widetilde{B}(B_0^{-1}\beta_0+\sum_{r=1}^{\bar{r}}\mathbf{X}_r'\mathbf{V}_r(\mathbf{S}_r\mathbf{Y}_r-\sigma_{\varepsilon z}\mathbf{Z}_r))$, $\widetilde{B}=(B_0^{-1}+\sum_{r=1}^{\bar{r}}\mathbf{X}_r'\mathbf{V}_r\mathbf{X}_r)^{-1}$, $\widetilde{\eta_r}=(\sigma_\varepsilon^2-\sigma_{\varepsilon z}^2)^{-1}\widetilde{M_r}\mathbf{l}_{n_r}'(\mathbf{S}_r\mathbf{Y}_r-\sigma_{\varepsilon z}\mathbf{Z}_r-\mathbf{X}_r^*\beta^*)$, and $\widetilde{M_r}=(\sigma_\eta^{-2}+(\sigma_\varepsilon^2-\sigma_{\varepsilon z}^2)^{-1}\mathbf{l}_{n_r}'\mathbf{l}_{n_r})^{-1}$, where $\mathbf{V}_r=(\sigma_\varepsilon^2-\sigma_{\varepsilon z}^2)I_{n_r}+\sigma_\eta^2\mathbf{l}_{n_r}\mathbf{l}_{n_r}'$, where $\mathbf{X}_r^*=(\mathbf{X}_r,\mathbf{G}_r^{*S}\mathbf{X}_r,\mathbf{G}_r^{*W}\mathbf{X}_r)$. The posteriors of β^*,$\{\eta_r\}$ and σ_η are available in closed forms and a usual Gibbs Sampler is used to draw from them. The other parameters are drawn using the Metropolis-Hastings (M-H) algorithm (Metropolis-within-Gibbs). [38]

Sampling Algorithm

We start our algorithm by picking $(\omega^{(1)},\phi^{L(1)},\phi^{S(1)},\beta^{*(1)},\sigma_\varepsilon^{2(1)},\sigma_{\varepsilon z}^{(1)},\sigma_\eta^{(1)},\eta^{(1)})$ as starting values. For $\beta^{*(1)},\eta^{(1)},\phi^{L(1)},\phi^{S(1)}$ we use OLS estimates, while we set the variances-covariances $\sigma_\varepsilon^{2(1)},\sigma_{\varepsilon z}^{(1)},\sigma_\eta^{(1)}$ at 0.[39] We ought to draw samples of $z_{i,r}^t$ from $P(z_{i,r}|Y_r,G_r^W,G_r^S,\rho)$, $i=1,\cdots,n$. To do this, we first draw a candidate $\widetilde{z}_{i,r}^t$ from a normal distribution with mean $z_{i,r}^{(t-1)}$, then we rely on a M-H decision rule: if $\widetilde{z}_{i,r}^t$ is accepted we set $z_{i,r}^t=\widetilde{z}_{i,r}^t$, otherwise $z_{i,r}^t=z_{i,r}^{t-1}$. Once all $z_{i,r}$ are sampled, we move to the sampling of β^*. By specifying a normal prior and a normal likelihood we can now easily sample β^t from a multivariate normal distribution. A diffuse prior for σ_ϵ^2 allows us to sample it from an inverse chi-squared distribution. We follow the Bayesian spatial econometric literature by sampling ϕ^S,ϕ^W from uniform distributions with support $[-\kappa_L,\kappa_L]$ and $[-\kappa_S,\kappa_S]$, as defined above. A M-H step is then performed over a normal likelihood: if accepted, then $\phi^{S^t}=\widetilde{\phi^S}^t$ and $\phi^{W^t}=\widetilde{\phi^W}^t$. For network fixed effects we deal again with normal prior and normal likelihood, so η is easily sampled from a multivariate normal. We sample $\sigma_\varepsilon^2,\sigma_{\varepsilon z}$ from a truncated bivariate normal over an admissible region Ξ such that the variance-covariance matrix is positive definite. Acceptance or rejection is determined by the usual M-H decision rule. A detailed step-by-step description of the algorithm is provided below.

Step 1: Sample $\mathbf{Z}_r^t$ from $P(\mathbf{Z}_r|\ \mathbf{Y}_r,\mathbf{G}_r^W,\mathbf{G}_r^S,\rho)$.

Propose $\widetilde{\mathbf{Z}}_r^t$ drawing each $\widetilde{z}_{i,r}^t$ from $N(z_{i,r}^{(t-1)},\xi_z)$, then set $z_{i,r}^t=\widetilde{z}_{i,r}^t$ with probability α_Z or $z_{i,r}^t=z_{i,r}^{t-1}$ with probability $1-\alpha_Z$ where

[38] See Tierney (1994) and Chib and Greenberg (1996) for details regarding the resulting Markov chain given by the combination of those two methods.

[39] The algorithm is robust to different starting values (see Chib and Greenberg, 1996). However, speed of convergence may increase significantly.

$$\alpha_Z = \min\left\{ \frac{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \widetilde{\mathbf{Z}}_r^t, \rho^{t-1})}{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r^{t-1}, \rho^{t-1})} \prod_i^{n_r} \frac{P(g_{ij,r}^W, g_{ij,r}^S|\widetilde{z}_{i,r}^t, z_{j,r}^{t-1}, \omega)}{P(g_{ij,r}^W, g_{ij,r}^S|z_{i,r}^{t-1}, z_{j,r}^{t-1}, \omega)} \frac{\phi(\widetilde{z}_{i,r}^t)}{\phi(z_{i,r}^{t-1})} \right\}$$

Step 2: Sample $\widetilde{\omega}^t$ from $P(\omega|\mathbf{Y}_r, \mathbf{G}_r^W, \mathbf{G}_r^S)$.

Propose $\widetilde{\omega}^t$ from $N^{2K+3}(\omega^{t-1}, \xi_\omega \Omega_0)$, then set $\omega^t = \widetilde{\omega}^t$ with probability α_ω or $\omega^t = \omega^{t-1}$ with probability $1 - \alpha_\omega$ where

$$\alpha_\omega = \min\left\{ \prod_{r=1}^{\overline{r}} \frac{P(\mathbf{G}_r^W, \mathbf{G}_r^S|\mathbf{Z}_r^t, \widetilde{\omega}^t)}{P(\mathbf{G}_r^W, \mathbf{G}_r^S|\mathbf{Z}_r^t, \omega^{t-1})} \frac{\phi^{2K+3}(\widetilde{\omega}^t, \omega_0, \Omega_0)}{\phi^{2K+3}(\omega^{t-1}, \omega_0, \Omega_0)} \right\}$$

Step 3: Sample $\widetilde{\phi^S}^t$ and $\widetilde{\phi^W}^t$ from $P(\phi^S, \phi^W|\mathbf{Y}_r, \mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r, \beta^*, \sigma_\varepsilon^2, \sigma_{\varepsilon z})$.

