Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Corporate Finance Policies and Social Networks

Cesare Fracassi

MANAGEMENT SCIENCE
Vol. 63, No. 8, August 2017, pp. 2420–2438
ISSN 0025-1909 (print), ISSN 1526-5501 (online)
http://pubsonline.informs.org/journal/mnsc/

Corporate Finance Policies and Social Networks

Cesare Fracassi[a]

[a] McCombs School of Business, University of Texas at Austin, Austin, Texas 78712
Contact: cesare.fracassi@mccombs.utexas.edu (CF)

Received: March 10, 2015
Revised: September 14, 2015; December 2, 2015
Accepted: December 21, 2015
Published Online in Articles in Advance: May 17, 2016

https://doi.org/10.1287/mnsc.2016.2433

Abstract. This paper shows that managers are influenced by their social peers when making corporate policy decisions. Using biographical information about executives and directors of U.S. public companies, we define social ties from current and past employment, education, and other activities. We find that more connections two companies share with each other, more similar their capital investments are. To address endogeneity concerns, we find that companies invest less similarly when an individual connecting them dies. The results extend to other corporate finance policies. Furthermore, central companies in the social network invest in a less idiosyncratic way and exhibit better economic performance.

History: Accepted by Amit Seru, finance.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/mnsc.2016.2433.

Keywords: corporate finance policy decisions • social networks • capital investments

A vast literature in sociology, starting with Coleman (1988), shows that social interactions influence economic behavior. Ellison and Fudenberg (1993, 1995) study the local and global effects of word-of-mouth communication and social networks on decision making; Ellison and Fudenberg (1995, p. 93) conclude that "economic agents must often make decisions without knowing the costs and benefits of the possible choices. Given the frequency with which such situations arise, it is understandable that agents . . . rely on whatever information they have obtained via casual word-of-mouth communication." Social network theory calls the tendency of individuals to change their preferences and decisions because of the actions of others a "decision externality."[1]

This paper investigates whether the presence of social, educational, and professional connections among directors and top executives of U.S. public companies affects firms' corporate policy decisions. It is important to understand how and why individuals imitate, learn, conform, or adopt contrarian behavior relative to the social environment. In particular, managers of large corporations face noisy and limited information environments, making social ties especially relevant. Information-based models (e.g., Banerjee 1992, Bikhchandani et al. 1992, Park and Sabourian 2011, Welch 1992) illustrate how information and network structures can play an important role in diffusing information, and determining herding and contrarianism. Other potential explanations of herding and imitation can be due to reputation concerns and preference for conformity (Scharfstein and Stein 1990, Trueman 1994).

We begin by collecting information about social, educational, and professional ties among 30,860 key executives and directors of 2,059 companies that at some point in the sample period belonged to the S&P 1500 index. We then track these social ties over a span of 11 years, from 1999 to 2009. Individual connections are then aggregated to define a measure of social connectivity between each firm pair, named the social network index (SNI). As main corporate policy, we use a firm's capital investment decisions, because such policy is a highly discretionary decision made by key executives and approved by the board of directors. We also present summary results for other common financial policies, such as research and development (R&D) expenditures, cash reserves, and financing decisions.

Second, we investigate how local connections between company pairs influence their corporate policy decisions. In particular, we want to test whether managers that are socially connected make more similar decisions. Obviously many factors determine the similarity in investment decisions. For example, firms in the same industry are more likely to invest similar amounts than firms in different industries. We thus use a two-stage econometric model to identify the role of social connections on corporate policy: In the first stage, we compute the residual unexplained (or excess) capital investment of each firm relative to a benchmark model of capital investment policy. In the second stage, for each pair of firms we create a measure of similarity in excess investment between the two firms, and related it to whether the two firms are socially connected or not.

After controlling for common drivers of investment decisions, we find that managers who share social connections have more similar levels of capital investments and change their investments over time more similarly. The presence of social ties increases the similarity in capital investments by approximately 3% for the median firm pair in our sample. The results are robust to controlling for macroeconomic shocks and cross-sectional endogeneity using pair and year fixed effects. We find similar results even after we control for the fact that managers with similar background and affiliations have similar preferences and styles of management. The results are also stronger if firms are in the same industry or region. In addition, we find that current employment and education connections are the most effective in influencing capital expenditure decisions. Similar results are found using other discretionary corporate finance policies, such as R&D expenses, cash reserves, and interest coverage ratio. Finally, we address endogeneity concerns using the death of directors as exogenous shocks to the SNI. In a difference-in-differences specification, we find that after the death of a connected director/executive, investment policies tend to diverge more than after the death of an unconnected director/executive. Although the departure of connected and unconnected directors could have a differential impact on firm policies for reasons other than social ties, the results suggest that social connections can have a causal effect on corporate policies.

Third, we investigate the overall network effects of social interactions on firms' policies and performance. Although we cannot directly test whether social herding has a positive or negative effect on firm value, we can investigate how the position of a company in the social networks influences its investment policy. Network analysis suggests that information diffuses through networks, and companies that are strategically positioned in the network can make more informed decisions. We find that companies more centrally located in the social network have a less idiosyncratic investment policy, relative to companies that are less connected. Finally, these companies display greater operating performance and firm value, suggesting that firms centrally located in the network can make better policy decisions. This last evidence is only suggestive, and results should be interpreted as correlation, and not causal, as endogeneity concerns cannot be fully addressed.

This paper relates to three strands of economic and finance literature. First, it contributes to research on managerial decision making. Several papers in the last decade have studied the large heterogeneity in the way companies make corporate finance policy decisions. Bertrand and Schoar (2003) show that chief executive officers (CEOs) have unique styles of managing corporations that are carried over when CEOs move from one company to another. Malmendier and Tate (2005) argue that managerial overconfidence can account for corporate investment distortions, finding that investment of overconfident CEOs is significantly more responsive to cash flow, particularly in equity-dependent firms. Finally, Graham et al. (2013) find that CEOs' behavioral traits such as optimism and managerial risk-aversion are related to corporate financial policies.

This paper also contributes to the literature on the impact of social networks in finance. Shue (2013) is the closest paper to our work. Using the random assignment of MBA students to different sections as an identification strategy, Shue (2013) finds that executives who graduated from Harvard Business School have more similar firm policies if they were assigned to the same core-class section, with the strongest effects in executive compensation and mergers and acquisitions (M&A). The identification in her paper comes from the fact that students are randomly allocated to each class. In contrast, our paper investigates the effect of social ties on the entire universe of executives and directors in the S&P 1500, relying on controls and instruments to establish causality. In addition, we look at a variety of social connections, such as current and past employment, education, and social activities. Finally, we provide evidence that corporate policies are correlated to the position of firms in the overall social network, even though we can not rule out alternative explanations for these results. With respect to asset pricing, Cohen et al. (2008) focus on the education network between mutual fund managers and corporate board members. They find that mutual fund managers invest more and perform significantly better on stock holdings for which the board members went to school together with the mutual fund managers. Brown et al. (2008) provide evidence of a causal relationship between an individual's decision to own stock and the average stock market participation of the individual's home community. With respect to corporate governance, Hwang and Kim (2009) show that CEO compensation is higher in companies where directors are more socially connected to CEOs. Fracassi and Tate (2012) find that powerful CEOs hire directors that are more socially connected with them, leading to weaker monitoring and more value-destroying mergers. Barnea and Guedj (2013) and Nguyen (2012) study the impact of social networks on a firm's corporate governance. Cai and Sevilir (2012) finds that board connections influence M&A activity. Finally, Engelbert et al. (2012) finds that social ties are viable conduit of information between banks and firms.

Finally, this paper relates to the literature on social learning, herding, and contrarianism in financial markets: Hong et al. (2000) and Clement and Tse (2005) study herding behavior among equity analysts and find that career concerns and experience are important determinants of herding and bold earning forecasts. Graham (1999) studies herding among investment newsletters. Lakonishok et al. (1992), Grinblatt et al. (1995), Wermers (1999), and Sias (2004) investigate herding behavior among mutual fund managers.

1. Data and Definitions

All public companies in the United States are required by the Securities and Exchange Commission to disclose information about their board members and top five earners.[2] BoardEx of Management Diagnostics Limited, an independent, privately owned corporate research company, collects and classifies such information and supplements it with additional publicly available information. For this study, we consider all board members and the top five executives with the highest compensation, for all companies in the current and historical S&P 500 (large cap), S&P 400 (mid cap), and S&P 600 (small cap) indices. The starting database includes 2,059 firms and 30,860 individuals (49.3% nonexecutive directors, 14.7% executive directors, and 36% top managers), and 12,820,029 firm-pair-year observations. BoardEx provides biographical information on the current employment, the past employment, the education, and other activities of each individual from 1999 to 2009.[3] Employment information is available for all individuals, whereas education and other activities information is available only for 25,737 (83%) and 19,018 (62%) individuals, respectively. Overall, during their careers, executives and directors shared past employment in 35,188 different firms, of which 70% are private companies, 29% are public companies, and 21% are non-for-profit companies. The most common past employer is Bank of America, followed by American International Group and Freddie Mac. In addition, executives and directors went to 2,078 different schools, the most common of which is Harvard Business School, followed by Harvard University, Stanford University, and the Wharton School. Finally, executives and directors occupied an active role in 9,742 nonprofit organizations, among which the most common are the Boy Scouts of America, the National Association of Manufacturers, and the American Red Cross.

We use this biographical information to define four social networks representing different social interactions among pairs of individuals in the data sample:

- *Current Employment* (*CE*) *Network*: Two individuals are socially connected through their current employment network if they work in the same company and sit together either on the board of directors or on the top management group. The CE network includes both the traditional interlocking directorship network (where two companies share the same director) and connections where individuals from two companies sit on the board of a third company.
- *Past Employment* (*PE*) *Network*: Two individuals are socially connected through their past employment network if they worked in the past in the same company at the same time, either on the board of directors or in the top management group.
- *Education* (*ED*) *Network*: Two individuals are socially connected through their education network if they went to the same school and graduated within one year of each other.
- *Other Activities* (*OA*) *Network*: Two individuals are socially connected through their other activity network if they share membership in clubs, organizations, or charities, and had active roles in them.[4]

For example, Richard Goeltz, an independent director of Delta Airlines and Aviva, earned an MBA from Columbia Business School in 1966 together with Patrick Stokes, chairman of Anheuser-Busch Companies, Inc. Because Mr. Goeltz and Mr. Stokes went to the same school at the same time, they are connected through the education network. Mr. Goeltz also worked in the past at Seagram Company in various positions from 1970 to 1991 together with Mrs. Marie-Josee Kravis, current director of IAC Corp and Ford Company, and thus they are connected through the past employment network.

