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Abstract

This paper studies the importance of social interactions for the adoption of financial products. We exploit a unique dataset of friendships among United States students and a novel estimation strategy that accounts for possibly endogenous network formation. We find that not all social contacts are equally important: only those with a long-lasting relationship influence financial decisions. Moreover, the correlation in agents' behavior only arises among long-lasting ties in cohesive network structures. This evidence is consistent with an important role of trust in financial decisions. Repeated interactions generate trust among agents, which in turn aggregate in tightly knit groups. When agents have to decide whether or not to adopt a financial instrument they face a risk and might place greater value on information coming from agents they trust. These results can help to understand the growing importance of face-to-face social contacts for financial decisions.

Key words: financial market participation, social interactions, trust, network formation, endogeneity, bayesian estimation

JEL classification: C11, C31, D1, D14, D81, D85, G11, M31

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1 Introduction

What factors drive banking decisions? How people choose financial products? A recent study conducted by the Financial Brand in 2011 reveals that, in the previous two years, the percentage of consumers choosing online and offline word-of-mouth (i.e. face-to-face) as the most important driver of banking product and service purchases has increased significantly, whereas the share of those reporting past experience as the crucial factor slightly decreased.[1] The face-to-face channel drives about a third of consumers' checking, savings and mortgage account choices. It also explains about one-quarter of credit card brand choices. When looking at the factors influencing banking decisions by age groups, the study reveals that for young people (18-29 years old), face-to-face communication is the most important factor. Its share of almost 50% largely dominates both past experience and online word-of-mouth (both with shares lower than 30%). The low importance of past experience is expected because of the young age of this group, but why face-to-face social contacts are more important than online social contacts is not obvious This may be further puzzling for those who think online/social media has tremendous power to influence a large number of consumers.

Using an unique data set of friendships among a representative sample of United States students, we investigate the role of social interactions for financial decisions during the early adulthood.

Our identification strategy hinges on three main features, which are novel to the financial literature. First, the uniqueness of our dataset lies in the fact that it is based on direct friends' nominations and provides complete information on all nominated friends. This allows us to control not only for individual characteristics but also for peers' characteristics, thus controlling for sorting (into peer groups) more effectively. Second, because we observe individuals over networks we can employ a pseudo-panel data method and control for network fixed effects. This strategy helps accounting for sorting along unobserved dimensions, given that the influence of any factor which is constant across individuals in the same network is washed away. It is particularly effective in clearing out the error term, when networks are small -as it is in our case. Third, we borrow from the most recent literature on the econometrics of networks and model jointly network formation and behavior over networks. This strategy enables to control also for the influence of individual-level unobserved factors that might affect both friends' choice and financial decisions.

Our analysis uncovers one main novel and important feature. We find that not all social contacts are equally important: only those with a long-lasting relationship (strong ties) influence financial decisions. Moreover, the correlation in agents' behavior only arises among strong ties in cohesive network structures. The length of the relationship does not seem to proxy for its intensity. The richness of our datasets allows us to distinguish between the two effects, finding that it is the length of time spend together that matters the most.

This evidence is consistent with the literature in finance showing an important role of trust in financial decisions (see, most notably Guiso et al., 2008; Guiso et al., 2004).[2] When agents have to decide whether to adopt or not a financial instrument they face a risk and they might value more the

[1] The report is based on the Large Purchase Study conducted by S. Radoff Associates in summer 2010 on a nationally representative sample of 1,000 U.S. adults aged 18 and up.

[2] Butler et al. (2012) highlight financial advice as an important example of trust-based exchange. In the US, 73% of all retail investors consult a financial advisor before purchasing shares (Hung et al., 2008).

information coming from agents they trust. Our analysis thus helps understanding why face-to-face social contacts are more important than online social contacts. Online word-of-mouth can be seen as a less reliable source of information, since the agents spreading the information are not personally known and consequently not necessarily trustworthy.

Financial and payment instruments are fundamental in the economy smooth functioning as a support for money and asset transfers among agents. The adoption of novel and technology-based financial instruments are trust-intensive decisions, people might trust other people when collecting private information about a specific financial product.[3] The role of social interactions is thus at the crux of a full understanding of potential diffusion of technological changes.[4]

There are ony a few papers that look at the importance of social interactions in finance.

Hong et al. (2004) find that social households, as defined as those who interact with their neighbors or attend church, are more likely to invest in the stock market than non-social households. They present a model where social investors differ from non-socials in that their net cost of participating in the market is influenced by the choices of their peers.[5] Their model predicts an higher participation rate among social investors than among non-socials, and also that a social multiplier is likely to arise from the correlation between individual and peers' financial decisions. Because of the absence of information on precise social interaction patterns in their data (i.e. about who interacts with whom), their empirical analysis focuses on testing the first model prediction only.[6] Our analysis complements their findings, as it provides evidence on the existence and the extent of the social multiplier in financial decisions. As Hong et al. (2004) argue, the presence of a social multiplier may help understanding changes in aggregate stock-market participation over time. If the increase of stock market participation in the last decades can be associated with a decrease in participation cost, then social interactions may have had a crucial role by amplifying the cost shock.

Using a high-stakes field experiment conducted with a financial brokerage, Bursztyn et al. (2012) find that both social learning and social utility channels have statistically and economically significant effects on investment decisions. Indeed, a peer's act of purchasing an asset would affect one's own choice because one may acquire information from the choice of the peer (social learning)[7] and because one's utility from possessing an asset may depend directly on the possession of that asset by another individual (social utility).[8] Although it is virtually impossible to investigate separately those two mechanisms with non-experimental data, our paper presents novel evidence that it is not in contrast

[3] Algan and Cahuc (2014) characterize trust as an important driver of economic development, and identify financial markets as one of the main channels through which trust influences economic outcomes of a society. The relationship between *individual* trust and *individual* economic outcomes is investigated by Butler et al. (2010).

[4] Economists have been optimistic that currency will be replaced by technologically more advanced electronic transfers and e-moneys of assorted varieties (see, e.g. Craig, 1999; Drehmann et al., 2002). The cost of a country's payment system is usually between 2% and 3% of GDP. Since the cost of an electronic payment ranges between one-third to one-half that of a check or paper giro payment (see e.g. Gresvik, 2009; Humphrey and Berger, 1990), promoting a shift to electronic would reduce this cost. In addition, the use of cash is affected by the extent of illegal activities including the avoidance of taxes (see e.g. Humphrey et al., 1996).

[5] Specifically, the cost for any social investor in a given peer group is reduced—relative to the value for an otherwise identical non-social—by an amount that is increasing in the number of others in the peer group that are participating.

[6] They provide evidence consistent with a peer-effects story by finding that the impact of sociability is stronger in states where stock-market participation rates are higher.

[7] Theoretical models of herding and asset-price bubbles focus on learning from peers' choices (see, Bikhchandani and Sharma, 2000; Chari and Kehoe, 2004).

[8] A number of paper consider the "keeping up with the Joneses" hypothesis in explaining stock market behavior (most notably, Gali, 1994; Abel, 1990; Campbell and Cochrane, 1999).

with any of them. If one considers the learning mechanism, then our paper reveals that agents learn more from peers they trust. A social utility -based interpretation instead suggests that long-lasting (and hence trustworthy) social contacts are the relevant reference group. If a conformism (herding) behavior or conspicuous consumption is driving the purchase of financial products (i.e., if it is the behavior relative to the peers that matters), then it is important to understand who the peers are with whom each individual is compared to.

Our paper is organized as follows.

We begin by describing our data in Section 2. Section 3 presents our empirical model and identification strategy, whereas Sectin 4 discusses our main estimation results. We collect some additional evidence in Section 5. In Section 6 we use simulation experiments to show the implications of social interactions for the adoption of financial products. Section 7 concludes.

2 Data description

Our analysis is made possible by the use of a unique database on friendship networks from the National Longitudinal Survey of Adolescent Health (AddHealth).[9] The AddHealth survey has been designed to study the impact of the social environment (i.e. friends, family, neighborhood and school) on students' behavior in the United States by collecting 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 AddHealth data is the friendship information, which is based upon actual friend nominations. Indeed, students were asked to identify their best friends from a school roster (up to five males and five females).[10] 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. 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 best friend. Indeed, even if agent j does not nominate i as best friend, it is reasonable to think that social interactions have

[9] This research uses data from AddHealth, 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 to 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.