Propose $\widetilde{\phi^S}^t$ from $N(\phi^{S^{t-1}}, \xi_\phi)$ and $\widetilde{\phi^W}^t$ from $N(\phi^{W^{t-1}}, \xi_\phi)$, then set $\phi^{S^t} = \widetilde{\phi^S}^t$ and $\phi^{W^t} = \widetilde{\phi^W}^t$ with probability α_ϕ or $\phi^{S^t} = \phi^{S^{t-1}}$ and $\phi^{W^t} = \phi^{W^{t-1}}$ with probability $1 - \alpha_\phi$ where

$$\alpha_\phi = \min\left\{ \prod_{r=1}^{\overline{r}} \frac{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r^{t-1}, \widetilde{\phi^S}^t, \widetilde{\phi^W}^t, \beta^{*t-1}, \sigma_\varepsilon^{2^{t-1}}, \sigma_{\varepsilon z}^{t-1}, \sigma_\eta^{t-1})}{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r^{t-1}, \phi^{L^{t-1}}, \phi^{S^{t-1}}, \beta^{*t-1}, \sigma_\varepsilon^{2^{t-1}}, \sigma_{\varepsilon z}^{t-1}, \sigma_\eta^{t-1})} \cdot \mathbf{I}(\widetilde{\phi^S}^t \in [-\kappa_L, \kappa_L])\mathbf{I}(\widetilde{\phi^W}^t \in [-\kappa_S, \kappa_S]) \right\}$$

Step 4: Sample $\widetilde{\sigma}_\varepsilon^t$ and $\widetilde{\sigma}_{\varepsilon z}^t$ from $P(\sigma_\varepsilon^2, \sigma_{\varepsilon z}|\mathbf{Y}_r, \mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r, \phi^S, \phi^W)$.

Propose $\widetilde{\sigma}_\varepsilon^t$ and $\widetilde{\sigma}_{\varepsilon z}^t$ from $N^2((\sigma_\varepsilon^{2^{t-1}}, \sigma_{\varepsilon z}^{t-1}), \xi_\sigma, \Sigma_0)$, then set $\sigma_\varepsilon^t = \widetilde{\sigma}_\varepsilon^t$ and $\sigma_{\varepsilon z}^t = \widetilde{\sigma}_{\varepsilon z}^t$ with probability α_σ or $\sigma_\varepsilon^t = \sigma_\varepsilon^{t-1}$ and $\sigma_{\varepsilon z}^t = \sigma_{\varepsilon z}^{t-1}$ with probability $1 - \alpha_\sigma$ where

$$\alpha_\sigma = \min\left\{ \prod_{r=1}^{\overline{r}} \frac{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r^{t-1}, \phi^{L^{t-1}}, \phi^{S^{t-1}}, \beta^{*t-1}, \widetilde{\sigma}_\varepsilon^t, \widetilde{\sigma}_{\varepsilon z}^t, \sigma_\eta^{t-1})}{P(\mathbf{Y}_r|\mathbf{G}_r^W, \mathbf{G}_r^S, \mathbf{Z}_r^{t-1}, \phi^{L^{t-1}}, \phi^{S^{t-1}}, \beta^{*t-1}, \sigma_\varepsilon^{t-1}, \sigma_{\varepsilon z}^{t-1}, \sigma_\eta^{t-1})} \frac{\phi_T^2((\widetilde{\sigma}_\varepsilon^t, \widetilde{\sigma}_{\varepsilon z}^t), \sigma_0, \Sigma_0)}{\phi_T^2(\sigma_\varepsilon^{t-1}, \sigma_{\varepsilon z}^{t-1}, \sigma_0, \Sigma_0)} \mathbf{I}((\widetilde{\sigma}_\varepsilon^t, \widetilde{\sigma}_{\varepsilon z}^t) \in \Xi) \right\}$$

where Ξ is a region in which the variance-covariance matrix is definite properly.

Step 5: Sample β^{*t-1}, η^t and σ_η^t from conditional posterior distributions.

Step 6: Repeat previous steps updating values indexed with t.

In each of the M-H steps (1-4) the algorithm accepts the new random values (proposals) if the likelihood is higher than the current one. In the algorithm, ξ_z ,ξ_ω, ξ_σ, and ξ_ϕ are tuning parameters chosen by the econometrician. This choice determines the rejection rate of proposals in the M-H steps (1-4). We set a dynamic algorithm for calibrating those tuning parameters so that they converge to the optimal ones. Optimality means that the proposals are accepted about 50% of the times.[40] The Figure below shows the time-series of rejection rates for all of the parameters. It appears that convergence is achieved around an acceptance rate of 50% for all of the parameters.[41]

[40]The intuition is that if a tuning parameter is too high, the draws are less likely to be within "high density regions" of the posterior and then rejection is too frequent. The "step" is too long and the chain "does not move enough". On the other hand if the "step" is too short, the proposal is more likely to be accepted and the chain "moves too much". Given that we want a mixing chain with a balanced proportion of rejections and acceptances, an optimal step must be chosen. Setting it manually requires a huge amount of time and many manual operations. The dynamic setting of tuning parameters is as follows:

if $t_A/t \leq 0.4$ then $\xi_{t+1} = \xi_t/1.1$,

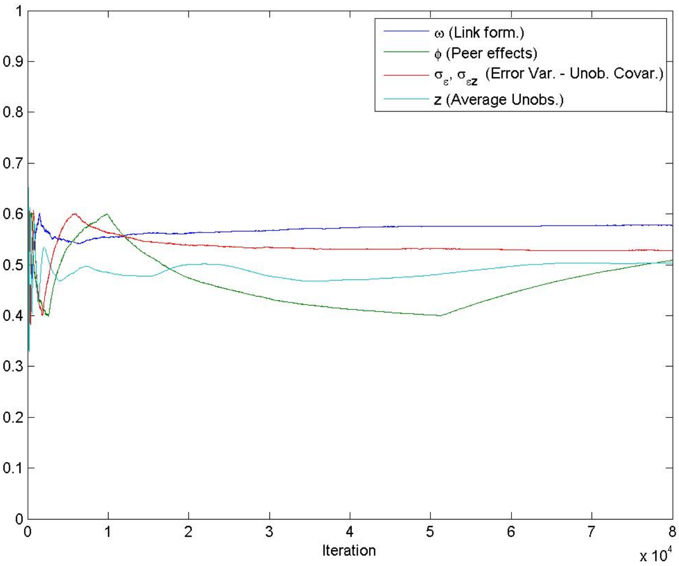
if $t_A/t \geq 0.6$ then $\xi_{t+1} = \xi_t \times 1.1$,

if $0.4 \leq t_A/t \leq 0.6$ then $\xi_{t+1} = \xi_t$,

where t_A is the acceptance rate at iteration t. The procedure decreases the tuning parameter (the "step") when proposals are rejected too frequently, while it increases the tuning parameter when proposals are accepted too frequently. This mechanism guarantees a bounded acceptance rate and convergence to optimal tuning.

[41]Given that the rejection rate-based correction of tuning parameters has 0.4 and 0.6 as boundaries, rejection rates oscillate between these values. The likelihood of reaching the boundaries decreases as the number of draws increases and the rejection rates tend to 0.5, as the Figure shows.