We then aggregate the social ties of all pairs of individuals, building a 30,860-by-30,860 nondirectional (symmetric) binary adjacency matrix, for each network type (CE, PE, ED, OA) for each year. These matrices represent the social connections existing among the entire universe of individuals in the sample. We then proceed to aggregate the data at the firm-pair level: For each type of connection, we measure the social connectivity between firms A and B by defining a dummy variable equal to 1 if at least one executive/director of firm A is connected to one executive/director of firm B. Finally, we define the social network index as the sum of the social connectivity dummies across the four types of connections. Thus, two companies have a SNI strength of zero if they do not share any connection in any of the networks, up to a value of four if they share connections in all four types of networks.

For each network and each year, we thus have a 2,059-by-2,059 valued matrix where the value in each cell represents the strength of the connection between two firms. A unique feature of this study is the dynamic nature of the sociomatrices: We can track how connections between firms change over the years and therefore perform a longitudinal analysis of the relationship between corporate finance policies and social ties. Panels A and B of Table 1 tabulate the summary statistics of the social tie measures for each firm pair. On average, there is a more than a one-third chance that two firms are socially connected. The other activities network is the largest network, accounting for approximately 54% of all social ties, whereas the

Table 1. Summary Statistics

Panel A: Social ties variables

				Mean		Mean—Industry		Mean—Region	
Variable	No. of obs.	Mean	Std. dev.	Direc.	Exec.	Within	Across	Within	Across
Strength SNI	8,581,520	0.362	0.670	0.332	0.023	0.466	0.358	0.499	0.340
Strength CE	8,581,520	0.030	0.172	0.029	0.001	0.044	0.030	0.050	0.027
Strength PE	8,581,520	0.050	0.219	0.048	0.001	0.077	0.049	0.081	0.045
Strength ED	8,581,520	0.086	0.280	0.071	0.006	0.091	0.086	0.107	0.082
Strength OA	8,581,520	0.196	0.397	0.183	0.015	0.255	0.193	0.260	0.185
PE Style	8,581,520	0.088	0.283	0.084	0.002	0.130	0.086	0.136	0.079
ED Style	8,581,520	0.674	0.469	0.593	0.117	0.682	0.673	0.732	0.664

Panel B: Centrality measures

	SNI	CE	PE	ED	OA
No. of Companies	2,059	2,059	2,059	2,059	2,059
Avg. Degree	0.3615	0.0286	0.0469	0.0843	0.2000
Avg. Between	0.0005	0.0008	0.0007	0.0005	0.0005
Avg. Closeness	0.0003	0.0026	0.0009	0.0003	0.0003
Avg. Eigenvector	0.0197	0.0148	0.0160	0.0194	0.0198

Panel C: Control variables

Variable	Mean	Std. dev.	No. of obs.
Firm-pair-level control variables			
Investment Dissimilarity	0.216	0.339	6,909,219
Leverage Dissimilarity	0.168	0.151	6,900,461
Interest Coverage Ratio Dissimilarity	111.222	172.708	5,379,659
Cash Ratio Dissimilarity	0.136	0.415	6,888,747
SG&A Ratio Dissimilarity	0.404	16.369	5,607,742
R&D Ratio Dissimilarity	0.144	1.263	6,944,921
No. Exec. and Direc.	24.049	4.247	8,581,520
Age Exec. and Direc.	57.139	2.851	8,581,520
Same Industry	0.041	0.198	8,581,520
Same BEA Economic Region	0.148	0.355	8,581,520
Abs. Diff. Total Assets	10,442.438	35,635.262	8,571,931
Abs. Diff. Age Exec. and Direc.	4.323	3.374	8,581,520
Abs. Diff. No. Exec. and Direc.	3.354	2.570	8,581,520
Firm-level control variables			
Bond Dummy	0.529	0.499	15,257
Cash Flow	0.875	3.801	14,494
Cash Flow Volatility	235.071	1,014.05	15,242
Cash Ratio	0.146	0.173	15,244
Dividend Dummy	0.570	0.495	15,257
Firm Age	8,533.942	6,144.566	15,257
Interest Coverage Ratio	49.698	149.592	12,079
Investment Ratio	0.310	0.410	13,993
No. Exec. and Direc.	12.352	3.324	15,257
No. of Employees	19.216	60.851	15,234
Leverage	0.233	0.223	15,165
R&D Ratio	0.051	0.319	15,247
Return on Assets	0.067	0.123	13,332
Sales	5,578	17,121	15,251
SG&A Ratio	0.267	0.359	12,497
Stock Return	1.144	0.622	14,893
Stock Return Volatility	0.389	0.246	15,105
Tangibility	0.245	0.225	14,590
Tobin's Q	1.96	1.654	15,216
Total Assets	15,079	81,035	15,250

Notes. This table shows the summary statistics for all the variables used in this paper. Panel A presents statistics on social network variables at the firm-pair level for the entire sample (first three columns), for board members only (fourth column), for executives only (fifth column), for firm pairs within the same industry and region (sixth and eighth columns), and for firm pairs not in the same industry and region (seventh and ninth columns). Panel B presents means of the centrality measures for the SNI, current employment, past employment, education, and other activities networks. *Avg. Degree* is the number of valued links for each company divided by the number of companies in the network. *Avg. Between* is the average number of shortest paths linking every dyad in the network that pass through the company node. *Avg. Closeness* is the inverse of the average distance between the firm and all other firms in the network. *Avg. Eigenvector* is the eigenvector centrality for the network. Panel C presents financial statistics at the firm-pair level and firm level. *Strength SNI* is the overall number of social ties between firm pairs. *No. Exec. and Direc.* is the sum of all directors on the board and key executives for each company pair. *Age Exec. and Direc.* is the average age of all directors on the board and key executives for each company pair. *Same Industry* is a dummy variable equal to 1 if the two firms are in the same FF49 industry. *Same BEA Economic Region* is a dummy variable equal to 1 if the two firms are in the same BEA region. *Abs. Diff. Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) is the absolute difference between *Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) of the two firms. *PE* (*ED*) *Style* is equal to 1 if at least two individuals in a firm pair went to the same school (worked for the same past employer) at any point in time. Refer to the appendix for the detailed definitions of the variables.

past employment, education, and current employment networks represent 24%, 14%, and 8% of total connections, respectively. Fifteen percent of firm pairs are located in the same Bureau of Economic Analysis (BEA) economic region, and 4% of firm pairs belong to the same Fama–French 49 (FF49)[5] industry. Firms in the same region are more likely to have social connections relative to firms located in different regions (50% versus 34%). Similarly, firms in the same industry are more likely to have social connections relative to firms in different industries (47% versus 36%). Connections that are not necessarily overlapping in time, used in the study to control for homophily effects, occur frequently: educational ties that may or may not overlap in time are eight times more frequent than overlapping educational ties; past employment connections are almost twice as frequent as overlapping past employment connections.

The social network measures are computed using the full sample of 30,860 executives and directors, 2,059 firms, 15,329 firm-year observations, and 12,820,029 firm-pair-year observations. The data are then merged with stock price and accounting data from the Center for Research in Security Prices (CRSP)/Compustat using Committee on Uniform Security Identification Procedures identifiers, and consistent with papers in the investment literature, excluding 371 companies in the financial service industry,[6] reducing the sample to 1,688 firms, 1,400,235 firm pairs, and 8,581,520 firm-pair-year observations spanning the fiscal years from 1999 to 2009. The final number of observations in all firm-pair regressions is then further reduced to 6,897,241 because the independent variables are lagged one year. Panel C of Table 1 shows summary statistics of the financial variables for the firms in the sample: On average, there are 24 executives and directors for each pair of companies, with an average age of 57 years. The average firm has $5.6 billion in sales and $15.1 billion in total assets. In addition, 57% of firms pay dividends, and 53% of firms have rated public bonds.

The investment ratio, defined as the ratio of capital expenditure to lagged property, plant, and equipment (PP&E), is the main corporate finance policy variable used in this study. We also present summary results for other common corporate finance policies, such as R&D expenditures, cash reserves, and financing decisions. Capital investment is a discretionary decision made by key executives and approved by the board of directors. In addition, investment is only partially persistent over time and exhibits large heterogeneity across firms, with a median of 20%, an average of 31%, and a standard deviation of 41% of PP&E. Although information about capital expenditures and other financial information can be easily found on company's 10-K filings, we argue that corporate managers assign more weight to the decisions of their social peers than the decisions of other managers with whom they are not socially connected. Overweighing information coming from social peers can be due to the fact that such information can be more relevant, or due to reputation concerns. Such conjecture is supported by a vast literature in economics and sociology (e.g., for a review of herding behavior in financial markets, see Bikhchandani and Sharma 2001).

In the online appendix, we also present the top and bottom 10 firms and industries sorted by the SNI index. Consistent with the findings in the correlation table, large companies are in the top 10 firms, whereas small firms are ranked at the bottom. By construction, firms with larger boards will be more likely to have more connections, and thus we add the number of executives and directors as controls in all regressions. In the online appendix, we also show that the results are robust to using alternative definitions of social connectivity, where we also normalize the connections by the product of the number of executives/directors in each firm, to further take into account that companies with larger boards are more likely to have more connections. Interestingly, the industry ranking does not reveal any striking patters, suggesting that social networks are pervasive across many industries. Nonetheless, we control for industry fixed effects in all regressions.

Figure 1 shows a visual representation of the 2005 current employment network. Like all other networks studied in this paper, it displays a core-periphery pattern, with a central group of companies that are closely interconnected and another group of companies that are less densely connected to the core and to each other. The figure helps to get a sense of the architecture of the network, which we will use extensively in Section 3.

In the next sections, we first illustrate our econometric model and then present the empirical results, first looking at the effect of social ties locally at the firm-pair level and then investigating the global network effect of social interactions on firm's policies and value.

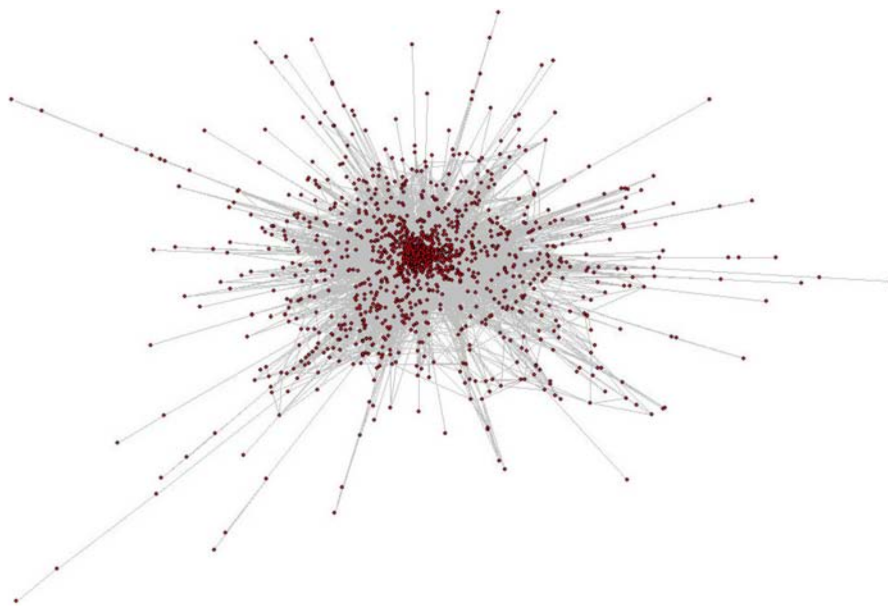
2. The Local Effect of Social Ties

This section presents the empirical analysis on the influence of social ties on the similarity in corporate policies between firm pairs. First, we illustrate the empirical methodology (Section 2.1). Second, we present the results of how social ties influence capital investment policies (Section 2.2). Finally, we extend the analysis to other corporate finance policies (Section 2.3).