[10] 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.

taken place.[11] 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 interacts with whom in a social group).

Moreover, one can distinguish between *strong* and *weak* ties in the data. We define a *strong* tie or relationship between two students if they have nominated each other in both waves (i.e. in Wave I in 1994-1995 *and* in Wave II in 1995-1996) and a *weak* tie or relationship if they have nominated each other in one wave only (Wave I *or* Wave II).

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, of which we have no information. The network of social contacts during high school remains however a good approximation of face-to-face information they are (or have been in a recent past) exposed to. The questionnaire of Wave III contains detailed information on the use of financial and payment instruments like saving and checking accounts, credit cards, loans, shares of stock in publicly held corporations, mutual funds, or investment trusts. Table 1 reports on the financial activity participation of the agents in our sample. More than 60% of the students have a checking account, a saving account, and a credit card. About 40% have a credit card debt and more than 30% has a student loan. Interestingly, 25% of individuals own shares of stock in publicly held corporations, mutual funds, or investment trusts, including stocks in IRAs. For each individual, we construct an index of financial activity participation using a traditional principal component analysis, where the loadings of these different activities are used to derive a total score. Our measure of financial activity is the first principal component. It explains over one-third of the total inertia.[12] 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 products that an individual uses, the higher the value of our indicator of financial participation. The index ranges between 0 and 2.64, with mean equal to 1.47 and substantial variation around this mean value (standard deviation equal to 0.77).

[*Insert Table* 1 *here*]

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 allow us to investigate the role of peers' adoption of financial instruments on individual decisions.

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 1 shows a representative network. Each node represents an agent, with the size of the node proportional to

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

[12] 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.

her/his level of participation to the financial market. The lines represent the connections between the agents; the thicker they are, the longer the interaction relationship between pairs of agents. As can be seen from the picture, agents in more cohesive groups characterized by a relatively high density of ties tend to show a higher and more similar level of financial activity. This stylized fact motivates our analysis in the following sections.

[*Insert Figure* 1 *here*]

The sample of individuals that are followed over time and have non-missing information for our target variables both in Waves I, II and III consists of 12,874 individuals. As is common with AddHealth data, a further reduction in sample size is due to the network construction procedure - roughly 20% of the students do not nominate any friends and another 20% cannot be correctly linked.[13] In addition, in this study we focus on networks with size between 10 to 50 agents to cope with the computational burden required by the use of Bayesian estimation procedures.[14] Our final sample consists of 569 individuals distributed over 21 networks.[15] The mean and the standard deviation of network size are roughly 27 and 13 students, respectively. Roughly 59% of the nominations are not renewed in Wave II, and about 56% new ones are made. On average, these individuals have 23% strong ties and 76% weak ties. Further details on nomination data can be found in Table A1 in Appendix A. Table A1 also gives precise definitions of the variables used in our study as well as their descriptive statistics.[16]

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.[17] Let $\mathbf{G}_r^* = [g_{ij,r}^*]$ be the row-normalized $\mathbf{G}_r$ such that $g_{ij,r}^* = g_{ij,r}/\sum_{k=1}^{n_r} g_{ik,r}$.

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 choice may depend on those

[13] The representativeness of the sample is preserved. Summary statistics are available upon request.

[14] Our results, however, do not depend crucially on these network size thresholds. They remain qualitatively unchanged when changing the network size window slightly.

[15] We report in Appendix E our main results which are obtained using traditional estimation techniques on the more extensive sample. Observe that even in this case we do not consider networks at the extremes of the network size distribution (i.e. consisting of 2-3 individuals or more than 400) because peer effects can show extreme values (too high or too low) in these edge networks (see Calvo-Armengol et al., 2009).

[16] Information at the school level, such as school quality and the teacher/pupil ratio, is also available. We do not use it since our sample of networks is within schools and we include fixed network effects in our estimation strategy.

[17] For ease of presentation, we focus on the case where the connections are undirected and no agent is isolated so that G_r is symmetric and $\sum_{j=1}^{n} g_{ij,r} \neq 0$ for all i.

of his/her contacts about the same activity.[18] $x_{ik,r}$ 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 index 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 types (weak and strong ties), then Model (1) becomes

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

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 activity on one's own financial choices respectively) while δ^S and δ^W capture the impact of the exogenous characteristics of the peers - which are allowed to have a varying effect by peer-type.

3.2 Identification and estimation

A number of papers have dealt with 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). Below, we review the crucial issues while explaining how we tackle 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' choice of effort (*endogenous effects*) and peers' characteristics (*contextual effects*) that do have an impact on their effort choice (the so-called reflection problem; 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 nearly 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).[19]

[18] Given we are modeling the financial activity of agents it seems more appropriate to consider an "aggregate" model instead of an "average" one. The first type of models allows the number of peers to be relevant in shaping the agents' activity, while the second do not consider this information, i.e. it uses average values of peers' activity (see Liu et al., 2011).

[19] Formally, social effects are identified (i.e. no reflection problem) if $\mathbf{G}_r^2 \neq \mathbf{0}$, where $\mathbf{G}_r^2$ keeps track of indirect

Correlated effects While a network approach allows us to distinguish endogenous effects from correlated 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 the 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 2. 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.

[*Insert Figure* 2 *here*]

Sorting In most cases, individuals sort into groups non-randomly. For example, students whose parents are low-educated (or worse than average in unmeasured ways) would 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 way out by the use of *network fixed effects.* Network fixed effects are a remedy for the selection bias that originates from the possible sorting of individuals with similar unobserved characteristics into a network. The underlying assumption is that such unobserved characteristics are common to the individuals within each network. This is reasonable in our case study where the networks are quite small (see Section 3).

However, if there are individual-level unobservables that drive both network formation and outcome choice, this strategy fails. For example, one can envision the existence of unobservable (or unmeasurable) factors, such as risk aversion or optimism, which are possibly relevant both in social contexts and for financial decisions making. Recently, Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2011) highlight the fact that endogeneity of this sort can be included in the model. Individual-level correlated unobservables would motivate the use of parametric modeling assumptions and Bayesian inferential methods to integrate a network formation with the study of behavior over the formed networks. The next section contains the results which are obtained by applying this approach to our case.

3.3 Endogenous Network Formation

Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2011) propose two slightly different ways to estimate peer effects with unobservables driving both link formation and outcome.[20] In

connections of length 2 in each network r. This means that we need at least two individuals in the networks that have different links. This condition is generally satisfied in every real-world network.

[20]The Bayesian approach allows to model couple-specific unobserved heterogeneity, for each possible couple in the sample. A traditional Heckman-type selection model is configured to capture individual-specific unobserved heterogeneity. The inclusion of alter heterogeneity would imply the computation of high-dimensional multivariate

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 (2011).[21] They present a model with one peer-type - which correspond to Model (1). We implement here an extension of their method to the case of 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 - 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 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

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

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 is 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. From Model (4) - (5), the probability of observing a weak tie is

$$\begin{aligned} &P(g^W_{ij,r} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_t, \theta_t, \lambda, \gamma_{t-1}, \theta_{t-1}) \\ &= P(g_{ij,r,t} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_t, \theta_t, \lambda, g_{ij,r,t-1} = 0) \times P(g_{ij,r,t-1} = 0 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}) \\ &+ P(g_{ij,r,t} = 0 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_t, \theta_t, \lambda, g_{ij,r,t-1} = 1) \times P(g_{ij,r,t-1} = 0 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}) \end{aligned}$$

whereas the probability of observing a strong tie is

$$\begin{aligned} &P(g^S_{ij,r} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_t, \theta_t, \lambda, \gamma_{t-1}, \theta_{t-1}) \\ &= P(g_{ij,r,t} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_t, \theta_t, \lambda, g_{ij,r,t-1} = 1) \times P(g_{ij,r,t-1} = 1 | x_{ij,r}, z_{i,r}, z_{j,r}, \gamma_{t-1}, \theta_{t-1}). \end{aligned}$$

normal integrals, which is unfeasible using standard methods.

[21] Another difference between those two procedures is that Goldsmith-Pinkham and Imbens (2013) set the same unobservable in both link formation and outcome equation while Hsieh and Lee (2011) use different unobservables for those equations and let them to be correlated.