Bayesian Estimation Results - Acceptance Rates

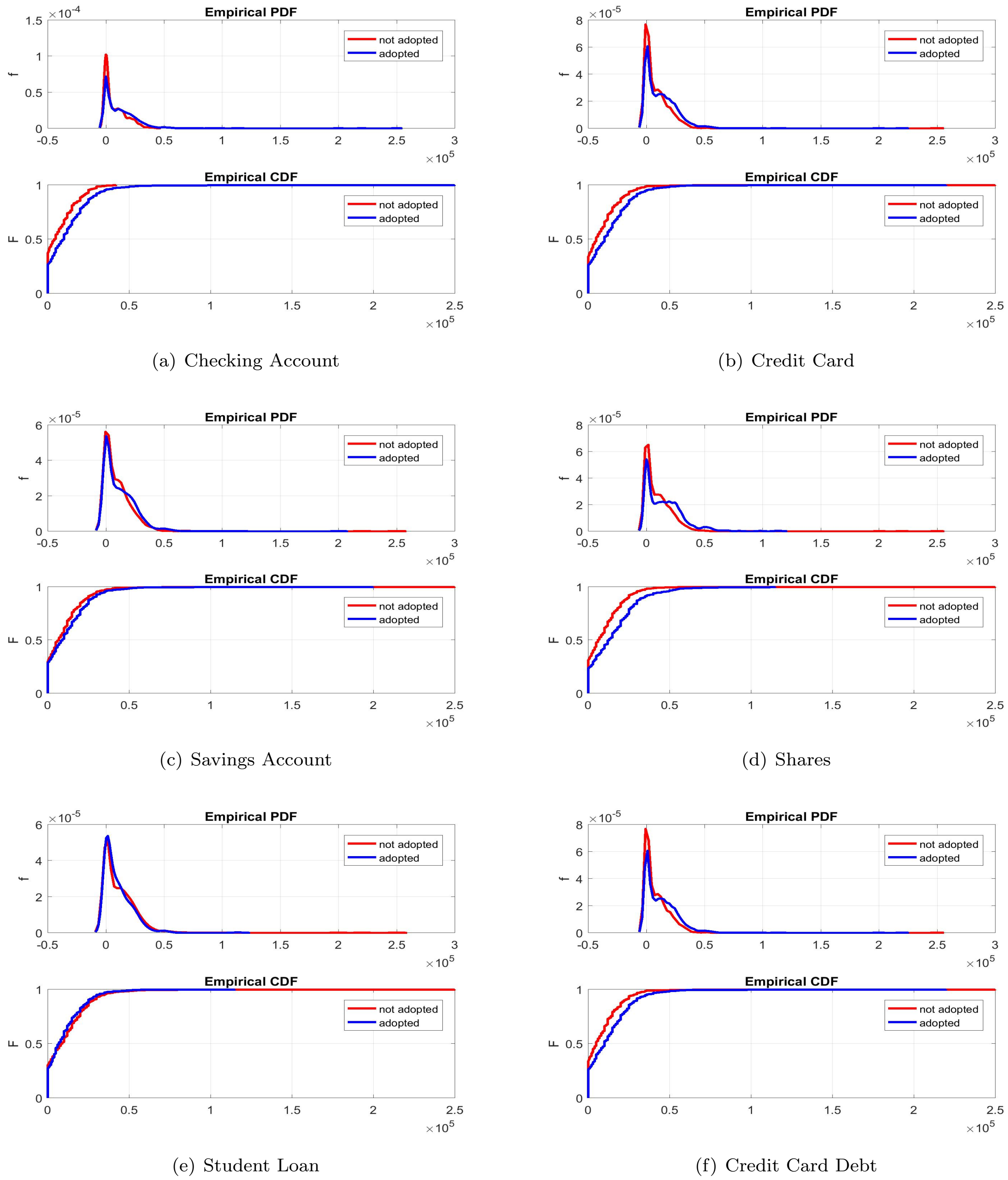


Appendix 2: Data Description and Additional Results

Table A.1: Data Description and Summary Statistics

Variables	Description	Wave(s)	Age Range
Financial Variables			
Checking Account	Dummy variable taking value one if the respondent has a checking account.	III	18 - 27
Savings Account	Dummy variable taking value one if the respondent has a savings account.	III	18 - 27
Shares	Dummy variable taking value one if the respondent has any shares of stock in publicly held corporations, mutual funds, or investment trusts, including stocks in IRAs.	III	18 - 27
Credit Card	Dummy variable taking value one if the respondent has at least one credit card.	III	18 - 27
Student Loan	Dummy variable taking value one if the respondent has any student loans or other educational loans that have not yet been paid.	III	18 - 27
Credit Card Debt	Dummy variable taking value one if the respondent has any credit card debt.	III	18 - 27
Financial Activity Index	The financial activity index is measured using the respondent's financial activities listed above. The index is the first principal component score.	III	18 - 27
Financial Activity Index of Peers	Sum of financial activity index of respondent's peers.	III	18 - 27
Individual Socio-demographic Variables			
Male	Dummy variable taking value one if the respondent is male.	III	18 - 27
Latino	Race dummies. "White" is the reference group	III	18 - 27
Black	//		
Age	Age of student in the current year.	III	18 - 27
Mathematics Score	Mathematics score. Score in mathematics at the most recent grading period, coded as A=4, B=3, C=2, D=1. The variable is zero if missing, a dummy for missing values is included.	II	14 - 22
GPA	The school performance is measured using the respondent's scores received in wave II in several subjects, namely English or language arts, history or social science, mathematics, and science. The scores are coded as 1=D or lower, 2=C, 3=B, 4=A. The final composite index is the first principal component score.	II	14 - 22
Married	Dummy variable taking value one if the respondent is married.	III	18 - 27
Family Size	Number of people living in the household.	II	14 - 22
Employed	Dummy variable taking value one if the respondent is employed.	III	18 - 27
Occ. Manager	Occupation dummies. Closest description of the job. Reference category is "other occupation".	III	18 - 27
Occ. Prof. Tech.	=	III	18 - 27
Occ. Manual	=	III	18 - 27
Occ. Sales	=	III	18 - 27
Income	Respondent's total yearly personal income before taxes in thousand of dollars, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment. Interest or dividends (from stocks, bonds, savings, etc.), unemployment insurance, workmen's compensation, disability, or social security benefits, including SSI (supplemental security income) are included.	III	18 - 27
Education	Years of education attained by the individual.	III	18 - 27
Family Background			
Father Education	Years of education attained by the father of the respondent. The variable is zero if missing. A dummy for missing values is included.	I	13 - 21
Parental Income	Total family income in thousand of dollars (before taxes). It includes own income, income of everyone else in the household, income from welfare benefits, dividends, and all other sources.	I	13 - 21
Contextual Effects	Average of peers' characteristics of all listed variables.		
Networks			
Links in Wave I	Number of individual links in Wave I.	I	13 - 21
Links in Wave II	Number of individual links in Wave II.	II	14 - 22
Strong Ties	Percentage of total individual links that are strong ties.	I,II	13 - 22
Weak Ties	Percentage of total individual links that are weak ties.	I,II	13 - 22

Figure A.1: Distribution of Income for Adopters and Non-adopters



(a) Checking Account

(b) Credit Card

(c) Savings Account

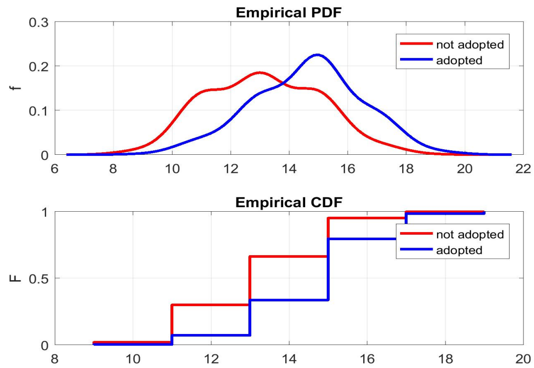
(d) Shares

(e) Student Loan

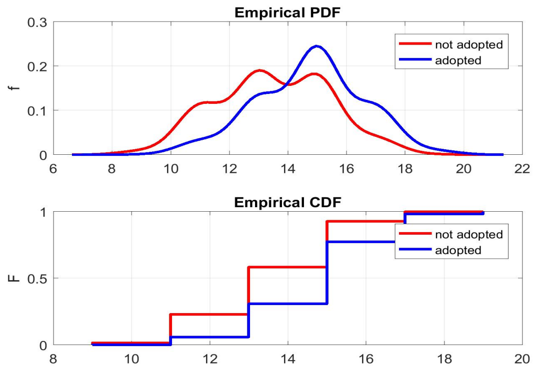
(f) Credit Card Debt

Notes. Respondent's total yearly personal income before taxes in dollars. Blue curves refer to the population adopting the specific service, red curves refer to the population adopting the specific service. The empirical PDF is approximated by a normal kernel density procedure. The distributions are computed on our final sample consisting of 569 individuals distributed over 21 networks.