2.1. Methodology—Pair Model

We propose a two-stage pair model to measure the influence of social neighboring companies on a firm's corporate financial policies. We use each pair of companies in the sample as the unit of analysis, and, given 2,059 companies in the sample, there are more than 2 million unique firm pairs. For each pair, we measure

Figure 1. (Color online) Social Network—2005 Current Employment



Notes. This figure was drawn using the Pajek software for large social networks. We used the 2D Fruchterman–Reingold energy algorithm with random starting positions to draw the network. The network shows all the connections between companies whose individuals share a professional connection because they sit on the same board of directors or on the executive board.

the strength of the social connection, i.e., the intensity of connectivity between the two companies. Using the pair model, we can test whether two companies that are more socially connected have a more similar investment policy compared to two companies that are not as socially connected.

In the first stage of the model, we account for as much of a firm's policy as possible using common control variables. We then compare the residual (or excess) policy for each pair of firms to define a measure of investment similarity. In the second stage, we check whether social ties between managers drive the similarity in investments.

We begin with the first stage, regressing company i's corporate finance policy decision $Policy_{i,t}$ over the control variables $X_{Pi,t}$ commonly used in the literature for each specific policy decision, as shown in Equation (1):

$$Policy_{i,t} = \alpha_0 + \alpha_1 X_{Pi,t} + \varepsilon_{i,t}. \tag{1}$$

In all regressions, we add geography-year and industry-year dummies to control for industry and local/macroeconomic shocks.[7] We also add controls related to the number of directors and executives, for the total number of all employees in the firm, and for the age of the firm. In the investment policy regression, we also control for size (log *Total Assets*), investment opportunities (*Tobin's Q*), cash flow, leverage, and cash reserves ratio following Chava and Roberts (2008) and many other papers on investment–cash flow sensitivity. In the R&D policy regression, we use sales (log), market-to-book, and cash flow following Brown et al. (2009). In the cash reserves and selling, general, and administrative (SG&A) regressions, we control for size (log *Total Assets*), investment opportunities (*Tobin's Q*), cash flow, investment, cash flow volatility, R&D expenditure, acquisitions, a bond issuance dummy, and a dividend-paying dummy following Harford et al. (2008). In the leverage and interest coverage ratio regressions, we use sales (log), investment opportunities (*Tobin's Q*), tangibility, cash flow, cash flow volatility, and a dividend-paying dummy following Lemmon et al. (2008). We control for industry leverage by adding industry-year dummies, instead of controlling for industry leverage to control for unobserved heterogeneity, following Gormley and Matsa (2014). Table 2 presents the results of the first-stage regressions. The coefficients of the main control variables are consistent with the ones found in the literature.

The residual $\varepsilon_{i,t}$ in Equation (1) represents the excess, or idiosyncratic, component of the policy of company i at time t, relative to the expected policy according to the standard model. For each pair of companies i and j, we define the policy dissimilarity as the absolute value of the difference in their residual:

$$Policy\ Dissimilarity = |\Delta\varepsilon_{i,j,t}| = abs(\varepsilon_{i,t} - \varepsilon_{j,t}). \tag{2}$$

The variable is a proxy for the difference in the corporate finance policy decisions of the two companies. The smaller is the variable, the more similar the policies of the two firms are with each other.

In the second stage, a gravity model tests how social ties influence similarity in policies.[8] We thus proceed

Table 2. First-Stage Regressions

	Investment ratio (1)	R&D ratio (2)	SG&A ratio (3)	Cash ratio (4)	Leverage (5)	Interest coverage ratio (6)
Tobin's Q	0.03302***	0.00294*	0.01112***	0.02227***	−0.03878***	28.61893***
	(6.03)	(1.71)	(4.12)	(6.19)	(−7.48)	(4.84)
Cash Flow	0.02109***	−0.00540***	−0.00546*	0.00098	−0.00311***	5.24624***
	(4.50)	(−3.03)	(−1.90)	(0.93)	(−2.66)	(3.18)
Cash Reserves Ratio	0.28984***					
	(6.27)					
Sales (log)		−0.01944**			0.03960***	
		(−2.18)			(6.13)	
Tangibility		−0.08060***			0.08466***	7.24252
		(−4.31)			(3.23)	(0.34)
Cash Flow Volatility		0.00001*	−0.00001	0.00001***	−0.00000	0.00188
		(1.71)	(−0.75)	(3.07)	(−0.06)	(0.99)
Dividend Paying Dummy		−0.01642***		−0.02268***	−0.02196***	4.15334
		(−4.27)		(−3.89)	(−2.83)	(0.65)
Investment Ratio			0.03759***	0.01441**		
			(4.31)	(2.13)		
R&D Ratio			1.51229***	0.16176***		
			(3.19)	(5.64)		
Acquisition Ratio			0.02336	−0.11237***		
			(0.98)	(−10.12)		
Sales Growth			−0.28590***			
			(−3.34)			
Bond Dummy				−0.02365***		
				(−3.66)		
Total Assets (log)	0.00153		−0.00030	0.00538		
	(0.27)		(−0.02)	(1.30)		
No. of Employees (log)	−0.01576***	0.00032	−0.02037	−0.02455***	−0.01494**	−7.40709***
	(−2.73)	(0.06)	(−1.10)	(−5.95)	(−2.55)	(−3.19)
No. Exec. and Direc. (log)	−0.06159***	0.05075***	0.03443	0.00144	−0.00573	−54.29282***
	(−2.92)	(3.09)	(1.30)	(0.11)	(−0.40)	(−3.58)
Firm Age	−0.03838***	0.00114	−0.00913	−0.00015	0.00557	1.13919
	(−5.87)	(0.53)	(−0.57)	(−0.04)	(1.36)	(0.34)
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geography-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.275	0.218	0.369	0.508	0.472	0.171
No. of obs.	11,660	11,995	9,919	11,529	11,962	9,809

Notes. This table shows the results of the first stage of the models in the paper. The dependent variables are shown in the header line. Refer to the text for the description of the models and the appendix for the detailed definitions of the variables. The investment ratio is capital expenditure over lagged PP&E. The R&D ratio is R&D expenses over lagged sales. The SG&A ratio is SG&A expenses over sales. The cash ratio is cash reserves over assets. The leverage ratio is the total debt over total debt plus market value of equity. The interest coverage ratio is EBITDA over interest expenses. The models include industry-year (using the Fama–French 49 industry classification) dummies and geography-year (using BEA economic regions) dummies. All independent variables are lagged one year. The OLS coefficients are reported, with the *t*-statistics in parentheses. Standard errors are corrected for clustering of the error term at the firm level. Constant included.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

to take the log of the policy dissimilarity measure and use it as a dependent variable in the second stage.[9] We regress it over the lagged natural logarithm of the strength of the social connection $S_{i,j}$ between the two companies. As defined in Section 1, the strength of the connection is a measure of the intensity of the social ties existing between the two companies:

$$\ln(1+|\Delta\varepsilon_{i,j,t}|) = \beta_0 + \beta_1 \ln(1+S_{i,j,t-1}) + \beta_2 \ln(X_{Ci,j,t-1}) + \eta_{i,j,t}. \qquad (3)$$

In theory, the second-stage specification (3) should not need any further controls, because any determinant of firm policy should be controlled for in the first-stage specification (1). However, adding X_C in the second stage is important to control for possible heteroskedasticity in the second moments of the investment variable across X_C that can influence and bias the second-stage results: For example, if some industries have greater investment dispersion across firms than other industries (i.e., the errors are heteroskedastic), then belonging to a specific industry might still influence the similarity in policies across firms.

When estimating the second-stage equations above, we account for serial correlation by allowing for clustering of the error term at the firm level for both company i and company j using the double-clustering algorithm from Petersen (2009).[10] In the online appendix, we also present a model where we investigate whether two socially connected companies change their investment over time more similarly than two companies that are not socially connected.

2.2. The Role of Social Ties on Capital Investments

2.2.1. Main Results. We first test whether social ties between directors and executives influence the similarity of capital investment between firms, following Equation (3). The null hypothesis is that these social connections are not a conduit for information or influence. The social network literature suggests two alternative hypotheses: social ties could lead individuals, and thus firms, to behave more similarly (see, e.g., Banerjee 1992, Scharfstein and Stein 1990, Bikhchandani et al. 1992). According to this hypothesis, we would expect a negative coefficient β_1 for the strength variable in second-stage equation (3). Alternatively, individuals could try to distinguish themselves from their peers, and thus choose alternative and strategically opposite policies (see, for e.g., Park and Sabourian 2011). This second alternative hypothesis would predict a positive coefficient β_1. It is important to point out that the analysis does not provide any evidence on the optimality of the investment decision. The objective of the paper is to show that social ties do influence corporate finance policy decisions, but we leave to future research the task of investigating the optimality of such influence.

Table 3 shows the results of the second stage of the pair model using the strength of the aggregate SNI as the main social tie variable. In column (1), we present the baseline regression that includes only the strength variable as the independent variable. In theory, the second-stage regression should not require any other control variables, since the first-stage regression already controls for industry, region, year, size, investment opportunities, and profitability. We find a strong and negative effect of the strength of social connections on the investment dissimilarity, supporting the hypothesis that social ties make firms' investment decisions more similar.