In this way, we have modeled the probability of being a strong or weak ties including unobservables that are allowed to be correlated with the error term in the outcome equation.[22] 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

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

where $u_{i,r} \sim N(0, \sigma_z^2 - \frac{\sigma_{\varepsilon z}^2}{\sigma_z^2})$. 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. Bayesian inference requires the computation of marginal distribution for all parameters. However, 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 usually 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.[23]

4 Estimation results

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

4.1 Peer effects

Table 2 collects the estimation results of 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 a possible network endogenity. Columns (1) to (3) report OLS estimates with an increasing set 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 be simply driven by common shocks or sorting into groups according to network-specific unobserved

[22] The procedure can be easily extended to include more than one unobservable factor.

[23] See Appendix B for more details on the estimation procedure. An introduction to Monte Carlo methods in Bayesian econometrics can be found in Chib (1996) and Robert and Casella (2004).

characteristics. Column (4) presents the estimation results using ML, that is when the simultaneity which is endemic in spatial models is accounted for.[24] 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 3 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.[25] 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 biased-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 3 and 4 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.[26] Table 2 shows that the coefficients are quite stable across columns.[27] It reveals that the effect of peers' financial activity on own activity is significant and positive, i.e. there are *peer effects in financial activity*. When observable and unobservable characteristics are controlled for (estimates in column 7), in an average group of four agents, a standard deviation increase in the level of financial activity of each of the peers translates into a roughly 22% increase of a standard deviation in the individual's financial activity. In terms of the different financial activities embedded in the composite index, the estimate implies an increase of about 9% in the individual probability of getting a credit card, 6% in the probability of opening a checking or saving account, 4% in the probability of buying shares, 3% in the probability of getting a loan, and 8% in the probability of having a credit card debt.[28] These are non-negligible effects, especially given our long list of individual and peers' controls.[29] Observe that the policy maker can rarely manipulate peer outcomes. Peer effects can be seen as a mechanism through which an exogenous shock could propagate through the networks. We devote Section 6 to analyze these diffusion mechanisms via Monte Carlo simulations.

[24] 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 statistics for η_r when the adjacency matrix is not row-normalized (see Lee et al., 2010).

[25] See Appendix C 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 $\phi^S = \phi^W$.

[26] The kernel densities and the time-series of the values of the chain for the parameters of the control variables are reported in Appendix D, Figure D1-D3.

[27] The estimate of peer effects (ϕ) using OLS is not surprisingly upper-biased. The IV estimates also suffer from a bias due to the large number of IVs, that are employed when estimating a spatial model (see Appendix C)

[28] We compute these estimated probabilities using the marginal effect of an increase of the financial activity index on the probability of adopting each of the different financial products. Marginal effects are evaluated at the sample mean: $m(\beta) = \phi(\overline{x}\beta)\beta$, where $\phi(\cdot)$ is the normal probability density function. Results do not change significantly if the average of individual marginal effects is instead considered.

[29] Although the computational burden requested by the Bayesian procedure prevents us from performing this type of estimation on the entire sample, we report in Appendix E, Table E1, the OLS, ML and IV results for the entire sample.

[*Insert Tables* 2 *and* 3 *here*]

[*Insert Figures* 3 *and* 4 *here*]

4.2 Peer effects by peer-type

Table 4 collects the estimation results of Model (2). It has a structure similar to Table 2.[30] Column (4) shows the Bayesian estimation results, which account for possible endogeneity of strong and weak tie networks. The results in Table 4 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.[31] OLS and IV estimates seem to overestimate the effects. The IV bias-corrected and Bayesian estimates are very close to each other. This also means that also unobservable factors influencing the *strength* of a tie are not relevant in the financial decisions of agents ($\sigma_{\varepsilon z}$ is not significantly different from zero).[32] Given that our networks are quite small in size, it is thus likely that any correlated unobserved factor is already captured by the network fixed effects. The upper panel of Figures 5 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.[33] 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.

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 saving account, 5% in the probability of buying shares, 4% in the probability of getting a loan, and 10% in the probability of having a credit card debt.

[*Insert Table* 4 *and Figure* 5 *here*]

4.3 Network Formation

For completeness, Table 5 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

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

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

[32] 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.

[33] 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 5 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 B for model details.

behavior over network are simultaneously estimated.[34] The estimates of the outcome equation (first column) are the ones in column (4) of Table 4. 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 is the likelihood of a link between them. Interestingly, the factors predicting the existence of a link slightly change between Wave I and Wave II. While family background characteristics (such as parental education and income) are important in Wave I, when the student grows up individual characteristics (such as own income and employment status) acquire more importance. Importantly, it appears that there are unobserved factors which 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 2 and in columns (3) and (4) in Table 4 are similar.

[*Insert Table* 5 *here*]

5 Understanding 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 depend 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) . The greater the trust in a social tie, the greater the trust in her choice. Repeated interactions play an important role in determining the level of trust. Several theoretical papers 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 defection temptation. 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 let trust emerge among agents. The repeated interactions horizon generates a bilateral incentive in letting relationships with more trusted agents surviving over time. Karlan et al. (2009) view network connections as a "social collateral" and argue that the level of trust is

[34] The kernel densities and the time-series of the values of the chain for the parameters of the network formation equation at time t (equation (5)) are reported in Appendix D, Figure D4.

determined by the structure of the entire network. They focus on borrowing and lending optimal choices in informal contract enforcement by agents joining the network. 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.[35] 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.[36,37] 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 micro-foundation for the idea of "embeddedness" from Granovetter (1985).

The common vein of these theoretical models is broadly that repeated interactions generate trust among agents, who in turn aggregate in cohesive network structures. If our indicator of strong ties captures high level of trust between agents, then an evidence consistent with this line of reasoning should be the finding of an effect of strong ties on individual financial decisions in cohesive network structures only.

Jackson et al. (2012) use the concept of "supported" links to define a "social quilt", i.e. a union of groups of agents where everybody is connected with everybody else (cliques). They provide an analysis of repeated interactions where an individual's decisions are influenced by the network pattern of behavior in the community. Bilateral interactions may not provide natural self-enforcement of cooperation. Any robust equilibrium network must exhibit a specific trait: each of its link (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.[38]

The first panel of Table 6 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 network structures. Observe that the network structure per se is not a relevant driver of behavior correlation. Indeed, weak ties in highly cohesive networks do not show any similar behavior. It is only when agents have long-lasting friendship relationships that a significant relationship arises. This evidence is thus in line with the idea that a trust-based mechanism is driving our results.

Another possible explanation is that our indicator of strong ties, which is based on the length of the friendship relationship, simply captures the frequency of interactions. This story is not in

[35] 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.

[36] 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.

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

[38] 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.

contrast with our trust-based mechanism described above. Indeed, to the best of our knowledge there is no theoretical model or empirical evidence indicating that the repeated interactions that generate trust should be measured using the length or the frequency of the interactions. However, it is important to understand whether correlated choices of financial products in social networks are to be found only between agents with long lasting friendship ties, or if random, intense encounters in a short amount of time could also be influential. The richness of information provided by the AddHelath allows us to shed light on this issue. More specifically, the Addhealth questionnaire asks detailed questions about the frequency of interactions for each nominated friend. The questions listed are: "Did you go to {NAME}'s house during the past seven days?"; "Did you meet {NAME} after school to hang out or go somewhere during the past seven days?"; "Did you spend time with {NAME} during the past weekend?"; "Did you talk to {NAME} about a problem during the past seven days?"; "Did you talk to {NAME} on the telephone during the past seven days?". We define a *high frequency* friend if the respondent has shared at least two of these activities with the friend, and *low frequency* friend otherwise. The second panel of Table 6 shows the estimation results of Model (2) when strong and weak ties are split according to the frequency of interactions. It appears that the frequency of interactions does not matters at all. The weak tie effect remains not different from zero, regardless of the strength of interactions, whereas the strong tie effect remains always statistically significant, with no statistical significance in terms of magnitude between high and low frequency strong tie.[39]

[*Insert Table* 6 *here*]

6 Policy experiments

Using our data and the estimates of the parameters in Model (2),[40] 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. 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 implications of strong and weak ties effects.

Our analysis can be used to understand which agents (or which type of agents) should be targeted to maximize the aggregate financial activity participation or to converge to a desired distribution of individual financial activity.