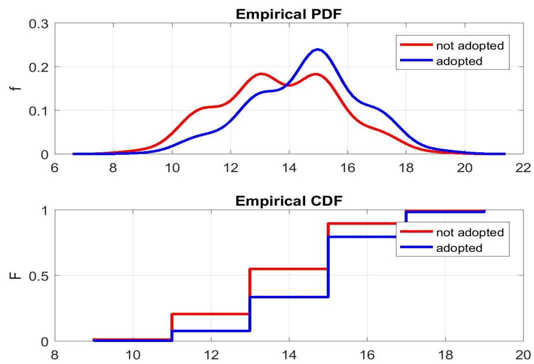
Figure A.2: Distribution of Education for Adopters and Non-adopters



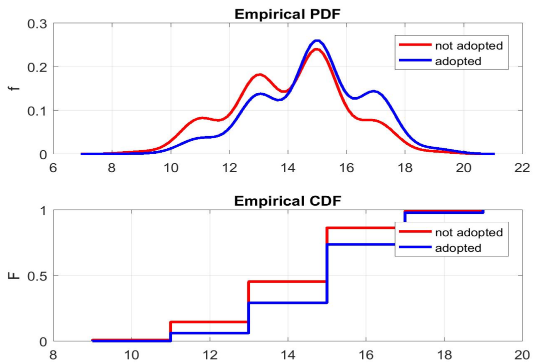
(a) Checking Account



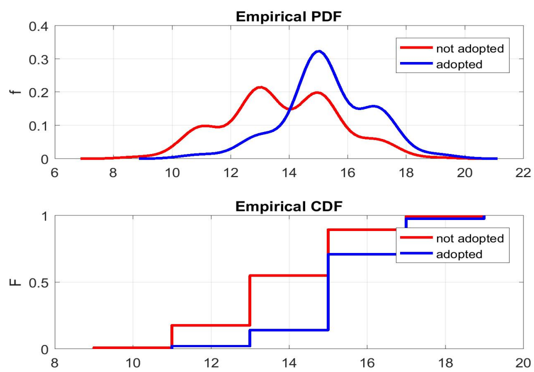
(b) Credit Card



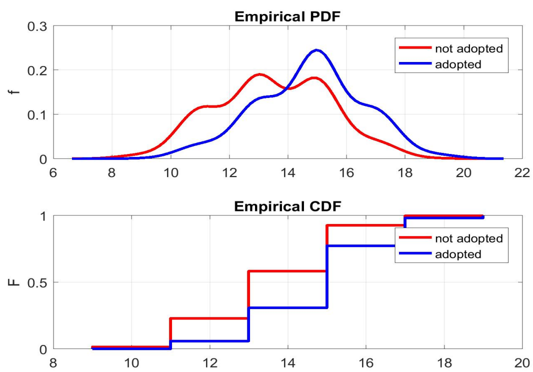
(c) Savings Account



(d) Shares



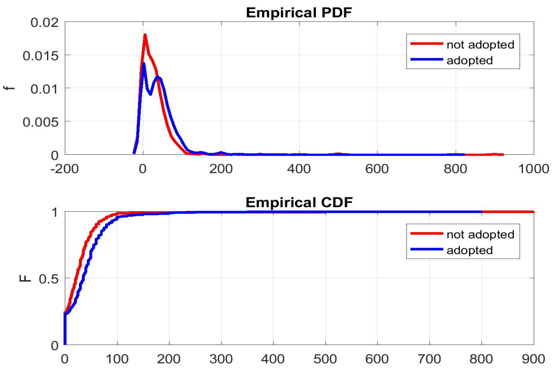
(e) Student Loan



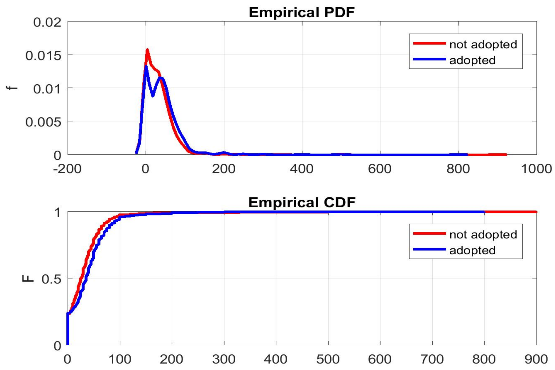
(f) Credit Card Debt

Notes. Respondent's total years of education. See Figure A.1.

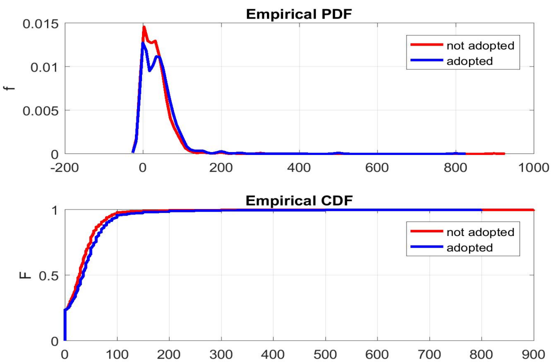
Figure A.3: Distribution of Parental Income for Adopters and Non-adopters