In column (2), we add several control variables: First, we add the number and average age of key executives and directors for each firm pair to control for the fact that larger and older boards and management groups tend to have more social connections.[11] We also add an industry dummy that takes the value of 1 if the pair of companies are in the same industry and a region dummy that takes the value of 1 if the firms are in the same BEA economic region. As we have seen in Table 1, social ties tend to be more common for firms within the same industry and region. Even though we already control for industry and regional effects in the first stage, the industry and geography dummies in the second stage control for possible heteroskedasticity in the second moments of the investment variable across industries and regions, as explained in Section 2.1. It turns out that empirically the heteroskedasticity concern driven by industry and geography is not important in the data, because the coefficients are marginally or not significant. However, this should not be interpreted as though industry and geography do not matter in determining investment policies. They do matter, but they are controlled for in the first stage. In fact, the *F*-values of the test of jointly significance of the industry-year and region-year dummies in the first-stage regression are, respectively, 132.39 and 141.72, highly statistically significant. For the same reason, we add year dummies to control for idiosyncratic differences in the second moments across years. We also control for the size of the board and the top management team and the age of the directors and executives. We find that older and larger boards have more similar investment policies. This can be due to the fact that older and larger boards might be more conservative and stable in their investment decisions. We also add the difference in assets, age, and board size between the paired firms to rule out that the similarity in investment policy is driven by similarity in size and age. We find that similarity in age and size are positively associated with similarity in investment. After controlling for industry, year, and board size, the coefficient on the SNI variable remains negative and statistically significant.

To get a sense of the economic magnitude of the results, we have to consider that in gravity models, both dependent and independent variables are logged. Two companies that are socially connected have capital expenditures that are 0.4% of PP&E more similar than two unconnected companies. To put this into perspective, the median difference in capital expenditure across all firms in our sample is 13.8% of PP&E, so the presence of social ties reduces the difference in capital investments by approximately 3% for the median firm pair in our sample. This is a lower bound estimate of the real effects of social ties on corporate policies, considering the noise in the definition of social ties.

One possible concern could be that the results are driven by outlier firms that have very unique investment policies and weak social ties. To control for outliers, we run quantile regressions from the first to the 10th lowest decile of the dependent variable. We find that the social network coefficient is negative and statistically significant across all the deciles of the investment dissimilarity between firm pairs. These results are available in the online appendix from the author's website. There, we also report results where we investigate how social ties influence how companies change investment policies over time. Using a similar empirical specification, we find that connected companies not only have similar levels of investment, but also change their investments over time more similarly.

Table 3. Social Ties and Similarity in Capital Investment

	Full sample				Only pairs in the same industry		Only pairs in the same region	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strength SNI	−0.04377***	−0.00337*	−0.00370**	−0.00377***	−0.00542*	−0.00596**	−0.00385*	−0.00505**
	(−16.01)	(−1.81)	(−2.10)	(−2.62)	(−1.93)	(−2.14)	(−1.93)	(−2.46)
No. Exec. and Direc.		−0.18686***	−0.18828***	−0.04718**	−0.22178***	−0.05650*	−0.21272***	−0.05395**
		(−13.29)	(−13.24)	(−2.08)	(−12.51)	(−1.69)	(−12.97)	(−1.97)
Age Exec. and Direc.		−0.42103***	−0.41990***	−0.25371***	−0.51956***	−0.37718***	−0.51347***	−0.28515***
		(−8.05)	(−8.04)	(−2.86)	(−8.62)	(−2.98)	(−8.23)	(−2.71)
Same Industry		−0.00057	−0.00056	−0.00451*			0.00657**	−0.00120
		(−0.29)	(−0.28)	(−1.88)			(2.02)	(−0.33)
Same Region		0.00221*	0.00209*		0.01084***			
		(1.82)	(1.73)		(3.49)			
Abs. Diff. Total Assets		−0.00024	−0.00028	−0.00182	−0.00168	−0.00157	−0.00040	−0.00180
		(−0.39)	(−0.46)	(−0.91)	(−1.53)	(−0.46)	(−0.51)	(−0.68)
Abs. Diff. Age Exec. and Direc.		0.01117***	0.01117***	0.00223	0.01356***	0.00225	0.01098***	0.00134
		(5.30)	(5.30)	(1.17)	(6.18)	(0.99)	(4.75)	(0.63)
Abs. Diff. No. Exec. and Direc.		0.01647***	0.01649***	0.00394**	0.01689***	0.00619***	0.01569***	0.00307*
		(9.34)	(9.34)	(2.24)	(7.11)	(2.90)	(8.22)	(1.67)
PE Style			−0.00114	−0.00286*	0.00636	0.00156	0.00283	−0.00230
			(−0.66)	(−1.72)	(1.63)	(0.35)	(1.09)	(−0.98)
ED Style			0.00383	−0.00116	0.01844***	−0.00429	0.01127***	−0.00030
			(1.35)	(−0.39)	(4.63)	(−0.99)	(3.22)	(−0.08)
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	No	No	No	Yes	No	Yes	No	Yes
R^2	0.009	0.064	0.064	0.441	0.099	0.458	0.082	0.457
No. of obs.	6,897,241	6,897,241	6,897,241	6,897,241	286,985	286,985	1,030,715	1,030,715

Notes. The dependent variable is investment dissimilarity between firm pairs. The table shows the results of the second stage of the pair model. Refer to the text for the descriptions of the models and the appendix for the detailed definitions of the variables. Columns (1)–(4) include all observations. Columns (5) and (6) include only observations for pairs in the same FF49 industry. Columns (7) and (8) include only observations for pairs in the same BEA region. *Strength SNI* is the number of social ties between firm pairs. *No. Exec and Direc.* is the sum of all directors on the board and key executives for each company pair. *Age Exec. and Direc.* is the average age of all directors on the board and key executives for each company pair. *Same Industry* dummy is a variable equal to 1 if the two firms are in the same FF49 industry. *Same Region* is a dummy variable equal to 1 if the two firms are in the same BEA region. *Abs. Diff. Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) is the absolute difference between *Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) of the two firms. The variable *ED* (*PE*) *Style* is equal to 1 if at least two individuals in a firm pair went to the same school (worked for the same past employer) at any point in time. All dependent and independent variables, excluding dummies, are logged. All independent variables are lagged one year. The OLS coefficients are reported, with t-statistics in parentheses. Standard errors are corrected for clustering of the error term at both firms level using the double-clustering algorithm from Petersen (2009). A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

2.2.2. Controlling for Common Characteristics/Preferences. The main hypothesis of this paper is that social connections are important channels of communication and influence in corporations. A possible channel is that information flows more freely and at a lower cost through these networks. An alternative explanation could be that the social connection measures are just a proxy for homophily, the fact that similar people behave similarly because they have similar management styles. For example, executives that went to Harvard together have similar experiences and backgrounds, and thus manage their companies more similarly, without any information exchange or influence.[12]

The specification in column (3) of Table 3 partially addresses this concern. We define a dummy control variable named *PE Style* that is equal to 1 if one or more executives or directors from one firm worked in the past with one or more executives or directors from the other firm in the pair, irrespective of whether they overlapped in time or not. Similarly, we define a dummy control variable named *ED Style* that is equal to 1 if one or more executives or directors from one firm went to the same school with one or more executives or directors from the other firm in the pair, irrespective of whether they graduated a year apart from each other or not. These control variables can be considered a proxy for the management style associated with going to the same school or working in the same company. Columns (3) and (4) shows that the coefficient on *PE Style* is negative, even though marginally or not statistically significant, suggesting that indeed individuals with similar background and experiences have similar investment policies. Nonetheless, the coefficient on the SNI variable, which now proxies for the contribution of social ties to investment policies after controlling for homophily/common preferences, is still negative and statistically significant. In addition, the economic magnitude of the social network effects is greater than the magnitude of the homophily effect (*PE Style*), suggesting that social network effects play as large a role as, if not a greater role than, common characteristics do.

Unfortunately, the PE and ED style variables are aggregated variables of common preferences, and they do not control for specific schools and employer effects. For example, at least one executive/director went to the same school at the same time with other executives/directors in 8% of firm pairs, but in well over 67% of firm pairs executives and directors belong to the same alumni network (irrespective of whether they overlapped in time or not). We will address this concern in panel B of Table 5 (see Section 2.2.5) by controlling for each specific past employer and school fixed effect.

2.2.3. Controlling for Industry and Region Effects. Despite the inclusion of industry-year and region-year fixed effects in the first stage of the model, and same-industry and same-region dummies in the second stage, we could be concerned that comparing the investment decision of firms in different industries and regions might be hard to interpret. For example, capital investments in the pharmaceutical industry are vastly different from capital investments in the steel industry. Furthermore, social ties could be a proxy for commonality in customer base and product similarity.

To address these concerns, in the last four columns of Table 3, we restrict the sample only to firm pairs in the same industry (columns (5) and (6)) and to firm pairs in the same region (columns (7) and (8)). In this way, we compare companies that face similar investment environments. Despite the significant reduction in sample size, we find that the intensity of social ties still predicts similar investment policy even for firm pairs in the same industry and the same region. Furthermore, the economic magnitude of the effect is greater (between 30% and 70% larger in the fixed effect specifications) in the reduced sample, suggesting that social ties are more important when firms are in the same industry or region. These results are consistent with recent evidence on the sensitivity of a firm's investment to the investments of other firms headquartered nearby, even those in very different industries (Dougal et al. 2015).

2.2.4. Controlling for Endogeneity and Reverse Causality. So far, we have found that a correlation exists between corporate finance policy decisions and social network connections. Specifically, companies that are more connected with each other have more similar investment styles. However, the results could be biased due to the presence of an omitted variable that could drives both social networks and corporate finance policies. Companies experience shocks in their investment opportunity sets and dynamically adjust their policies over time. Consequently, they hire new directors and key executives with specific social connections to match their new policy. For example, companies in financial distress might hire people with a specific education or past employment skills to turn the firm around. In addition, the causality might run in the opposite direction: successful companies with high investment levels and high return on assets might lead to an expansion of the social networks of its directors and executives.

We provide suggestive evidence that a causal relationship exists from social networks to corporate finance policy decisions. First, all the regressors in the equations are lagged one year relative to the dependent variables. Lagging per se does not solve the identification problem, especially when highly persistent variables are used as dependent variables or when companies hire new key executives prior to changes in corporate finance policies. However, it at least eliminates concerns of contemporaneous endogenous effects. Second, the past employment and education connections occur long before the policy decisions, and thus it is harder to construct a reverse causality story where social connections are driven by successful investment decisions. Third, we exploit the longitudinal feature of the data set: Social networks change over time, and we can track how changes in the network relate to changes in the investment policy. Column (4) of Table 3 shows the results adding a dummy for each firm pair. Pair dummies absorb any unobserved fixed pair-level omitted variables by looking at the correlation between a change in the lagged social network parameter and a change in the dependent variable over time for each pair of companies. The results of the fixed effect regressions are consistent with the results of the ordinary least squares (OLS) pooled regressions. The SNI coefficient is still negative and statistically significant, and economically very similar in magnitude to the coefficients in the cross-sectional tests.