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 an increasing income shock for a fixed number of agents (intensive margin) who have a different number 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

[39] A formal t-test on the difference between high and low frequency strong ties in a pooled model with interaction terms returns a value of 1.45.

[40] The Bayesian estimates in column (4) of Table 4 are used.

while decreasing the income of agents who have strong ties and look at the final aggregate financial activity. The fourth exercise reports on 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 6 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.[41] It appears that the higher is the number of strong ties the shocked agents have, the higher is 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 as the one 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.[42] 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. If policy interventions of this type have a cost, then our results show that targeting highly connected agents can help cutting costs while maintaining the same efficacy. Peer effects can in fact act as a mechanism through which a shock is propagated (and amplified) through the network.

Figure 7 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 shock),[43] and decrease the income of an increasing number of agents who have a different number of strong ties (i.e. with network diffusion of their shock).[44] 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 to explain why some policies targeting a large number of agents did not reach the desired effects. Even if the observable costs of using, say, a new digital credit card are lower than the cost incurred when 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 they do not know

[41] 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.

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

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

[44] 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.

anybody else that they trust who has adopted the product. From Figure 7 one can see that if highly connected agents have a negative shock, then the aggregate financial activity decreases even if there is a higher number of agents in the economy that experience a positive shock, provided that those agents have lower social interactions. For example, Figure 7 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 on average decreases. Social interactions may be responsible for this (seemingly) paradoxical result.

In order to better understand this result, in our last simulation exercise we consider the effects at the individual level of individual and peers' shocks. Each point of the surface represented in Figure 8 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.[45] The exercise is implemented for agents who have a different number 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 8 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 .

[*Insert Figures* 6, 7 *and* 8 *here*]

7 Conclusions

In spite of the common consensus about the importance of word-of-mouth on financial product purchases, the finance literature provides little evidence on the role of peer-to-peer communications. Much of the debate is about how to use social media innovatively and effectively. Yet, a large number of consumers rely on offline word-of-mouth when making banking product and brand choices, in particular young customers. The scarcity of studies on face-to face peer effects in finance is mainly motivated by the lack of appropriate data on personal contacts. In addition, endogeneity and reverse causality issues make the identification and estimation of peer effects a challenging empirical exercise.

This paper tries to fill this gap. By employing detailed data on each individual and friends' financial decisions for a representative sample of US students and a novel identification strategy, we are able to uncover the existence and extent of heterogeneous peer effects in financial decisions. Not all social contacts are equally important. 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 they might value the information more coming from agents they trust. A social multiplier may amplify consumers' preferences towards certain products. Even if the direct participation costs of adopting, say, a novel digital credit card are lower than the costs incurred with traditional cards, many consumers may be deterred from adopting the new technology largely because they do not

[45] 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.

know anybody they trust who does so. Thus, if social interaction helps to increase financial market participation, then an effective policy should not only be measured by its direct effects but also by the group interactions it engenders.

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Appendix

Appendix A: Descriptive Statistics

Table A1: Data Description and Summary Statistics

Variables	Description	Average (Std.Dev.)	Min - Max
Financial Variables			
Checking Account	Dummy variable taking value one if the respondent has a checking account.	0.76 (0.42)	0 - 1
Saving Account	Dummy variable taking value one if the respondent has a saving account.	0.63 (0.48)	0 - 1
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	0.24 (0.43)	0 - 1
Credit Card	Dummy variable taking value one if the respondent has credit card.	0.61 (0.49)	0 - 1
Student Loan	Dummy variable taking value one if the respondent has any student loans or other educational loans that have not yet been paid.	0.33 (0.47)	0 - 1
Credit Card Debt	Dummy variable taking value one if the respondent has any credit card debt.	0.40 (0.49)	0 - 1
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.	1.47 (0.77)	0 - 2.64
Financial Activity Index of Peers	Sum of financial activity index of respondent's peers.	5.76 (1.81)	0 - 15.10
Individual Socio-demographic Variables			
Male	Dummy variable taking value one if the respondent is male.	0.47 (0.49)	0 - 1
Latino	Race dummies. "White" is the reference group	0.12 (0.33)	0 - 1
Black	//	0.16 (0.37)	0 - 1
Age	Grade of student in the current year.	21.65 (1.58)	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.	2.15 (1.10)	0 - 4
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.	1.42 (0.72)	0 - 3.31
Married	Dummy variable taking value one if the respondent is male.	0.16 (0.37)	0 - 1
Family Size	Number of people living in the household	3.36 (1.96)	0 - 10
Employed	Dummy variable taking value one if the respondent is employed.	0.70 (0.46)	0 - 1
Occ. Manager	Occupation dummies. Closest description of the job. Reference category is "other occupation"	0.05 (0.23)	0 - 1
Occ. Prof. Tech.	=	0.17 (0.37)	0 - 1
Occ. Manual	=	0.25 (0.43)	0 - 1
Occ. Sales	=	0.20 (0.38)	0 - 1
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.	14.07 (14.66)	0 - 250
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.	10.73 (6.85)	0 - 19
Parental Income	Total income in thousand of dollars, before taxes of respondent's family. It includes own income, income of everyone else in the household, and income from welfare benefits, dividends, and all other sources.	49.40 (51.42)	0 - 900
Contextual Effects	Average of peers' characteristics of all listed variables.		
Networks			
Links in Wave I	Number of individual links in Wave I.	2.23 (1.88)	0 - 11
Links in Wave II	Number of individual links in Wave II.	2.22 (2.18)	0 - 11
Deleted links	Percentage of nominations in Wave I not renewed in Wave II.	0.59 (0.39)	0 - 1
New links	Percentage of new nominations in Wave II.	0.57 (0.39)	0 - 1
Strong Ties	Percentage of strong ties on total individual links.	0.23 (0.27)	0 - 1
Weak Ties	Percentage of weak ties on total individual links.	0.77 (0.27)	0 - 1

Appendix B: Bayesian Estimation

Prior and Posteriors 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 (2011) 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

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

where $\rho = (\omega,\phi^S,\phi^W,\beta^*,\sigma_\varepsilon^2,\sigma_{\varepsilon z},\sigma_\eta,\eta)$, $\boldsymbol{\phi}^l(\cdot)$ is the multivariate $l-$ dimensional normal density function, $\boldsymbol{\phi}_T^l(\cdot)$ 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).[46]

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.[47] 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. Acceptation or

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

[47] The algorithm is robust to different starting values. However, speed of convergence may increase significantly.

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

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

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

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

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

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

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

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

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.[48] Figure B1 shows the time-series of rejection rates for all of the parameters. It appears that

[48] 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 $\xi_{t+1} = \xi_t/1.1$, convergence is achieved around an acceptance rate of 50% for all of the parameters.[49]

[*Insert Figure B*1 *here*]

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.

[49] 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 Figure B1 shows.

Appendix C: IV Estimation

Let $\mathbf{Y}_r = (y_{1,r}, \cdots, y_{n_r,r})'$, $\mathbf{X}_r = (x_{1,r}, \cdots, x_{n_r,r})'$, and $\boldsymbol{\epsilon}_r = (\epsilon_{1,r}, \cdots, \epsilon_{n_r,r})'$. 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 trace of strong and weak ties, respectively. Then, model (2) can be written in matrix form as

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

For a sample with $\bar{r}$ networks, stack up the data by defining $\mathbf{Y} = (\mathbf{Y}_1', \cdots, \mathbf{Y}_{\bar{r}}')'$, $\mathbf{X}^* = (\mathbf{X}_1^{*\prime}, \cdots, \mathbf{X}_{\bar{r}}^{*\prime})'$, $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}_1', \cdots, \boldsymbol{\epsilon}_{\bar{r}}')'$, $\mathbf{G} = \mathrm{D}(\mathbf{G}_1, \cdots, \mathbf{G}_{\bar{r}})$, $\mathbf{G}^* = \mathrm{D}(\mathbf{G}_1^*, \cdots, \mathbf{G}_{\bar{r}}^*)$, $\boldsymbol{\iota} = \mathrm{D}(\mathbf{l}_{n_1}, \cdots, \mathbf{l}_{n_{\bar{r}}})$ and $\boldsymbol{\eta} = (\boldsymbol{\eta}_1, \cdots, \boldsymbol{\eta}_{\bar{r}})'$, 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