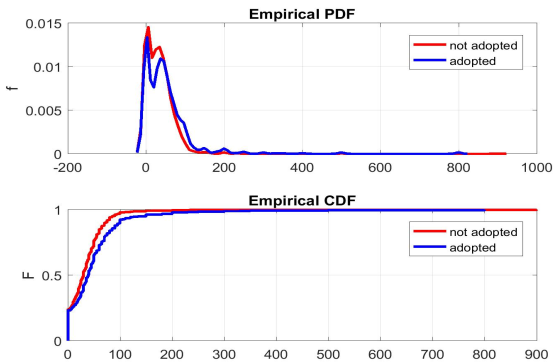
(a) Checking Account



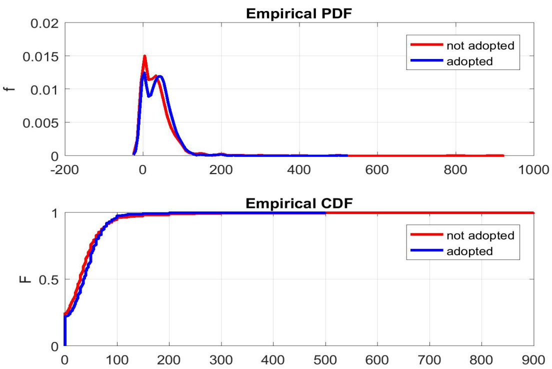
(b) Credit Card



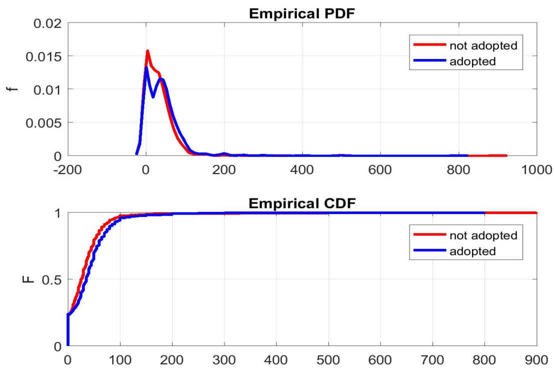
(c) Savings Account



(d) Shares



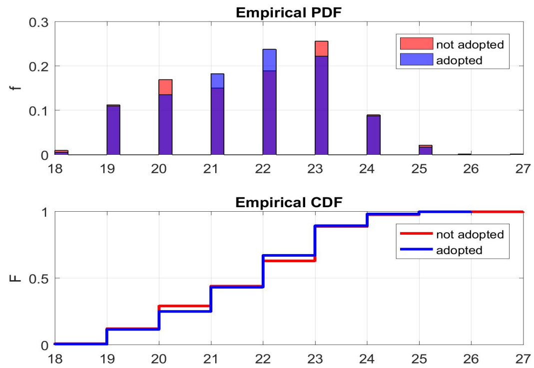
(e) Student Loan



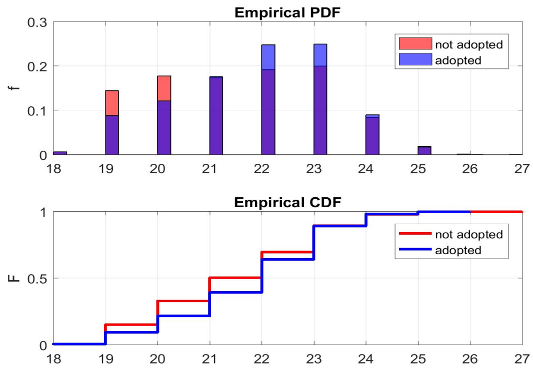
(f) Credit Card Debt

Notes. Total income in thousand of dollars (before taxes) of respondent's family. See Figure A.1.

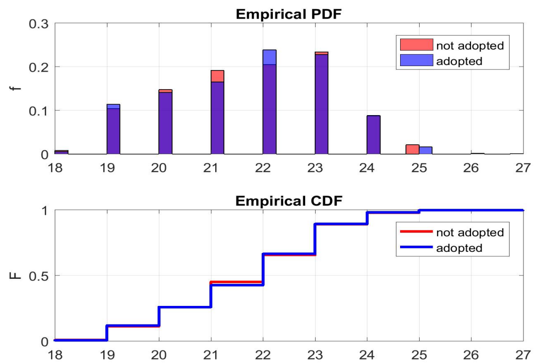
Figure A.4: Distribution of Age for Adopters and Non-adopters



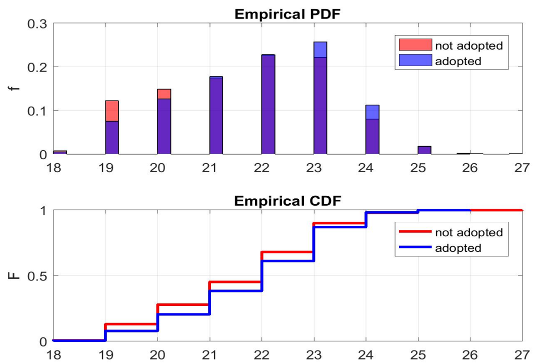
(a) Checking Account



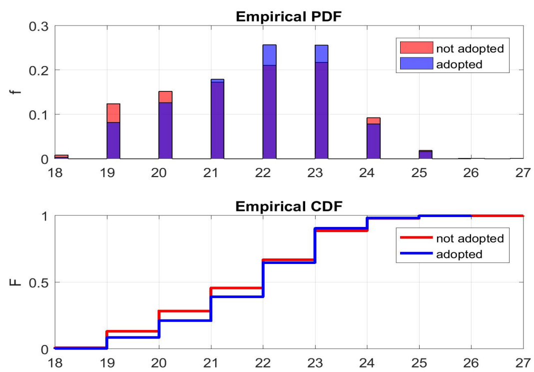
(b) Credit Card



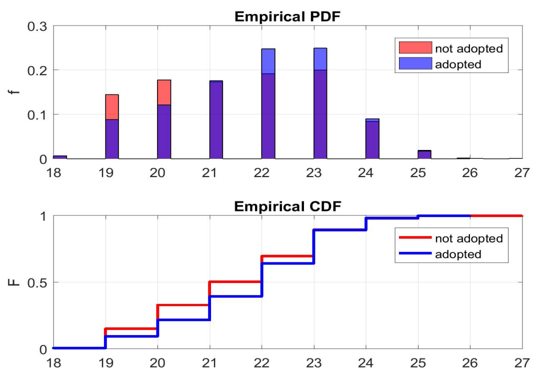
(c) Savings Account



(d) Shares



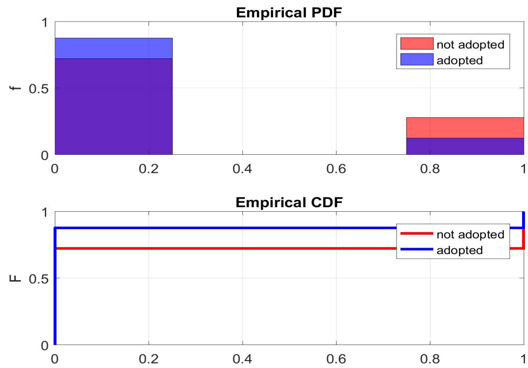
(e) Student Loan



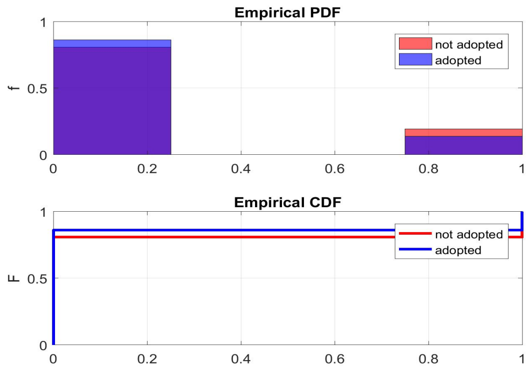
(f) Credit Card Debt

Notes. Age distribution. See Figure A.1.

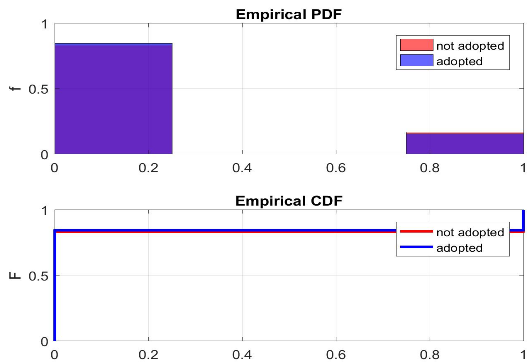
Figure A.5: Frequency of Black Students for Adopters and Non-adopters