One alternative reverse-causality explanation of the results could be that when companies want to change corporate finance policies, they hire people with the appropriate skills and social connections to implement the desired actions. Because this change occurs over time within the same company, pair dummies do not absorb such variation. An exogenous shock to the social network matrix is needed to test the direction of causality between social connections and corporate finance policies. We thus use individuals' deaths as an exogenous shock to a firm's social connectivity.[13] When an individual dies, his social ties with other individuals in the network cease to exist, altering exogenously the social connections between companies. At the same time, the death of a top manager or director is an event that can deeply influence corporations, and it can lead to large changes in corporate policies. To test the effect of social ties, we thus compare deaths of socially connected individuals, relative to death of individuals that are not socially connected.

The data on directors' deaths come from BoardEx of Management Diagnostics Limited. In the sample period considered, there are 3,123 director and executive deaths. Thirty-two percent of firm pairs experience at least one individual death during the sample period, and 5% of these deaths were of an individual who connected the pair. Panel A of Table 4 (columns (1) and (2)) shows the results of a difference-in-difference approach where we restrict the sample to all firm pairs in which there is an executive or director death during the sample period. We then compare the dissimilarity in corporate policies between firms, before and after the death. The variable of interest is the interaction between the variable *After* and the variable *Connected*, a dummy variable that is one if the two companies were connected by the deceased individual.[14] Furthermore, we present in panel B (columns (3) and (4)) the results including all observations in the sample, even the ones where firms did not experience a death during the sample period. These firm pairs do not directly affect the variable of interest, because the *After Death Dummy* is always zero in these cases, but their addition could help with a more precise estimation of the coefficients in the model.

Table 4. Endogeneity: Difference-in-Differences Using Individuals' Deaths

	Panel A: Restricted sample		Panel B: Full sample	
	(1)	(2)	(3)	(4)
After Death Dummy	−0.01663** (−2.07)	−0.01753** (−2.22)	−0.01225* (−1.82)	−0.01387** (−2.09)
After Death × Connected	0.01059** (2.21)	0.00875* (1.85)	0.01279** (2.47)	0.01082** (2.12)
No. Exec. and Direc.		−0.03544 (−1.52)		−0.04956** (−2.19)
Age Exec. and Direc.		−0.25571** (−2.38)		−0.26421*** (−2.98)
Same Industry		−0.00178 (−0.49)		−0.00455* (−1.90)
Abs. Diff. Total Assets		−0.00176 (−0.82)		−0.00180 (−0.90)
Abs. Diff. Age Exec. and Direc.		0.00220 (0.97)		0.00219 (1.15)
Abs. Diff. No. Exec. and Direc.		0.00274 (1.58)		0.00404** (2.30)
PE Style		−0.00525** (−2.27)		−0.00470*** (−2.76)
ED Style		−0.00363 (−0.96)		−0.00137 (−0.46)
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
R^2	0.404	0.404	0.441	0.442
No. of obs.	2,253,307	2,253,307	6,897,241	6,897,241

Notes. The dependent variable is investment dissimilarity between firm pairs. In panel A, the sample is restricted to only firm pairs where a director or top manager died during the sample period. In panel B, the full unrestricted sample is used. The term *After Death Dummy* is a dummy variable that equals 1 in the period after the decease of a director or executive and 0 before. *Connected* is a dummy variable that equals 1 if the deceased director or executive was socially connecting the two companies. *No. Exec and Direc.* is the sum of all directors on the board and key executives for each company pair. *Age Exec. and Direc.* is the average age of all directors on the board and key executives for each company pair. *Same Industry Dummy* is a variable equal to 1 if the two firms are in the same FF49 industry. *Abs. Diff. Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) is the absolute difference between *Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) of the two firms. *ED* (*PE*) *Style* is equal to 1 if at least two individuals in a firm pair went to the same school (worked for the same past employer) at any point in time. All dependent and independent variables, excluding dummies, are logged. All independent variables are lagged one year. The OLS coefficients are reported, with the t-statistics in parentheses. Standard errors are corrected for clustering of the error term at both firms level using the double-clustering algorithm from Petersen (2009). A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1%, levels, respectively.

First, it is interesting to notice that the coefficient on the *After Death Dummy* is negative and significant: A firm adopts investment policies that are, on average, less idiosyncratic after the death of a director or key executive. This is consistent with the results of Weisbach (1995), who found that at the time of a management change, there is an increased probability of divesting an acquisition considered unprofitable by the press, suggesting that new managers adopt policies that are more popular or less idiosyncratic. Nonetheless, the interaction coefficient between *Connected* and *After Death Dummy* is positive and statistically significant in all specifications: The death of a connected executive or director has the effect of making the investment policy more dissimilar, relative to the death of an individual who was not connecting the two companies.

Overall, the results of the difference-in-differences regression suggest that changes in social connections have a causal effect on changes in investment decisions. However, these results need to be taken cautiously, as connected directors might have different characteristics (e.g., hold more important position in the company) relative to unconnected directors, and thus their departure might affect the companies differently. Even if we believe that such bias would go against our results (the departure of an important director should make the company become more conservative, not less), we cannot rule out that differences in unobserved characteristics between connected and unconnected directors could also explain these results.

2.2.5. Subnetworks. In Table 5, we break down the main results by social network type (CE, PE, ED, OA). In panel A, we present results for each type of connection (current employment, past employment, education, and other activities) separately. Overall, current employment connections seem to be the most important connection influencing investment policies, followed by education connections, and at last by past employment and other activities connections, whose

Table 5. Social Ties Effects by Network Type

	Panel A				Panel B	
	Current empl. (1)	Past empl. (2)	Education (3)	Other activ. (4)	Past empl. (5)	Education (6)
Strength Network	−0.00557**	−0.00171	−0.00400**	−0.00311	−0.00446**	−0.00460***
	(−2.09)	(−1.00)	(−2.44)	(−1.21)	(−2.19)	(−3.31)
No. Exec. and Direc.	−0.18844***	−0.18819***	−0.19001***	−0.18769***	−0.18804***	−0.18584***
	(−13.56)	(−13.53)	(−13.52)	(−13.37)	(−13.53)	(−13.23)
Age Exec. and Direc.	−0.42226***	−0.42211***	−0.42175***	−0.42138***	−0.41977***	−0.40398***
	(−8.08)	(−8.07)	(−8.08)	(−8.07)	(−8.05)	(−7.92)
Same Industry	−0.00076	−0.00070	−0.00084	−0.00066	−0.00102	−0.00222
	(−0.38)	(−0.35)	(−0.42)	(−0.33)	(−0.52)	(−1.14)
Same Region	0.00199*	0.00205*	0.00179	0.00206*	0.00197*	−0.00024
	(1.65)	(1.70)	(1.48)	(1.70)	(1.65)	(−0.23)
Abs. Diff. Total Assets	−0.00032	−0.00030	−0.00037	−0.00028	−0.00036	−0.00047
	(−0.51)	(−0.49)	(−0.59)	(−0.45)	(−0.57)	(−0.76)
Abs. Diff. Age Exec. and Direc.	0.01123***	0.01123***	0.01124***	0.01122***	0.01119***	0.01099***
	(5.35)	(5.34)	(5.35)	(5.33)	(5.34)	(5.41)
Abs. Diff. No. Exec. and Direc.	0.01656***	0.01654***	0.01661***	0.01652***	0.01654***	0.01626***
	(9.46)	(9.45)	(9.50)	(9.39)	(9.48)	(9.43)
PE Style		−0.00272				
		(−1.28)				
ED Style			0.00350			
			(1.23)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Past Employer Dummies	No	No	No	No	Yes	No
School Dummies	No	No	No	No	No	Yes
R^2	0.064	0.064	0.064	0.064	0.066	0.071
No. of obs.	6,897,241	6,897,241	6,897,241	6,897,241	6,897,235	6,897,241

Notes. The dependent variable is investment dissimilarity between firm pairs. In columns (1)–(4) (panel A), the network refers to the current employment, the past employment, and the other activity networks, respectively. In panel B, column (5) (column (6)) uses the past employment (education) network, and it also includes a dummy variable for each past employer (school), equal to 1 if, for each firm pair, at least two individuals worked for the same past employer (went to the same school) at any point in time. The table shows the results of the second stage of the pair model. Refer to the text for the description of the models and the appendix for the detailed definitions of the variables. *Strength Network* for CE, PE, ED, and OA is a dummy variable equal to 1 if there is at least one social tie in the CE, PE, ED, or OA network, respectively, between individuals in the two companies. *No. Exec and Direc.* is the sum of all directors on the board and key executives for each company pair. *Age Exec. and Direc.* is the average age of all directors on the board and key executives for each company pair. The *Same Industry* dummy is a variable equal to 1 if the two firms are in the same FF49 industry. *Same Region* is a dummy variable equal to 1 if the two firms are in the same BEA region. The term *Abs. Diff. Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) is the absolute difference between *Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) of the two firms. All dependent and independent variables, excluding dummies, are logged. All independent variables are lagged one year. The OLS coefficients are reported, with the t-statistics in parentheses. All standard errors are corrected for clustering of the error term at both firms level using the double-clustering algorithm from Petersen (2009). A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

coefficients are still negative but not statistically significant. Although a formal theory that can guide us to interpret the results does not exist, these findings are consistent with results in other papers that have found employment networks to be relatively more effective in influencing corporate governance (Fracassi and Tate 2012) and mergers (Ishii and Xuan 2014) decisions.

Panel B of Table 5 shows the past employment and education connection results, where we include additional controls for style/common preferences. In Section 2.2.2 we used two dummy variables, *PE Style* and *ED Style*, to control for similar education and employment background. Here we want to control for each possible common past employer (column (5)) and common school (column (6)). We thus add a dummy variable for each of the 5,712 past public employers and 2,078 schools. Each dummy D_i is equal to 1 if executives or directors of one firm went to the same school i or worked for the same public firm i as one or more executive or director of the other firm in the pair. Columns (5) and (6) show that even after adding dummy controls for each past employer and school, the coefficient on the social connection is still negative, statistically significant, and economically larger than the one reported in columns (2) and (3). This is further evidence suggesting that the social ties drive firms' investment policies above and beyond the effect of similar characteristics/preferences. However, given the nature of the fixed effect model, the test can not rule out effects driven by time-varying past employer and school characteristics.

In the online appendix, we also report similar results when we look separately at connections among board members, and among top executives.

2.3. The Role of Social Ties on Other Corporate Finance Policies

The models in the previous sections showed that the capital investment policy of a firm is influenced by the social ties of their top executives and directors. However, capital investment is not the only discretionary decision that the top management group and the board of directors make. We thus study how social connections influence other corporate policy decisions that are within the discretion of the management team and board of directors: R&D expenses, SG&A expenses, cash reserves, leverage, and interest coverage ratio. We define the R&D ratio as the ratio of R&D expenses over lagged sales, the SG&A ratio as the ratio of SG&A over sales, the cash ratio as the ratio of cash and short-term investments over assets, leverage as the ratio of total debt (short term plus long term debt) over total debt plus market value of equity, and the interest coverage ratio as the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) over interest expenses.