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

We use the 2SLS estimation strategy from Liu and Lee (2010), and extend it to the case of two different network structures. Model (8) can be written as

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

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

We treat $\boldsymbol{\eta}$ 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

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

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

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

It follows that $\mathbf{G}^S \mathbf{Y} = \mathbf{G}^S \mathbf{M} \mathbf{X}^* \beta + \mathbf{G}^S \mathbf{M} \boldsymbol{\iota} \boldsymbol{\eta} + \mathbf{G}^S \mathbf{M} \boldsymbol{\epsilon}$ and $\mathbf{G}^W \mathbf{Y} = \mathbf{G}^W \mathbf{M} \mathbf{X}^* \beta + \mathbf{G}^W \mathbf{M} \boldsymbol{\iota} \boldsymbol{\eta} + \mathbf{G}^W \mathbf{M} \boldsymbol{\epsilon}$. $\mathbf{G}^S \mathbf{Y}$ and $\mathbf{G}^W \mathbf{Y}$ are correlated with $\boldsymbol{\epsilon}$ because $\mathrm{E}[(\mathbf{G}^S \mathbf{M} \boldsymbol{\epsilon})' \boldsymbol{\epsilon}] = \sigma^2 \mathrm{tr}(\mathbf{G}^S \mathbf{M}) \neq 0$ and $\mathrm{E}[(\mathbf{G}^W \mathbf{M} \boldsymbol{\epsilon})' \boldsymbol{\epsilon}] = \sigma^2 \mathrm{tr}(\mathbf{G}^W \mathbf{M}) \neq 0$. Hence, in general, (10) cannot be consistently estimated by OLS.[50] 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

[50] Lee (2002) has shown that the OLS estimator can be consistent in the spatial scenario where each spatial unit is influenced by many neighbors whose influences are uniformly small. However, in the current data, the number of neighbors are limited, so that result does not apply.

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.[51] 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 $E(\mathbf{Z}) = [\mathbf{G}^S\mathbf{M}(\mathbf{X}^*\beta + \boldsymbol{\iota}\cdot\boldsymbol{\eta}), \mathbf{G}^W\mathbf{M}(\mathbf{X}^*\beta + \boldsymbol{\iota}\cdot\boldsymbol{\eta}), \mathbf{X}^*]$. The best IV matrix for $\mathbf{JZ}$ is given by

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

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 $\mathbf{Q_0} = J[\mathbf{G}^S\mathbf{M}(\mathbf{X}^* + \boldsymbol{\iota}), \mathbf{G}^W\mathbf{M}(\mathbf{X}^* + \boldsymbol{\iota}), \mathbf{X}^*]$. As $\boldsymbol{\iota}$ 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 $\mathbf{M}\boldsymbol{\iota}$ can be approximated by linear combinations of

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

and

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

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

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

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 $n\times K_L$ submatrix of $\mathbf{Q}_{L\infty} = \mathbf{G}^S(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\boldsymbol{\iota}, \mathbf{G}^W\boldsymbol{\iota}, \mathbf{G}^W\mathbf{G}^S\boldsymbol{\iota}, \cdots)$ and $\mathbf{Q}_S$ an $n\times K_S$ submatrix of $\mathbf{Q}_{S\infty} = \mathbf{G}^W(\mathbf{G}^S\mathbf{X}^*, \mathbf{G}^W\mathbf{X}^*, \mathbf{G}^W\mathbf{G}^S\mathbf{X}^*, \cdots, \mathbf{G}^S\boldsymbol{\iota}, \mathbf{G}^W\boldsymbol{\iota}, \mathbf{G}^W\mathbf{G}^S\boldsymbol{\iota}, \cdots)$. We assume that $\frac{K_L}{K_S} = 1$. 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

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

given by

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

Note that, given that we are in a *multiple adjacency matrices* framework, if the approximation (K_L, K_S) is of high order, the many IV problem can arise even if the number of networks is small. The intuition is the following- the higher the number of adjacency matrices, the higher the number of adjacency matrices' combinations needed for approximating $\mathbf{JE}(\mathbf{Z})$. This should be clear looking at (13). If we want to approximate $\mathbf{Q}_\infty$ setting a P-order approximation, we will have $\sum_{p=1}^{P} b^p$ matrices to include, where b is the number of adjacency matrices.

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

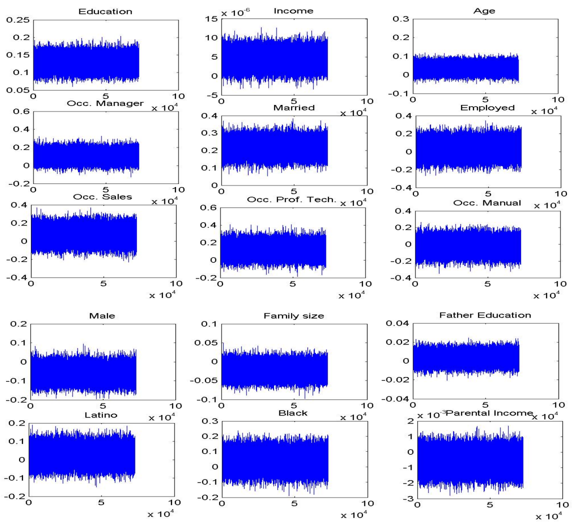
(i) *IV* : $\widehat{\boldsymbol{\theta}}_{2sls} = (\mathbf{Z}'\mathbf{P}_2\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{P}_2\mathbf{y}$, where $\mathbf{P}_2 = \mathbf{Q}_2(\mathbf{Q}_2'\mathbf{Q}_2)_2^{-1}\mathbf{Q}_2'$ and $\mathbf{Q_2}$ contains the linearly independent columns of $[\mathbf{Q}_1, \mathbf{JG}^S\boldsymbol{\iota}, \mathbf{JG}^W\boldsymbol{\iota}]$.

(ii) *IV Bias-corrected*: $\widehat{\boldsymbol{\theta}}_{c2sls} = (\mathbf{Z}'\mathbf{P}_2\mathbf{Z})^{-1}\{\mathbf{Z}'\mathbf{P}_2\boldsymbol{y} - \widetilde{\sigma}^2_{2sls}[\mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^S\widetilde{\mathbf{M}}\right), \mathrm{tr}\left(\mathbf{P_2}\mathbf{G}^W\widetilde{\mathbf{M}}\right), \mathbf{0}_{3m\times 1}]'\}$, 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 $b_{2sls} = \sigma^2\left(\mathbf{Z}'\mathbf{P_K}\mathbf{Z}\right)^{-1}\left[\mathrm{tr}\left(\boldsymbol{\Psi}_{K,L}\right), \mathrm{tr}\left(\boldsymbol{\Psi}_{K,S}\right), \mathbf{0}_{3m\times 1}\right]'$, where $\boldsymbol{\Psi}_{K,L} = \mathbf{P_K}\mathbf{G}^S\mathbf{M}$ and $\boldsymbol{\Psi}_{K,S} = \mathbf{P_K}\mathbf{G}^W\mathbf{M}$.

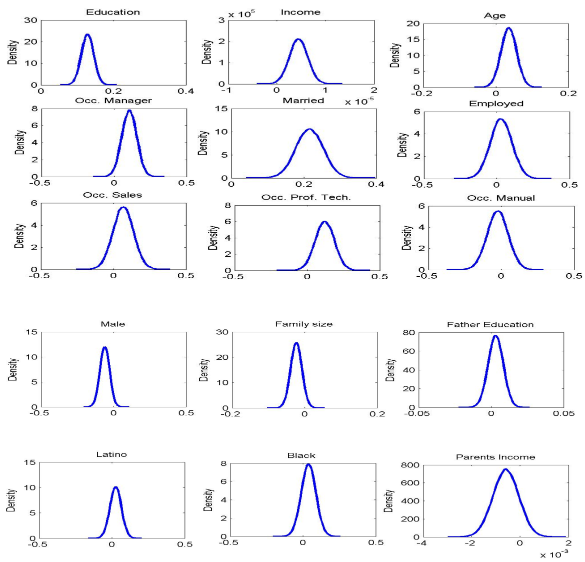
Appendix D: Bayesian Estimation - Additional Results

Figure D1: Bayesian Estimation Results
Control Variables (β)

Panel (a)