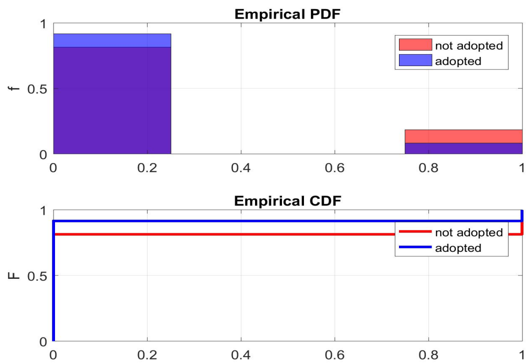
(a) Checking Account



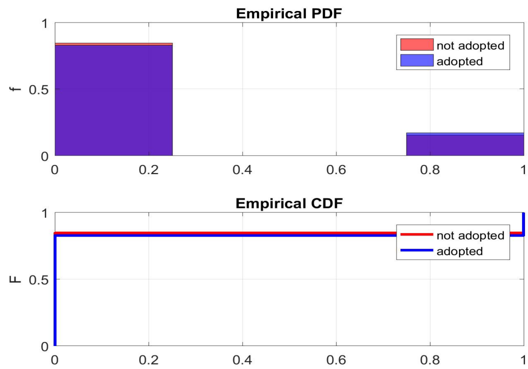
(b) Credit Card



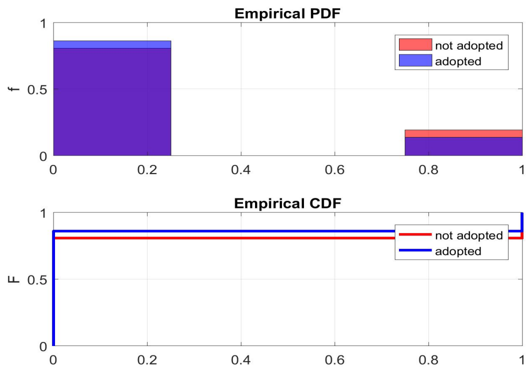
(c) Savings Account



(d) Shares



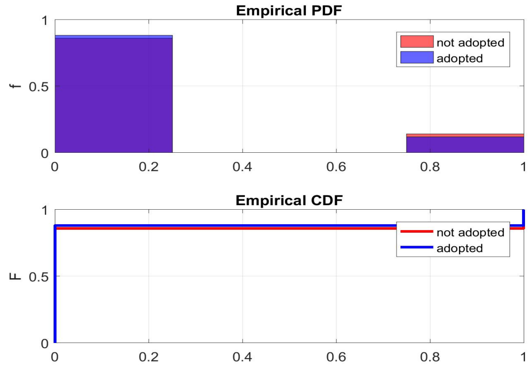
(e) Student Loan



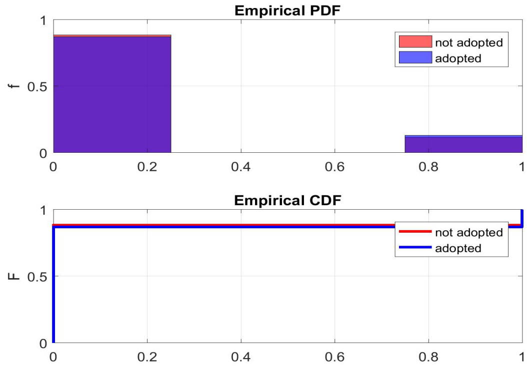
(f) Credit Card Debt

Notes. Frequency of black students. See Figure A.1.

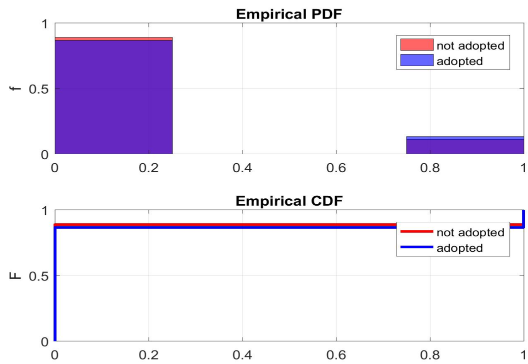
Figure A.6: Frequency of Latino Students for Adopters and Non-adopters



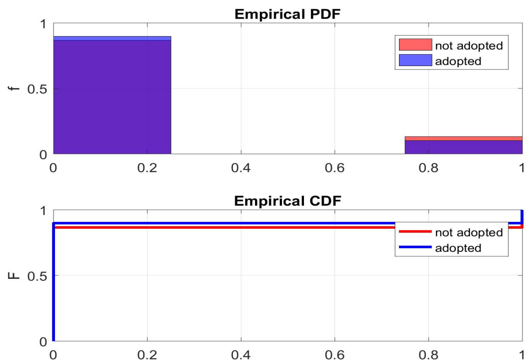
(a) Checking Account



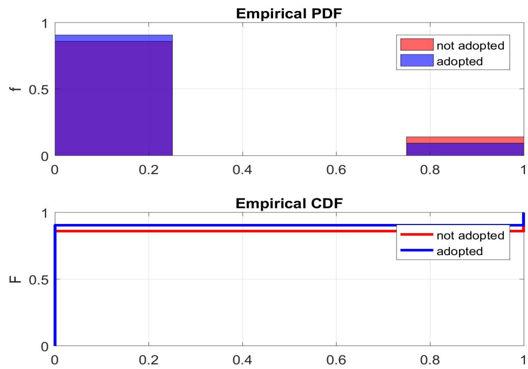
(b) Credit Card



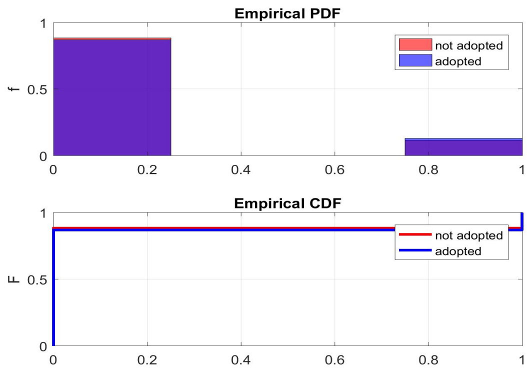
(c) Savings Account



(d) Shares



(e) Student Loan

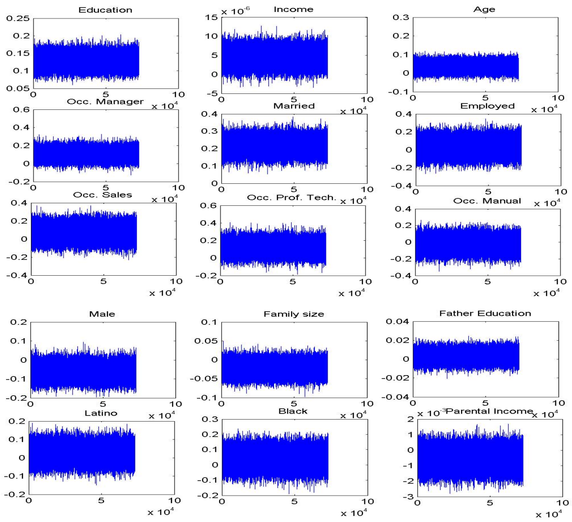


(f) Credit Card Debt

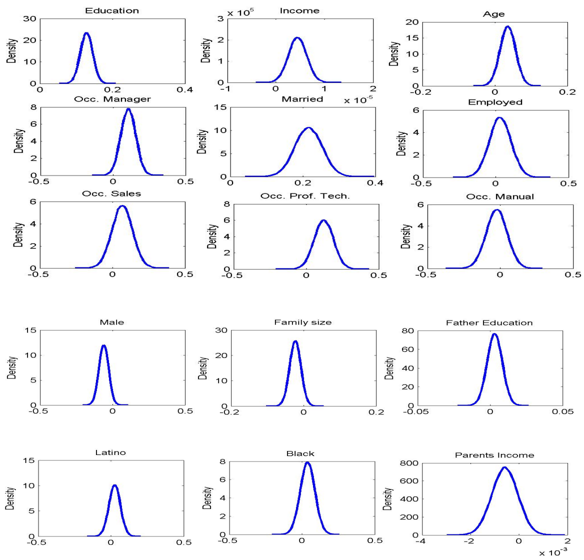
Notes. Frequency of latino students. See Figure A.1.