Following the methodology in Section 2.1, for each corporate policy we run a first-stage regression to compute the excess policy for each company, shown in Table 2, and then in the second stage we compare the policy dissimilarity among all the possible pairs of companies in the sample using a gravity model. In the second stage, we add the same control variables as in the investment policy regressions, i.e., board size and age, industry, geography, and year dummies. We also control for "style" effects adding the variables *PE Style* and *ED Style*.

Table 6 shows the results for several corporate finance policy decisions. In all specifications, except for the SG&A, all SNI coefficients are negative, indicating that stronger social network connections leads to more similar corporate policies. The R&D ratio, the cash ratio, and the interest coverage ratio are also statistically significant, whereas SG&A and leverage are not. A possible interpretation of the varying degree of influence of social ties on corporate policies is that the degree of managerial discretion differs among corporate policies. For example, leverage is affected by many outside drivers, such as stock price, and it is only partially controllable by the top management and directors, whereas the decision to invest or to keep an adequate level of cash reserves is more at the discretion of the management.

Overall, the findings of the effect of social ties on a firm's investment policy can be extended to other corporate policy decisions. In particular, discretionary financial decisions on R&D, cash reserves, and interest coverage ratio seem to be influenced by the social networks that directors and mangers share with each others.

3. The Network Effects of Social Ties

In the previous section, the unit of analysis is each pair of firms, and we showed how companies sharing social ties influence each others' financial policies. Thus far, we cannot make any statement about whether such social influence is good or bad for firms. However, firms are embedded in a network of social ties, and if firms influence each other, we would then expect that the global position of a firm in a social network is also a driver of corporate policies. First, in Section 3.1 we introduce four measures of network centrality. Second, in Section 3.2 we investigate how the global position of a company in the social network influences its investment policy. Finally, in Section 3.3 we look at the value implications of social networks, relating a firm's global position in the social network with its operating performance and Tobin's Q.

3.1. Methodology

We adopt four centrality variables commonly used in the social network literature to measure the position of a company in the social network:[15]

- *Degree*: The sum of all links that each firm has with other companies in the network, divided by the number of companies in the network. This measure is a local measure because it measures only a firm's first-degree connections, and not second or higher degree of separations.
- *Betweenness*: The number of shortest paths linking any two companies in the network that pass through a firm. This measure is the most effective in capturing the absolute position of a company in the network. *Betweenness* measures the connections beyond the first neighbors, and it takes into account the connections of the neighbors and the neighbors' neighbors.
- *Closeness*: The inverse of the average distance between a node and every other nodes in the network. This variable is used often in virus contagion models to measure the likelihood of contagion for each node in the network. It can be used in informational networks under the assumption that information diffuses equally from each node to its connected nodes.
- *Eigenvector*: The eigenvector centrality is a measure of the relative importance of a node in the network. It is the dominant eigenvector of the sociomatrix, and it is used in the network literature to measure the prestige of an individual, rather than to measure information flow through the network.

The literature on information diffusion in social networks is large and multidisciplinary. For example, Buskens (2002) introduces a stochastic model of information diffusion that predicts the transmission of information depending on the position of the node

Table 6. Social Ties and Similarity in Other Corporate Policies

	R&D ratio	SG&A	Cash ratio	Leverage ratio	Interest coverage
Strength SNI	−0.00327**	0.00142	−0.00525***	−0.00123	−0.07637***
	(−2.40)	(0.91)	(−4.36)	(−0.87)	(−4.74)
No. Exec. and Direc.	−0.04875***	−0.03812***	−0.09857***	−0.02749***	−1.12337***
	(−6.00)	(−2.94)	(−11.17)	(−2.90)	(−12.17)
Age Exec. and Direc.	−0.03516	−0.16895***	−0.12978***	0.00881	−2.04983***
	(−0.87)	(−5.04)	(−4.29)	(0.29)	(−5.50)
Same Industry	−0.00041	−0.00706***	0.00488***	−0.00660***	−0.17335***
	(−0.26)	(−2.74)	(4.11)	(−5.18)	(−8.94)
Same Region	−0.00131	0.00302*	0.00037	−0.00060	−0.06060***
	(−1.23)	(1.74)	(0.46)	(−0.81)	(−5.91)
Abs. Diff. Total Assets	0.00039	−0.00108*	−0.00134***	0.00291***	−0.00206
	(0.64)	(−1.80)	(−3.30)	(4.01)	(−0.41)
Abs. Diff. Age Exec. and Direc.	0.00293**	0.00284	0.00333***	0.00246**	0.09490***
	(2.04)	(1.53)	(2.59)	(2.02)	(6.00)
Abs. Diff. No. Exec. and Direc.	−0.00112	0.00182	0.00531***	−0.00008	0.17272***
	(−1.18)	(1.26)	(5.16)	(−0.07)	(13.49)
PE Style	−0.00348**	−0.00553	−0.00222*	0.00652***	−0.04342***
	(−2.29)	(−1.47)	(−1.92)	(4.01)	(−2.89)
ED Style	0.01002***	−0.00173	0.00498**	0.00095	−0.06212**
	(3.94)	(−0.55)	(2.55)	(0.49)	(−2.04)
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.012	0.009	0.042	0.027	0.064
No. of obs.	6,924,732	5,598,301	6,876,809	6,888,509	5,370,390

Notes. The dependent variable is policy dissimilarity between firm pairs. The policy for each column is shown in the header line. The table shows the results of the second stage of the pair model. Refer to the text for the description of the models and to the appendix for the detailed definitions of the variables. The policy related to each dependent variable is displayed at the top of the column. The R&D ratio is defined as the R&D expenditure over sales; the SG&A ratio is the SG&A expenses over sales; the cash ratio is the amount of cash reserves over total assets; the leverage ratio is the book value of long- and short-term debt over debt plus market value of equity; and interest coverage is EBITDA over interest expenses. Refer to the appendix for more information about the definition of the dependent variables. *Strength SNI* is the number of social ties between firm pairs. *No. Exec and Direc.* is the sum of all directors on the board and key executives for each company pair. *Age Exec. and Direc.* is the average age of all directors on the board and key executives for each company pair. *Same Industry* dummy is a variable equal to 1 if the two firms are in the same FF49 industry. *Same Region* is a dummy variable equal to 1 if the two firms are in the same BEA region. *Abs. Diff. Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) is the absolute difference between *Total Assets* (*Age Exec. and Direc.* or *No. Exec. and Direc.*) of the two firms. *ED* (*PE*) *Style* is equal to 1 if at least two individuals in a firm pair went to the same school (worked for the same past employer) at any point in time. All dependent and independent variables, excluding dummies, are logged. All independent variables are lagged one year. The OLS coefficients are reported, with the t-statistics in parentheses. Standard errors are corrected for clustering of the error term at both firms level using the double-clustering algorithm from Petersen (2009). A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

in the network. Central players are more exposed to word-of-mouth and private information; they can compare their decisions with the ones of their social peers. On the contrary, companies whose members are not socially connected do not have a reference with whom to compare their decisions, and therefore they might behave in a more unique fashion.

We test the hypothesis that the capital investment decisions of corporations are affected by the location of the firm in the social network. On the one hand, firms centrally located in the social network can use the signals they receive from social peers in their policy decisions. In a world with imperfect and costly information, we would thus expect that more central companies have less idiosyncratic policies relative to companies on the outskirts of the network. Alternatively, firms with more information might leverage this information to differentiate themselves from other firms in the same industry. If that was the case, we would expect more central firms to behave more idiosyncratically.

We thus follow a two-stage econometric Centrality model similar to the pair model. First, a company i's corporate finance policy decision $Policy_{i,t}$ is regressed over the typical control variables $X_{Pi,t}$ relative to the policy decision, as in the pair model. The absolute value of the residual $\varepsilon_{i,t}$ of the regression is a measure of the idiosyncratic behavior of company i at time t relative to all other firms in the network. In the second stage, the absolute value of the residual $abs(\varepsilon_{i,t})$ is regressed over the centrality measure $C_{i,t}$ and control variables $X_{Ci,t}$. The second-stage regression tests whether a correlation exists between the centrality measure and a firm's idiosyncratic behavior:

$$\text{1st stage:}\quad Policy_{i,t} = \alpha_0 + \alpha_1 X_{Pi,t} + \varepsilon_{i,t}; \tag{4}$$

$$\text{2nd stage:}\quad |\varepsilon_{i,t}| = \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{Ci,t} + \eta_{i,t}. \tag{5}$$

3.2. Investment Policies and Centrality

Table 7 shows the results of the second stage of the centrality model by regressing $|\varepsilon_{i,t}|$, the absolute value of the excess investment, over several centrality measures for the SNI network. Like in the pair model, we control for style effects, such as having a similar background of experiences, by adding centrality measures for PE and ED style connections. We also control for heteroskedasticity of the second moments adding year, geography, and industry fixed effects, as well as size controls.

Overall, we find strong evidence that companies that are more centrally positioned in the network have less idiosyncratic investment policies, suggesting that social ties influence firms not only locally at the dyad level, but also at the network level. The centrality coefficient is negative for all specifications and significant for most of the specifications. The centrality results are also economically significant. A one standard deviation increase in the centrality measure corresponds to a 6% to 11% standard deviation decrease in a firm's idiosyncratic investment. The lower level of significance for the closeness measure is expected, since closeness centrality is not directly related to information flow, as explained above.

We need to be cautious, though, in interpreting these results. In the pair model (Section 2.2.4), we used deaths of directors and key executives as a negative shock to the strength of the social connection between the two companies. Unfortunately, the same approach can not be used in the centrality model. The death of an individual has a more ambiguous effect on the position of the company in the network. If the person that replaces the deceased person is more connected, than the shock would be positive, and negative otherwise. In addition, the choice of the replacement is also an endogenous action. Finally, the exogenous departure of an individual from a company has a minimal impact in the overall structure of the network. The lack of a clear direction of causality and identification strategy between the death of an individual and its effect on the network makes the instrumental variable approach unsuitable for this analysis. For this reason, the results of the centrality model prove that a correlation exists between firm positions in the social network investment policies, but we can not claim that the relationship is causal. Other factors, like managers' and directors' skills, could both be correlated with firm performance and with the intensity of social ties.