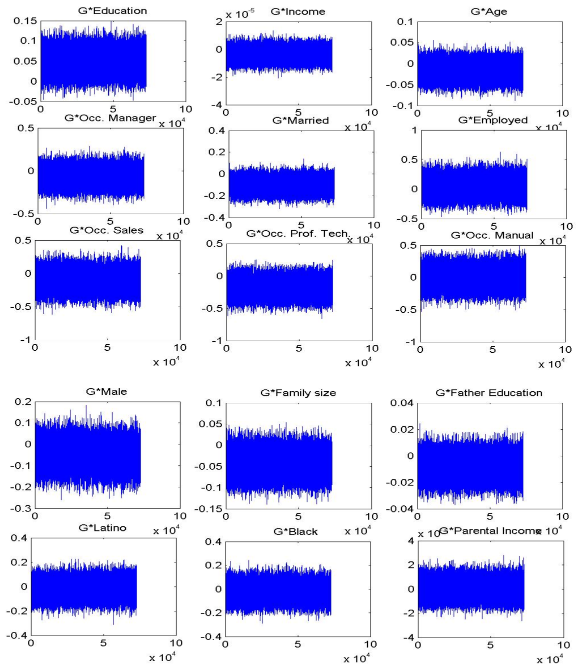
Panel (b)



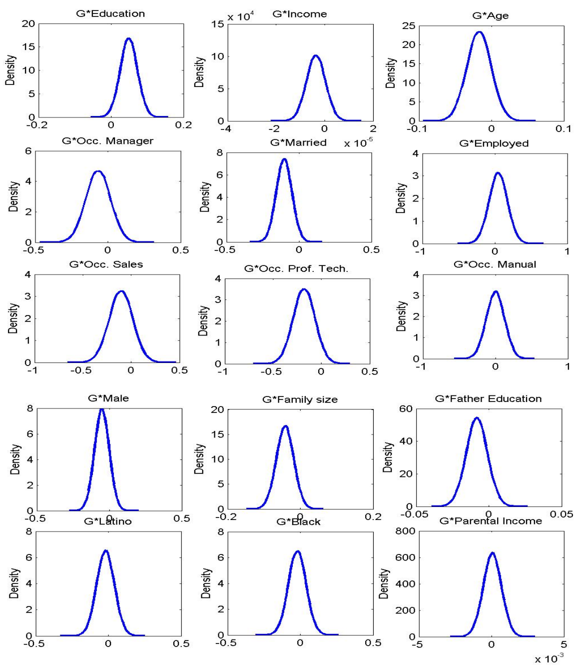
Notes: see Figure 3.

Figure D2: Bayesian Estimation Results
Contextual Effects (δ)

Panel (a)



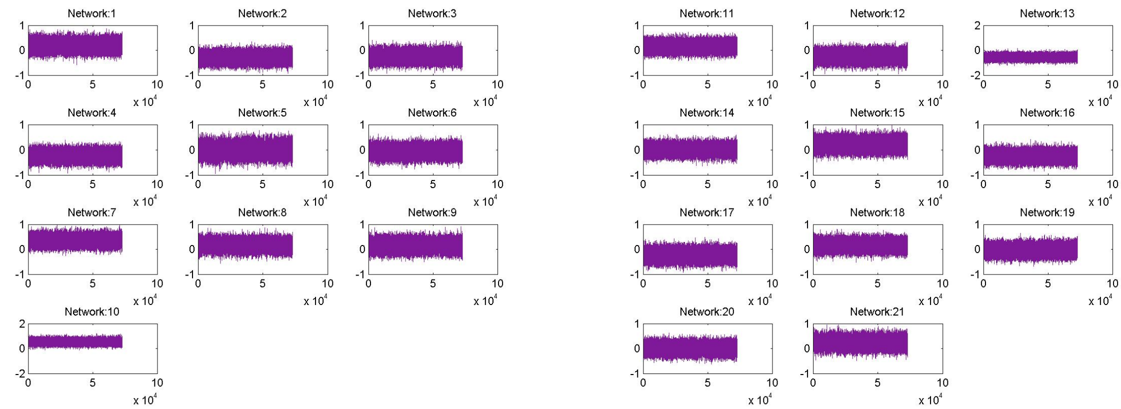
Panel (b)



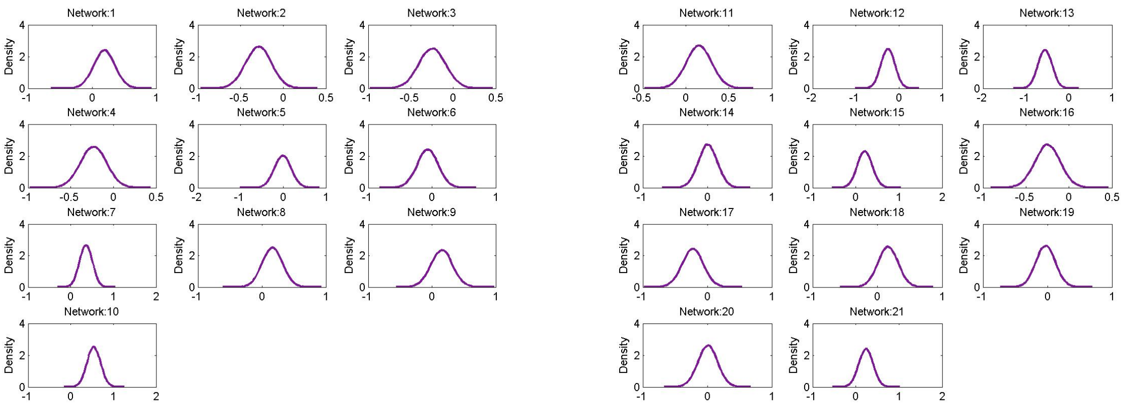
Notes: see Figure 3.

Figure D3: Bayesian Estimation Results
Network Fixed Effects (η)

Panel (a)



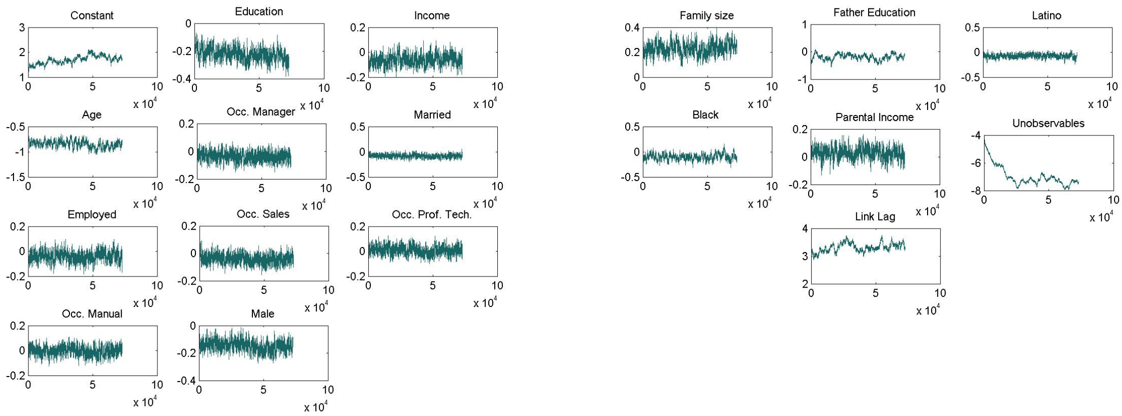
Panel (b)



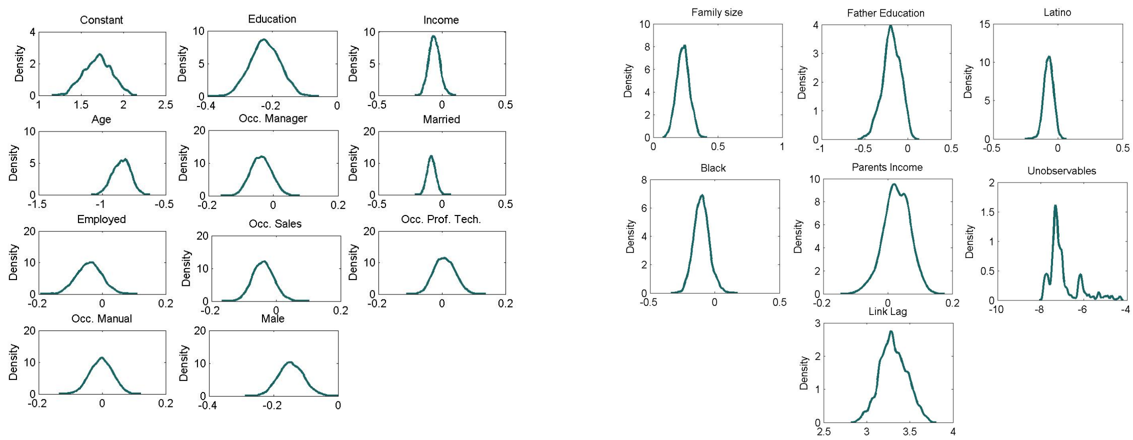
Notes: see Figure 3.