Figure A.7: Bayesian Estimation Results
Control Variables (β)

Panel (a)



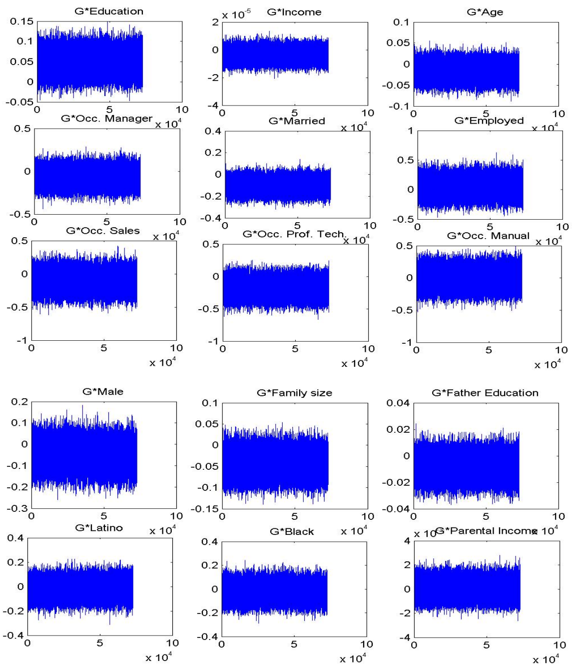
Panel (b)



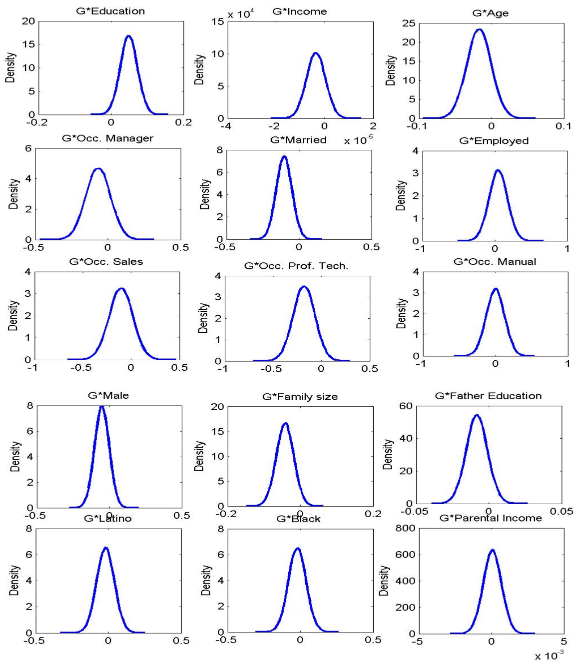
Notes. See Figure 4.

Figure A.8: Bayesian Estimation Results
Contextual Effects (δ)

Panel (a)



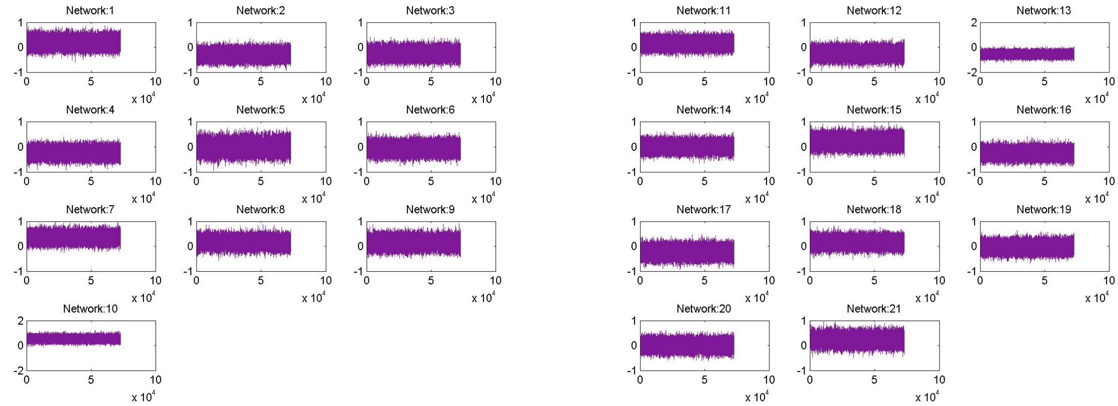
Panel (b)



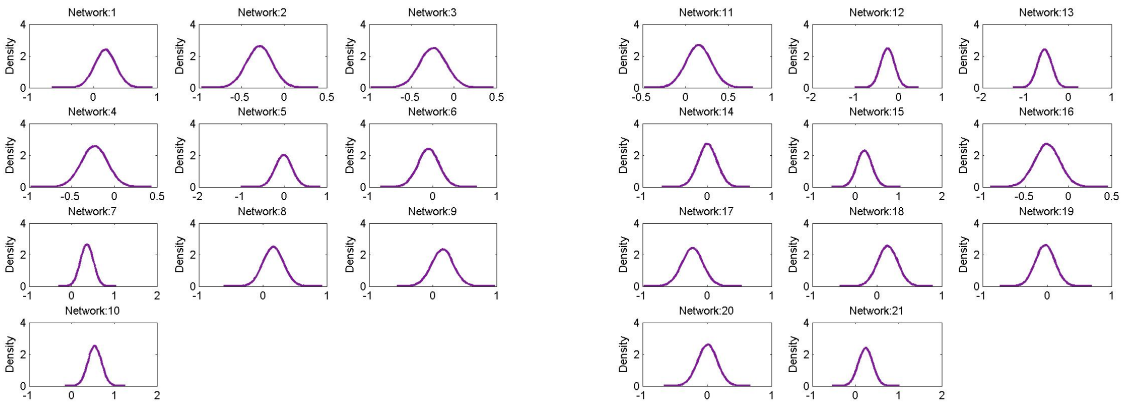
Notes. See Figure 4.

Figure A.9: Bayesian Estimation Results
Network Fixed Effects (η)

Panel (a)



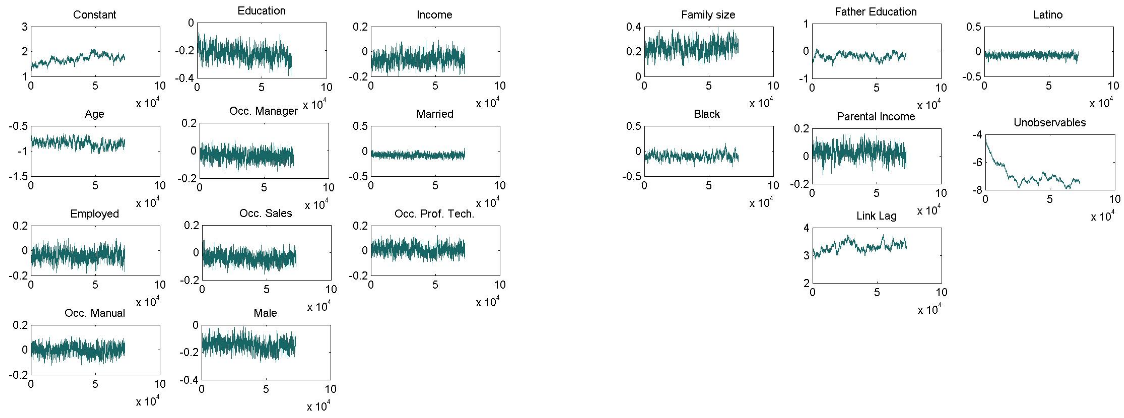
Panel (b)



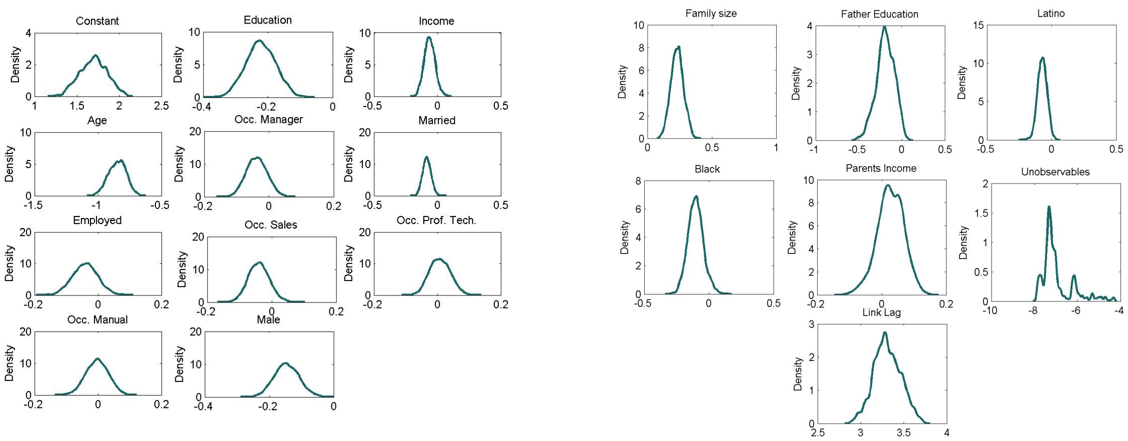
Notes. See Figure 4.