3.3. Firm Value and Centrality

As shown in the centrality model, the position in the social network is associated with firms' investment decisions. If a company is in a central position in the network, it could be exposed to a higher flow of word-of-mouth information and therefore could take decisions

Table 7. Centrality Model

	Degree		*Betweenness*		*Closeness*		*Eigenvector*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality SNI	−0.11838***	−0.07583**	−40.23085***	−23.18098**	−4.36.8311	−301.0137	−2.27440***	−1.57001**
	(−3.61)	(−2.52)	(−3.48)	(−1.99)	(−1.47)	(−1.08)	(−3.41)	(−2.53)
Total Assets	−0.13831***	−0.09876***	−0.13691***	−0.09698***	−0.13086***	−0.09463***	−0.13825***	−0.09866***
	(−7.27)	(−4.64)	(−7.16)	(−4.50)	(−6.70)	(−4.32)	(−7.27)	(−4.64)
Total Assets Squared	0.00762***	0.00477***	0.00739***	0.00469***	0.00671***	0.00436***	0.00762***	0.00475***
	(6.97)	(3.79)	(6.70)	(3.63)	(6.02)	(3.42)	(6.96)	(3.77)
Centrality PE Style	0.00869	0.10439	−3.63075	1.29400	−0.11183***	−0.14681***	0.16594	0.64087
	(0.09)	(1.22)	(−1.00)	(0.35)	(−8.28)	(−7.31)	(0.37)	(1.49)
Centrality ED Style	0.04734**	0.02298	−4.08652	−22.52404	24.22027	39.04991	1.45237**	0.82957
	(2.11)	(1.01)	(−0.11)	(−0.65)	(0.26)	(0.45)	(2.25)	(1.28)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Geography FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.043	0.099	0.041	0.099	0.040	0.099	0.043	0.099
No. of obs.	12,009	12,009	12,009	12,009	12,009	12,009	12,009	12,009

Notes. The dependent variable is excess investment. The table shows the results of the second stage of the centrality model. Refer to the text for the description of the models and to the appendix for the detailed definitions of the variables. The centrality measure used as the main independent variable is displayed at the top of each column. *Centrality SNI* for *Degree* is the number of valued links for each company divided by the number of companies in the SNI network, that for *Betweenness* is the average number of shortest paths linking every dyad in the SNI network that pass through the company node, that for *Closeness* is the closeness centrality for the SNI network, and that for *Eigenvector* is the eigenvector centrality for the SNI network. *Centrality ED* (*PE*) *Style* is the centrality measure of the ED (PE) style networks where individuals went to the same school (worked for the same past employer) at any point in time. Industries are defined as Fama–French 49 industry groups. Geographic regions are defined as the BEA Economic regions. The OLS coefficients are reported, with the t-statistics in parentheses. All standard errors are corrected for clustering of the error term at the firm level. A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Performance Model

	Return on assets				Tobin's Q			
	Degree	*Betweenness*	*Closeness*	*Eigenvector*	*Degree*	*Betweenness*	*Closeness*	*Eigenvector*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality SNI	0.04501***	12.76209***	−23.80554	0.91201***	0.44331***	208.48653***	81.62675	9.05133***
	(3.80)	(2.66)	(−0.62)	(4.09)	(3.00)	(3.51)	(0.19)	(3.19)
Total Assets	0.00461	0.00356	0.00321	0.00462	−0.53414***	−0.53935***	−0.55729***	−0.53284***
	(0.74)	(0.57)	(0.51)	(0.75)	(−7.88)	(−7.83)	(−8.00)	(−7.87)
Total Assets Squared	−0.00066*	−0.00052	−0.00038	−0.00067*	0.02146***	0.02334***	0.02630***	0.02118***
	(−1.86)	(−1.46)	(−1.05)	(−1.90)	(5.59)	(5.96)	(6.69)	(5.53)
Centrality PE Style	−0.03732	1.07513	0.03674***	−0.21733	0.59042	13.58449	1.00088***	2.38493
	(−0.99)	(0.61)	(4.07)	(−1.29)	(1.20)	(0.61)	(7.86)	(1.04)
Centrality ED Style	−0.02798***	−27.68472**	−13.30170	−0.85054***	0.05362	166.07319	1,016.87***	0.55198
	(−3.60)	(−2.27)	(−0.61)	(−4.00)	(0.50)	(1.00)	(3.39)	(0.19)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.081	0.078	0.076	0.082	0.269	0.265	0.263	0.270
No. of obs.	11,305	11,305	11,305	11,305	12,877	12,877	12,877	12,877

Notes. The dependent variables are return on assets and Tobin's Q. The table shows the results of the performance model. Refer to the text for the description of the models and to the appendix for the detailed definitions of the variables. The centrality measure used is displayed at the top of the column. *Centrality SNI* for *Degree* is the number of valued links for each company divided by the number of companies in the SNI network, that for *Betweenness* is the average number of shortest paths linking every dyad in the SNI network that pass through the company node, that for *Closeness* is the closeness centrality for the SNI network, and that for *Eigenvector* is the eigenvector centrality for the SNI network. *Centrality ED* (*PE*) *Style* is the centrality measure of the ED (PE) style networks where individuals went to the same school (worked for the same past employer) at any point in time. Industries are defined as Fama–French 49 industry groups. Geographic regions are defined as the BEA Economic regions. The OLS coefficients are reported, with the t-statistics in parentheses. Standard errors are corrected for clustering of the error term at the firm level. A constant is included, but not reported, in all specifications.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

that are less idiosyncratic. A natural extension of this argument is to ask whether being in a central position is associated not only to less idiosyncratic, but also better decisions. Centrally located companies that are exposed to a wider set of information could exploit such competitive advantages and have higher economic performance than companies that are not as socially connected. We thus investigate the correlation between the economic performance of a firm, measured by return on assets and Tobin's Q, and the centrality measure. We define return on assets as the ratio of income before extraordinary items over lagged total assets, and Tobin's Q as the ratio of the market value of assets (total assets plus market value of equity minus book value of equity) over total assets.

Table 8 illustrates the main results of the regressions of return on assets and Tobin's Q over the four centrality measures, after controlling for style effects. Overall, we find a positive and significant correlation between economic performance and the firm's centrality. The first four columns show that companies more centrally located in the network exhibit greater return on assets. The last four columns show that Tobin's Q is also positively affected by how central companies are in the social network. Consistent with what we found in the centrality model, the only centrality measure that is not significant is *Closeness*. The results are economically significant: a one standard deviation increase in the centrality of a firm is correlated with a 5%–15% standard deviation increase in performance. As we discussed above, the centrality results are only suggestive of a relationship between centrality and performance, but are not proof of a causal relationship between the two. Furthermore, we cannot conclude that social imitation leads to better or worse firm outcomes, but we provide suggestive evidence of network effects on firm policies and firm value.

4. Conclusion

Reliance on decision externalities is widespread in society and arises from constraints on our ability to process or obtain costly information. This paper provides evidence that decision externalities could also play an important role in large corporations. Managers seem to rely on their social networks when making corporate finance policy decisions. Using biographical information of key executives and directors, we create a matrix of social ties from current employment, past employment, education, and other activities. We demonstrate that these social connections influence the way companies make corporate finance decisions. In particular, companies are influenced in their policy decision-making process by their nearest social neighbors. We address concerns for endogeneity problems and direction of causality using proxies for similar characteristics and preferences of managers and directors, and using the deaths of directors as an exogenous shock to the social network parameters with a difference-in-differences specification. The results extend to other discretionary corporate finance policies such as R&D, cash reserves, and interest coverage ratio.

Although we cannot make any direct statement on whether social imitation leads to better or worse outcome for firms, we can analyze the position of firms in the social networks: Companies positioned more centrally in the universe of social networks invest in a less idiosyncratic way and have greater return on assets and Tobin's *Q*. These last results are only suggestive of a correlation between centrality and firm value, and not indicative of a causal relationship. Future research could explore the value implications of social imitation for corporations.

Acknowledgments

This paper is part of the author's doctoral dissertation. The author is deeply indebted to his dissertation committee members, Geoff Tate (cochair), Mark Grinblatt (cochair), Mark Garmaise, and Phillip Bonacich, for their guidance and advice. The author thanks Antonio Bernardo, his mentor over the years, for continuous support and inspiration. He also thanks Amit Seru (the department editor), an anonymous associate editor, Bruce Carlin, Bhagwan Chowdhry, Lauren Cohen, Stuart Gabriel, Robert Geske, Francis Longstaff, Richard Roll, Jan Schneider, Avanidhar Subrahmanyam, Walter Torous, Marc-Matos Vila, participants of the "Families, Networks and Firms" Conference at Bangkok Thammasat Business School, and all the participants of seminars at the University of Notre Dame, MIT Sloan, the UC Berkeley Haas School of Business, NYU Stern, London Business School, Washington University, Columbia University, University of Michigan, Boston College, University of Texas at Austin, University of Toronto, University of Rochester, Yale School of Management, Emory University, Stanford Graduate School of Business, and University of California, Los Angeles. The author acknowledges help from Naomi Kent and Shoshana Zysberg of BoardEx of Management Diagnostics Limited in providing data, and from the UCLA ATS/CCPR for the use of their supercomputer. A final word of gratitude goes to Albert Sheen and all the finance Ph.D. students at the UCLA Anderson School for their help and comments.

Appendix. Definitions of the Variables Used in the Paper

Most of the definitions for the financial variables follow the measures used in Fama and French (2002) and are considered standard in the literature. Data are available from Compustat and CRSP databases over the period from January 1997 to June 2010. The Compustat data refer to the end of the fiscal year. The item in parenthesis refers to the corresponding item in the Fundamentals Annual Compustat North America database.

The variables are as follows:

Acquisition Ratio is the ratio between the acquisition expenditures (aqc) and the total sales (sale).

Betweenness Centrality is the number of shortest paths linking any two companies in the network that pass through a firm.

Bond Dummy is a dummy equal to 1 if the firm has any public bond rated by Standard and Poor's (splticrm).

Cash Flow is the ratio (income before extraordinary items (ib) + depreciation and amortization (dp))/lagged property, plants, and equipment (ppent), winsorized at the [1,99] quantile.

Cash Flow Volatility is the four-year rolling window volatility of cash flow.

Cash Reserves Ratio is the ratio cash and short-term investments (che)/total assets, winsorized at the [1,99] quantile.

Closeness is the inverse of the average distance between a node and every other nodes in the network.

Degree Centrality is the sum of all direct valued links that each firm has with other companies in the network, divided by the number of companies in the network.

Dividend Paying Dummy is a dummy equal to 1 if the firm paid dividend (dvt) during the fiscal year.

Eigenvector is the dominant eigenvector of the sociomatrix associated with each network.

Firm Age is the time in days between the current fiscal-year-end date and the initial public offering (IPO) date (or the earliest fiscal-year-end date reported in Compustat if the IPO date is missing).

Interest Coverage is the ratio between operating income before depreciation and amortization (oibdp) and the interest expenses (xint), winsorized at the [1,99] quantile.

Investment Ratio is the ratio between capital expenditure (capx) and lagged PP&E (ppe), winsorized at the [1,99] quantile.