Figure D4: Bayesian Estimation Results
Link Formation Control Variables (ω)

Panel (a)



Panel b)



Notes: see Figure 3.

Appendix E: Results for the Entire Sample

Table E1: Peer Effects in Financial Decisions
-Entire Sample-

Dependent Variable: Financial Activity Index

	OLS (1)	OLS (2)	OLS (3)	ML (4)	IV (5)	IV bias-corrected (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: 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 400, minimum 4.

Table E2: Weak and Strong Ties in Financial Decisions
-Entire Sample-

Dependent Variable: Financial Activity Index			
	OLS (1)	IV (2)	IV bias-corrected (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 E1.

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
Saving 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. It is the first principal component, which explains 35 % of the total variance.

Table 2: 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: 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 3: 2SLS First Stage Results

Dependent Variable: GY			
Variables: X	X Own	GX Peers	G^2X Peers of peers (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		Yes	
Number of Networks		Yes	

Notes: OLS estimation results, standard errors in parentheses.*** p<0.01,** p<0.05,* p<0.1. Dummy variables for missing values in variables are included, see Table 2. The instrumental set also includes the individual number of connections. See Appendix C for further details on IV estimation of spatial models.

Table 4: Weak and Strong Ties in Financial Decisions

Dependent Variable: Financial Activity Index

	OLS (1)	IV (2)	IV bias-corrected (3)	Bayesian (4)
Strong Ties (ϕ^S)	**0.1686*** **	**0.1755*** **	**0.0671***	**0.0707*** **
	(0.0318)	**(0.0398)**	**(0.0402)**	**(0.0158)**
Weak Ties (ϕ^W)	**-0.0335**	**-0.0295**	**0.0128**	**-0.0027**
	(0.0286)	**(0.0206)**	**(0.0208)**	**(0.0123)**
Male	-0.0667	-0.0720	-0.0670	-0.0257
	(0.0634)	(0.0604)	(0.0603)	(0.0340)
Latino	0.1309	0.1356	0.1580	0.0138
	(0.1348)	(0.1297)	(0.1295)	(0.0392)
Black	-0.1097	0.2584*	0.3204**	0.0653
	(0.1405)	(0.1573)	(0.1570)	(0.0540)
Age	0.0058	0.0104	0.0165	0.0205
	(0.0245)	(0.0262)	(0.0262)	(0.0220)
Education	0.1097***	0.0913***	0.0996***	0.1327***
	(0.0205)	(0.0198)	(0.0198)	(0.0169)
Income	3.13E-06	2.63E-06	2.91E-06	3.54E-06**
	(2.13E-06)	(2.00E-06)	(1.99E-06)	(1.82E-06)
Employed	0.0711	-0.0313	-0.0131	0.0334
	(0.1530)	(0.1447)	(0.1445)	(0.0752)
Occ. Manager	0.2653	0.3662**	0.3461**	0.0935*
	(0.1870)	(0.1761)	(0.1757)	(0.0527)
Occ. Prof. Tech.	0.2151	0.2689*	0.2363	0.1332**
	(0.1638)	(0.1558)	(0.1556)	(0.0678)
Occ. Manual	0.0139	0.0783	0.0731	-0.0099
	(0.1534)	(0.1452)	(0.1449)	(0.0729)
Occ. Sales	0.1197	0.1755	0.1762	0.0760
	(0.1560)	(0.1501)	(0.1498)	(0.0717)
Married	0.3849***	0.4404***	0.4097***	0.2248***
	(0.0844)	(0.0807)	(0.0806)	(0.0389)
Family Size	-0.0063	-0.0116	-0.0143	-0.0200
	(0.0199)	(0.0189)	(0.0188)	(0.0153)
Father Education	0.0229*	0.0016	0.0062	0.0021
	(0.0140)	(0.0141)	(0.0141)	(0.0050)
Parental Income	0.0005	-0.0002	-0.0006	-0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Constant	-2.0713***			
	0.5558			
$\sigma_{\epsilon z}$				**-0.0338**
				(0.0643)
School Performance Variables	Yes	Yes	Yes	Yes
Contextual Effects	Yes	Yes	Yes	Yes
Network Fixed Effects	No	Yes	Yes	Yes
Number of Observations	569	569	569	569
Number of Networks	21	21	21	21

Notes: see Table 2.

Table 5: Network Formation and Financial Activity
Bayesian Estimation

	Outcome	Link Formation	
		$t-1$	t
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 2. We report peer effects estimate when network formation an behavior over network are jointly considered. Column (1) reports on the results for Model (2), columns (2)-(3) report on the results for Model (4)-(5).

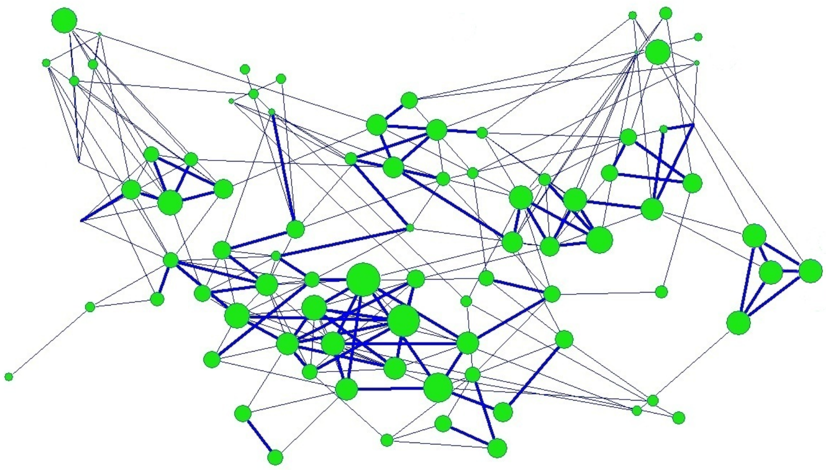
Table 6: Understanding the Mechanism

Dependent Variable: Financial Activity Index

	Network Topology			Frequency of Interactions		
	% of links	OLS	IV bias-corrected	% 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)			
Strong Ties High Frequency				78%	0.1589***	0.0675**
					(0.0223)	(0.0218)
Strong Ties Low Frequency				22%	0.2543***	0.0790**
					(0.0357)	(0.0367)
Weak Ties High Frequency				84%	-0.0272	-0.0114
					(0.0273)	(0.0276)
Weak Ties Low Frequency				16%	-0.0318	0.0073
					(0.0549)	(0.0559)
Male		-0.0657	-0.0703		-0.0699	-0.0650
		(0.0610)	(0.0604)		(0.0610)	(0.0606)
Latino		0.1756	0.1876		0.1708	0.1837
		(0.1313)	(0.1293)		(0.1315)	(0.1298)
Black		0.2567*	0.3269**		0.2504	0.3286**
		(0.1548)	(0.1575)		(0.1540)	(0.1564)
Age		0.0102	0.0146		0.0093	0.0113
		(0.0266)	(0.0261)		(0.0266)	(0.0263)
Education		0.0935***	0.0991***		0.0931***	0.1005***
		(0.0201)	(0.0197)		(0.0201)	(0.0197)
Income		0.0000	0.0000		0.0000	0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Employed		0.0210	0.0061		0.0075	-0.0102
		(0.1476)	(0.1449)		(0.1475)	(0.1453)
Occ. Manager		0.3036*	0.3164*		0.3193*	0.3359**
		(0.1786)	(0.1757)		(0.1787)	(0.1764)
Occ. Prof. Tech		0.2472	0.2187		0.2501	0.2187
		(0.1571)	(0.1555)		(0.1567)	(0.1557)
Occ. Manual		0.0408	0.0589		0.0483	0.0672
		(0.1478)	(0.1455)		(0.1474)	(0.1455)
Occ. Sales		0.1546	0.1633		0.1624	0.1727
		(0.1515)	(0.1504)		(0.1514)	(0.1507)
Married		0.4169***	0.3943***		0.4211***	0.4099***
		(0.0830)	(0.0797)		(0.0829)	(0.0800)
Family Size		-0.0088	-0.0116		-0.0104	-0.0159
		(0.0193)	(0.0188)		(0.0194)	(0.0189)
Father Education		0.0042	0.0058		0.0051	0.0044
		(0.0144)	(0.0140)		(0.0145)	(0.0141)
Parental Income		-0.0002	-0.0007		-0.0002	-0.0007
		(0.0006)	(0.0006)		(0.0006)	(0.0006)
School Performance Variables	Yes	Yes	Yes	Yes	Yes	
Contextual Effects	Yes	Yes	Yes	Yes	Yes	
Network Fixed Effects	No	Yes	Yes	Yes	Yes	
Number of Observations		569	569		569	569
Number of Networks		21	21		21	21