Figure A.10: Bayesian Estimation Results
Link Formation Control Variables (ω)

Panel (a)



Panel (b)



Notes. See Figure 4.

Table A.2: Peer Effects in Financial Decisions

Dependent variable: Financial Activity Index						
	OLS	OLS	OLS	ML	IV	IV bias-corrected
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Effects ϕ	**0.0520*****	**0.0450*****	**-0.0081**	**0.0308*****	**0.0779*****	**0.0451****
	(0.0145)	**(0.0184)**	**(0.0184)**	**(0.0133)**	**(0.0233)**	**(0.0234)**
Male	-0.0950***	-0.0980***	-0.1046***	-0.1027***	-0.1095***	-0.1102***
	(0.0360)	(0.0374)	(0.0366)	(0.0400)	(0.0383)	(0.0381)
Latino	-0.0089	0.0251	0.0342	-0.0059	0.0228	0.0137
	(0.0731)	(0.0796)	(0.0868)	(0.0867)	(0.0908)	(0.0905)
Black	-0.1239***	-0.1267**	0.0419	-0.1706***	0.0694	0.0559
	(0.0466)	(0.0583)	(0.0886)	(0.0648)	(0.0927)	(0.0924)
Age	-0.0094	-0.0051	-0.0172	-0.0956***	-0.0054	-0.0022
	(0.0127)	(0.0140)	(0.0173)	(0.0096)	(0.0178)	(0.0177)
Education	0.1463***	0.1456***	0.1261***	0.1499***	0.1218***	0.1246***
	(0.0116)	(0.0119)	(0.0123)	(0.0125)	(0.0129)	(0.0129)
Income	6.32E-06***	6.21E-06***	5.99E-06***	9.31E-06***	6.00E-06***	6.06E-06***
	(1.45E-06)	(1.47E-06)	(1.47E-06)	(1.81E-06)	(1.54E-06)	(1.53E-06)
Employed	0.2451***	0.2465***	0.2773***	0.2672***	0.2825***	0.2854***
	(0.0685)	(0.0694)	(0.0684)	(0.0749)	(0.0714)	(0.0711)
Occ. Manager	0.2112	0.2330	0.2367	0.2513	0.3295**	0.3422**
	(0.1712)	(0.1700)	(0.1817)	(0.1872)	(0.1629)	(0.1718)
Occ. Prof. Tech	-0.1247*	-0.1310*	-0.1238	-0.1205	-0.1122	-0.1191
	(0.0756)	(0.0764)	(0.0750)	(0.0807)	(0.0787)	(0.0784)
Occ. Manual	-0.1741***	-0.1864***	-0.1848***	-0.2255***	-0.1818***	-0.1827***
	(0.0690)	(0.0698)	(0.0689)	(0.0750)	(0.0718)	(0.0715)
Occ. Sales	-0.0591	-0.0591	-0.0619	-0.0695	-0.0609	-0.0651
	(0.0725)	(0.0730)	(0.0723)	(0.0777)	(0.0757)	(0.0754)
Married	0.3267***	0.3289***	0.3719***	0.3879***	0.3575***	0.3618***
	(0.0510)	(0.0522)	(0.0519)	(0.0537)	(0.0540)	(0.0538)
Family Size	-0.0247**	-0.0230*	-0.0233*	-0.0346***	-0.0221*	-0.0245*
	(0.0118)	(0.0120)	(0.0120)	(0.0124)	(0.0126)	(0.0125)
Father Education	0.0204**	0.0226***	0.0069	-0.0016	0.0091	0.0100
	(0.0083)	(0.0084)	(0.0089)	(0.0086)	(0.0093)	(0.0093)
Parental Income	0.0001	0.0001	-0.0001	0.0003	-0.0002	-0.0002
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Constant	-2.1605***	-2.2904***		-2.3642***		
	(0.3047)	(0.3227)		(0.4822)		
School Performance Variables	Yes	Yes	Yes	Yes	Yes	Yes
Contextual Effects	No	Yes	Yes	Yes	Yes	Yes
Network Fixed Effects	No	No	Yes	No	Yes	Yes
Number of Observations	1497	1497	1497	1497	1497	1497
Number of Networks	151	151	151	151	151	151

Notes. See Table 3. Maximum network size 400, minimum 4.

Table A.3: Weak and Strong Ties in Financial Decisions

Dependent variable: Financial Activity Index			
	OLS	IV	IV bias-corrected
	(1)	(2)	(3)
Strong Ties ϕ^S	**0.0526****	**0.1571*****	**0.0443****
	(0.0215)	**(0.0221)**	**(0.0221)**
Weak Ties ϕ^W	**0.0228**	**-0.0700**	**0.0237**
	(0.0169)	**(0.0425)**	**(0.0427)**
Male	-0.0965***	-0.1005***	-0.0962***
	(0.0383)	(0.0399)	(0.0415)
Latino	0.0407	0.0645	0.0817
	(0.0812)	(0.0904)	(0.0940)
Black	-0.1557***	0.0771	0.0882
	(0.0657)	(0.0947)	(0.0985)
Age	-0.0114	-0.0266	-0.0342*
	(0.0146)	(0.0190)	(0.0197)
Education	0.1431***	0.1227***	0.1192***
	(0.0121)	(0.0130)	(0.0135)
Income	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Employed	0.2432***	0.3045***	0.3115***
	(0.0696)	(0.0722)	(0.0751)
Occ. Manager	0.2493	0.3762**	0.3482**
	(0.1703)	(0.1681)	(0.1711)
Occ. Prof. Tech	-0.1337*	-0.1363*	-0.1342
	(0.0770)	(0.0798)	(0.0830)
Occ. Manual	-0.1689***	-0.1958***	-0.2041***
	(0.0701)	(0.0728)	(0.0757)
Occ. Sales	-0.0447	-0.0844	-0.0950
	(0.0733)	(0.0771)	(0.0801)
Married	0.3493***	0.3982***	0.4052***
	(0.0526)	(0.0553)	(0.0575)
Family Size	-0.0236*	-0.0267**	-0.0268**
	(0.0121)	(0.0128)	(0.0133)
Father Education	0.0178**	0.0044	0.0027
	(0.0086)	(0.0095)	(0.0099)
Parental Income	0.0001	-0.0001	0.0000
	(0.0003)	(0.0004)	(0.0004)
Constant	-2.0534***		
	0.3384		
School Performance Variables	Yes	Yes	Yes
Contextual Effects	Yes	Yes	Yes
Network Fixed Effects	No	Yes	Yes
Number of Observations	1497	1497	1497
Number of Networks	151	151	151

Notes. See Table A.2.

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