Leverage is the ratio (debt in current liabilities (dlc) + long-term debt (dltt))/(debt in current liabilities (dlc) + long-term debt (dltt)) + common shares outstanding (csho) * price close at the end of fiscal (prcc_f).

No. of Employees is the total number of employees in the firm (emp).

No. Exec. and Direc. is the total number of board members and highest five earners in the firms.

PE/ED Style is a dummy variable equal to 1 if there is at least one individual in a firm that went to the same school (*ED*) or to the same past employer (*PE*), at the same time or not, with one or more individuals in the other firm.

R&D Ratio is the ratio R&D expense (xrd)/lagged sales (sale), trimmed at the [1,99] quantile.

Return on Assets is the ratio income before extraordinary items (ib)/lagged total assets (at), trimmed at the [1,99] quantile.

Sales is the net sales turnover (sale).

SG&A Ratio is the ratio selling, general and administrative expense (xsga)/sales (sale).

Stock Return is the annual total stock return during the fiscal year.

Stock Return Volatility is the 12-month rolling volatility of monthly stock returns.

Strength CE (*PE/ED/OA*) is a dummy variable equal to 1 if in the firm pair there is at least one individual in a firm with a current employment (past employment/education/other activity) connection with one or more individuals in the other firm.

Strength SNI is the sum of *Strength CE*, *Strength PE*, *Strength ED*, and *Strength OA*.

Tangibility is the ratio (net property, plant and equipment (ppent)/total assets (at).

Tobin's Q is the ratio (total assets (at) − stockholders' equity (seq) + common shares outstanding (csho) ∗ price close at the end of fiscal (prcc_f))/total assets (at), trimmed at the [1,99] quantile.

Total Assets is the total assets of the company (at).

Endnotes

[1] Reliance on decision externalities is widespread in society: for example, when we have to choose a restaurant or a movie, we are constrained in our ability to process or obtain costly information; therefore we give weight to other people's actions. For an introduction to social networks and decision externalities, refer to Watts (2003). For a more in-depth discussion on social networks and organizations, refer to Kilduff and Tsai (2003).

[2] BoardEx provides information also on midlevel management, with biographical information gathered from publicly available sources. For this study, we limit the analysis to the top key executive and directors on the board to avoid introducing sample selection biases due to the heterogeneity in the optional disclosure policy among companies, and because midlevel management are less involved in the overall corporate finance policy decision-making process.

[3] BoardEx provides a list of all current and past board positions and current and past employers, with specific information on job description, committees served, and dates started in the organization and in the current role. In addition, it provides a list of all the undergraduate and graduate programs attended, with details on the institution, degree awarded, concentration, and degree date, and a list of current and past memberships in nonprofessional organizations, such as golf clubs, nonprofit organizations, and business roundtables, with details on the role served and, when available, date started and ended in the organization.

[4] An active role means that the role description needs to be more than just "member" for all organizations except clubs. Examples of the most frequent active roles are "trustee," "president," "advisor," "board member," etc. The other activity data set does not report the starting and ending dates for the large majority of the observations (86% of the observations do not have information about start and end dates). Thus, we do not require positions to overlap in time for the OA network.

[5] The FF49 classification is available on Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] These are Standard Industrial Classification codes with a first digit of 6 or Fama–French industry codes 45–48.

[7] As industry and geography classification systems, we use the Fama–French 49 industries and the Bureau of Economic Analysis regions (New England, Mideast, Great Lakes, Plains, Southeast, Rocky Mountain, Far West) throughout this paper.

[8] Gravity models are used when outcomes are affected by the distance between objects, like gravity. In economics, gravity models have been used in international trade to explain differences in trade. See, for example, Frankel and Romer (1999).

[9] The residual $\varepsilon_{i,t}$ is an estimated value with measurement error. However, because the measurement error is used as dependent variable in the second-stage regression, the OLS estimation is unbiased and consistent under regular OLS assumptions.

[10] In the online appendix, we show that the results are robust to using bootstrapping techniques and clustering at the pair level as alternative corrections for correlation in the residuals.

[11] In the online appendix we show that the findings are similar even if we use a measure of SNI that is standardized by board size.

[12] An excellent survey of the sociology literature on style and homophily effects in social networks is McPherson et al. (2001).

[13] Salas (2010) and Bennedsen et al. (2007) also investigate the effect of CEO and senior executive deaths as exogenous shocks to the composition of the board of directors. Fracassi and Tate (2012) also uses deaths as exogenous shocks to social ties to test governance implications.

[14] The variable *Connected* does not enter in the equation because it does not vary within a firm pair.

[15] For an extensive explanation of the centrality measures, refer to Wasserman and Faust (1997). Other papers, such as Barnea and Guedj (2013), used similar network centrality measures in the context of corporate governance.

References

Banerjee AV (1992) A simple model of herd behavior. *Quart. J. Econom.* 107(3):797–817.

Barnea A, Guedj I (2013) Director networks. Working paper, HEC Montreal, Montreal, Canada.

Bennedsen M, Perez-Gonzalez F, Wolfenzon D (2007) Do CEOs matter? Working paper, INSEAD, Fontainebleau, France.

Bertrand M, Schoar A (2003) Managing with style: The effect of managers on firm policies. *Quart. J. Econom.* 118(4):1169–1207.

Bikhchandani S, Sharma S (2001) Herd behavior in financial markets. *IMF Staff Papers* 47(3):279–310.

Bikhchandani S, Hirshleifer D, Welch I (1992) A theory of fads, fashion, custom, and cultural change as informational cascades. *J. Political Econom.* 100(5):992–1026.

Brown JR, Fazzari SM, Petersen BC (2009) Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *J. Finance* 64(1):151–185.

Brown JR, Ivkovic Z, Smith PA, Weisbenner S (2008) Neighbors matter: Causal community effects and stock market participation. *J. Finance* 63(3):1509–1531.

Buskens V (2002) *Social Networks and Trust* (Kluwer Academic Publishers, Norwell, MA).

Cai Y, Sevilir M (2012) Board connections and M&A transactions. *J. Financial Econom.* 103(2):327–349.

Chava S, Roberts MR (2008) How does financing impact investment? The role of debt covenants. *J. Finance* 63(5):2085–2121.

Clement MB, Tse SY (2005) Financial analyst characteristics and herding behavior in forecasting. *J. Finance* 60(1):307–341.

Cohen L, Frazzini A, Malloy C (2008) The small world of investing: Board connections and mutual fund returns. *J. Political Econom.* 116(5):951–979.

Coleman JS (1988) Social capital in the creation of human capital. *Amer. J. Sociology* 94:S95–S120.

Dougal C, Parsons CA, Titman S (2015) Urban vibrancy and corporate growth. *J. Finance* 70(1):163–210.

Ellison G, Fudenberg D (1993) Rules of thumbs for social learning. *J. Political Econom.* 101(4):612–643.

Ellison G, Fudenberg D (1995) Word-of-mouth communication and social learning. *Quart. J. Econom.* 110(1):93–125.

Engelbert J, Gao P, Parsons CA (2012) Friends with money. *J. Financial Econom.* 103(1):169–188.

Fama EF, French KR (2002) Testing tradeoff and pecking order predictions about dividends and debt. *Rev. Financial Stud.* 15(1):1–33.

Fracassi C, Tate G (2012) External networking and internal firm governance. *J. Finance* 67(1):153–194.

Frankel JA, Romer D (1999) Does trade cause growth? *Amer. Econom. Rev.* 89(3):379–399.

Gormley TA, Matsa DA (2014) Common errors: How to (and not to) control for unobserved heterogeneity. *Rev. Financial Stud.* 27(2):617–661.

Graham JR (1999) Herding among investment newsletters: Theory and evidence. *J. Finance* 54(1):237–268.

Graham JR, Harvey CR, Puri M (2013) Managerial attitudes and corporate actions. *J. Financial Econom.* 109(1):103–121.

Grinblatt M, Titman S, Wermers R (1995) Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *Amer. Econom. Rev.* 85(5):1088–1105.

Harford J, Mansi SA, Maxwell WF (2008) Corporate governance and firm cash holdings in the US. *J. Financial Econom.* 87(3): 535–555.

Hong H, Kubik JD, Solomon A (2000) Security analysts career concerns and herding of earnings forecasts. *RAND J. Econom.* 31(1):121–144.

Hwang BH, Kim S (2009) It pays to have friends. *J. Financial Econom.* 93(1):138–158.

Ishii J, Xuan Y (2014) Acquirer-target social ties and merger outcomes. *J. Financial Econom.* 112(3):344–363.

Kilduff M, Tsai W (2003) *Social Networks and Organizations* (Sage Publications, Thousand Oaks, CA).

Lakonishok J, Shleifer A, Vishny RW (1992) The impact of institutional trading on stock prices. *J. Financial Econom.* 32(1):23–43.

Lemmon ML, Roberts MR, Zender JF (2008) Back to the beginning: Persistence and the cross-section of corporate capital structure. *J. Finance* 63(4):1575–1608.

Malmendier U, Tate G (2005) CEO overconfidence and corporate investment. *J. Finance* 60(6):2661–2700.

McPherson M, Smith-Lovin L, Cook JM (2001) Birds of a feather: Homophily in social networks. *Annual Rev. Sociol.* 27:415–444.

Nguyen BD (2012) Does the rolodex matter? Corporate elite's small world and the effectiveness of boards of directors. *Management Sci.* 58(2):236–252.

Park A, Sabourian H (2011) Herding and contrarian behavior in financial markets. *Econometrica* 79(4):973–1026.

Petersen MA (2009) Estimating standard errors in finance panel data sets: Comparing approaches. *Rev. Financial Stud.* 22(1): 435–480.

Salas JM (2010) Entrenchment, governance, and the stock price reaction to sudden executive deaths. *J. Banking Finance* 34(3): 656–666.

Scharfstein D, Stein JC (1990) Herd behavior and investment. *Amer. Econom. Rev.* 80(3):465–479.

Shue K (2013) Executive networks and firm policies: Evidence from the random assignment of MBA peers. *Rev. Financial Stud.* 26(6): 1401–1442.

Sias RW (2004) Institutional herding. *Rev. Financial Stud.* 17(1): 165–206.

Trueman B (1994) Analyst forecasts and herding behavior. *Rev. Financial Stud.* 7(1):97–124.

Wasserman S, Faust K (1997) *Social Network Analysis: Methods and Applications* (Cambridge University Press, Cambridge, UK).

Watts DJ (2003) *Six Degrees—The Science of a Connected Age* (W. W. Norton & Company, New York).

Weisbach MS (1995) CEO turnover and the firm's investment decisions. *J. Financial Econom.* 37(1):159–188.

Welch I (1992) Sequential sales, learning and cascades. *J. Finance* 47(2):695–732.

Wermers R (1999) Mutual fund herding and the impact on stock prices. *J. Finance* 54(2):581–622.