Notes: see Table 2. Percentage of links is referred to the total of same type of tie (strong or weak).

Figure 1: 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 lines is proportional to the length of the relationship between agents. Thicker lines represent strong ties, while thinner ones represent weak ties.

Figure 2: Identification with Network Data

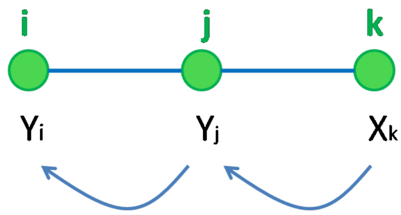
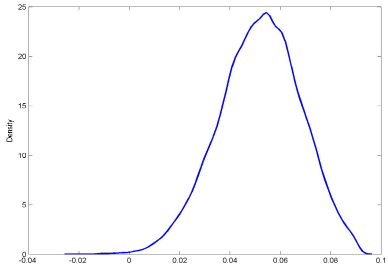
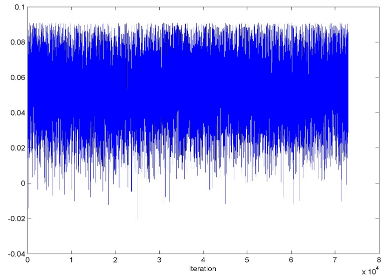


Figure 3: Bayesian Estimation Results
Peer Effects (ϕ)



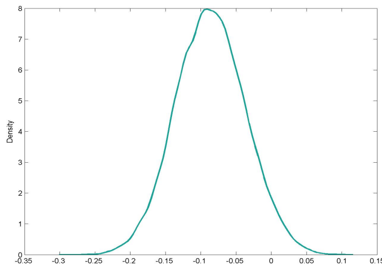
(a) Posterior Distribution



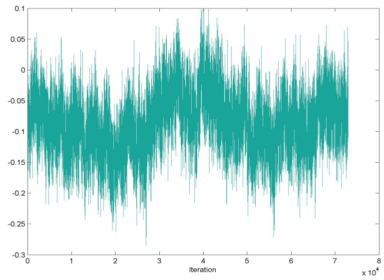
(b) Markov Chain

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

Figure 4: Bayesian Estimation Results
Covariance between Unobservables ($\sigma_{\epsilon,z}$)



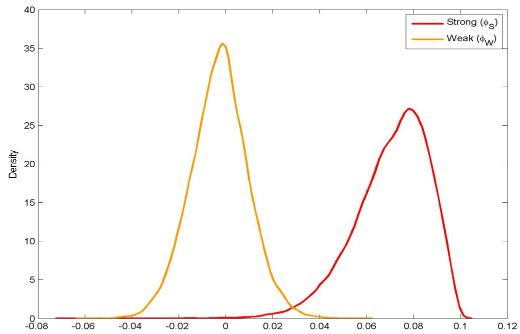
(a) Posterior Distribution



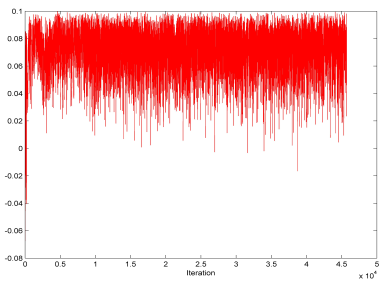
(b) Markov Chain

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

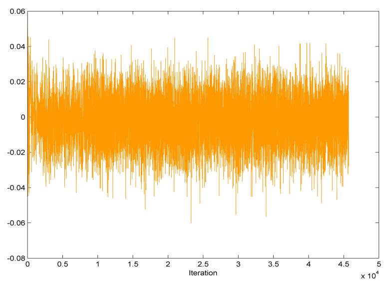
Figure 5: Bayesian Estimation Results.
Strong (ϕ_S) vs Weak (ϕ_W) Tie Effects



(a) Posterior Distributions



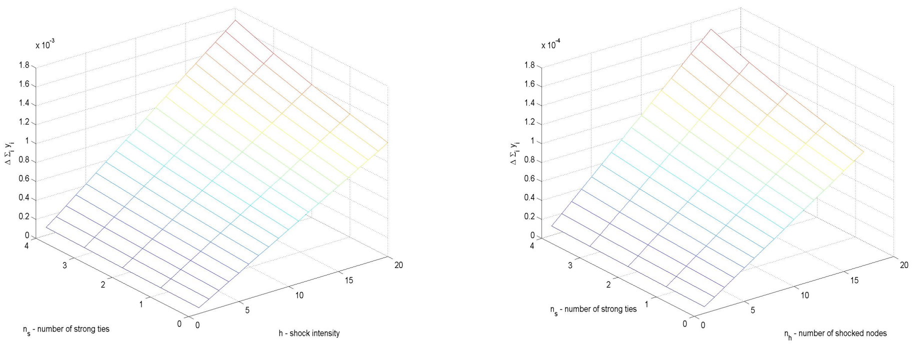
(b) Markov Chain



(c) Markov Chain

Notes: panel (a) shows the kernel density estimates of the posterior distributions. Panel (b) and panel (c) show the Markov chain draws.

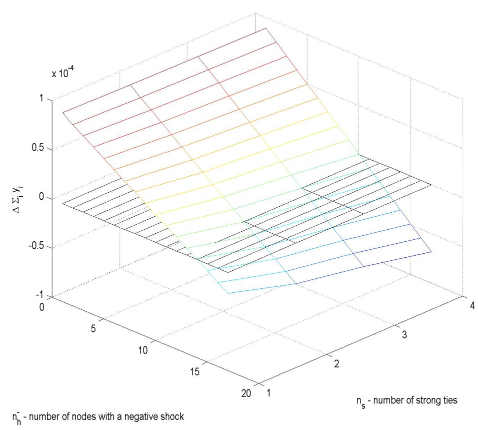
Figure 6: Simulation Results
Income Shocks and Strong Tie Effects



(a) Intensive Margin (b) Extensive Margin

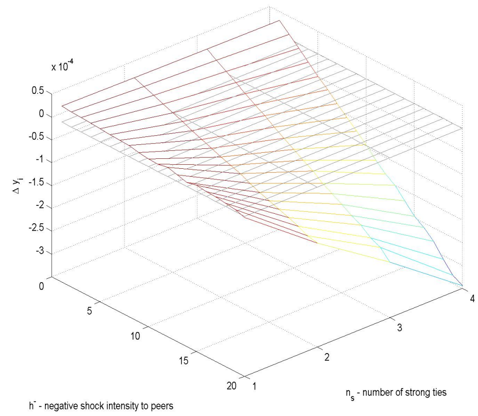
Notes: the surfaces represent $\sum_i \Delta y_i$, which is the variation of the financial activity of agent i, y_i, after the shock. n_s is the number of strong ties of the shocked agents. In Panel (a) shock intensity (h) goes from 1 to 20 income std points, while the number of shocked agents is constant 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 7: Simulation Results
Heterogeneous Income Shocks and Strong Tie Effects



Notes: see Figure 6. 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 8: 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.

Figure B1: Bayesian Estimation Results
Acceptance Rates