Three Essays on Network Peer Effects on Firms and Financial Markets

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ABSTRACT

Three Essays on Network Peer Effects on Firms and Financial Markets

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This dissertation consists of three essays that address recent topics in corporate finance that concern for scholars, policymakers, and investors. Main body of this dissertation has been developed based on the "nexus of contracts" theory of the firm which in recent years has sparked renewed debates on the motivation underlying firm size and boundary. The first essay explores a network of interconnected firms and examines the impact of the firm's relationships with peers, rivals, and customers on its capital structure, and how the firm's revealed peers influence its financing decisions. We demonstrate that industry classification approach is fraught with measurement error, and instead implement an alternative peer identification scheme that designates peer groups as those explicitly disclosed by managers to shareholders. The results contrast with previous studies that find only weak evidence for peer effects on capital structure. We find that peer effects are particularly strong when focal firms have persistent rivals, in the sense of supplying common customers for at least two consecutive years. While constructing the firm's actual network poses a challenge, the new approach can lead to more real-world insights about firm behavior.

In the second essay, I approach to a challenging version of peer effects model with firm's and peer's multinomial decision outcome as endogenous and financial fundamentals as exogenous

explanatory variables. I show that managers do not set dividend policy independently and they are significantly under the influence of few self-disclosed diverse competitors rather than industry peers. The test results show that firm's dividend change actions are significantly correlated with past dividend actions of its peers and it is highly predictable for the next period. I also investigate and report marginal effects of firm's and peers' different endogenous and exogenous determinants on the outcome decision variable for example a peer group with an overall dividend increase action in the past 180 days, increases the chance of the dividend increase in the focal firm. Considering the market capitalization of dividend paying firms, the identified marginal effects and prediction of the cash distribution are economically meaningful and important.

In the third essay, I propose a new approach to model and measure intangible value of the firm as the joint of network feature and book value of the firm. Despite the growing importance, the empirical asset pricing research has struggled to evaluate the effects of intangible assets on firms' market value. Utilizing characteristics of the firm network, I propose a network-centric value factor to replace the under-performing traditional value factor (HML) in a series of asset pricing factor model. I show that the new value factor portfolio provides stronger performance in all periods of the sample. I also explore short and long strategies to better understand effects of the networks on value of the firms. Initial findings emphasize that asset pricing studies should adjust the factor models by including intangible network value of the firm.

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CONTRIBUTION OF AUTHORS

Although I employ the author's "we" in all three essays, I am the sole author of this thesis. My use of "we" equally reflects my discomfort with the pronoun "I" in my written productions, the theoretical and technical guidance of my thesis committee and other mentors, and my intention to enlist co-authors on the way to publication.

The manuscript has been reformatted and reorganized according to the requirements set out in the guideline of the School of Graduate Studies

To my mother and father.

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Chapter 1: Disclosed Peer Effects on Corporate Capital Structure

We study a network of interconnected firms and examine the impact of the firm's business relationships with peers, rivals, and customers on its capital structure. Peer effect models commonly define peers based on static standard industrial classification (SIC) codes. This renders them susceptible to measurement error and identification problems. These issues are of consequence, since we show that: a) many firms change industries over time and b) over one-half of peers revealed by managers to shareholders in a given year reside in industries that differ from the firm's SIC code. We find that peer effects on financial policy are robust when the firm's revealed peer group consists of self-disclosed rivals that share at least one customer with the firm in a two-year time window.

1.1. Introduction

Business networks initially appeared in the industrial organization literature, as an application of embeddedness theory of social networks.1 A burgeoning literature has emerged that applies social network theory to numerous areas of financial economics, including: asset pricing, trading strategies, investment and dividend policies, corporate governance, IPOs, and household financial decision making.2 The approach augments traditional determinants of firm and

[1] Miner, et al. (1990) demonstrates inter-organizational linkages can act as a source of organizational buffering for insulating the organization from its environment and reducing the effects of environmental uncertainty. Uzzi (1996) argues that organizational networks operate in an embedded exchange that can promote economic performance through inter-firm resource sharing and cooperation. In a follow up study, Uzzi (1997) focus on the role of firm networks for a sample of firms in the apparel industry in the New York area and argues that inter-firm networks are important mechanisms for resource allocation and valuation. Bruderl and Preisendorfer (1998) show that entrepreneurs in newly founded firms who can refer to a broad and diverse social network and who receive much support from their network are more successful.

[2] See for example, Kaustia, and Knupfer (2012) , Bailey et al. (2016), Leary and Roberts, (2014), Parsons et al (2018), Grennan (2019) Ouimet and Tate, (2020) Fracassi (2008) Bouwman (2011) Lee and Yeh (2004) Engelberg et al. (2012) Fogel et al. (2018), Bhagwat (2013), El-Khatib et al. (2015), Bajo et al. (2016), Di Maggio, et al. (2019), Kalda (2019), Erol, and Lee (2019), Richmond (2019), and . Cao, Liang, and Zhan (2019).

individual strategic choices with a behavioral component. Traditional theory recognizes peer effects as manifested in market competition at the firm and industry level. Applying network theory to financial decisions has a more limited history. Much of the recent literature has focused on industry peer effects. These effects have been documented for firms' precautionary cash holding decisions (Hoberg et al. 2014), corporate investment decisions (Foucault and Fresard, 2014, Bustamante and Fresard, 2020), dividend policies (Kaustia and Rantala, 2015, and Grennan, 2019), financial misconduct (Parsons et al. 2018), voluntary disclosure (Lin et al. 2019) as well as M&As and IPOs (Hsu et al. 2010, and Servaes and Tamayo, 2014).

In this study, our objective is to examine peer effects on corporate financial policies not from an industry classification basis, but in a broader setting of business relationships (networks). We show that the common approach to identify the firm's peer group using Standard Industrial Classification (SIC) codes is problematic. SIC classified peers are often inconsistent with the firm's self-disclosed peer group. To the best of our knowledge, our study is the first to incorporate firm operational level data to construct networks. These networks in turn, encapsulate relationships between firms, their peers and rivals, as well as

as well as their customers. Based on a sample of 23,347 firm-year observations of 4,582 firms whose shares are listed on U.S. exchanges over the period 2004 to 2016, we find significant associations between focal firms' financial policies and their network peers' policies. This suggests that firms monitor and follow not the entire industry, but rather only a small and diverse group of rival firms as they compete for the same customers. Our empirical findings show that firms' capital structures are significantly influenced by their network-peers, indicating that the primary channel through which peer effects work is via network connections and contractual agreements rather than industry related peers. We find a strong and positive association between the financial policies of firms and their peers that are revealed to shareholders. These effects are enhanced when we demarcate the peer group to include self-disclosed rivals that share at least one customer with the firm in a two-year time window.

The remainder of this paper is organized as follows. In the section 1.2, we provide a brief review of the literature that relates peer effects to corporate financial decisions. In section 1.3, we exhibit some of challenges of using industry-based peer group formation. In section 1.4, we present our base empirical model, the network structure, as well as our hypotheses. The data and variables are described in section 1.5. The results follow in section 1.6. The chapter concludes in section 1.7.

1.2. Literature Review

Our study is closely related to the body of literature that provides evidence for peer effects on corporate financial policies and capital structure determinants (e.g., Leary and Roberts, 2014, and Kaustia and Rantala 2015). The seminal paper of Leary and Roberts (2014) shows that that the firm's corporate financial policies are correlated with their peer group from same industry (common 3-digit SIC code). Similarly, industry effects using SIC codes have been incorporated in several papers on firm financial policy (see e.g. Graham and Harvey, 2001; Welch, 2004; Frank and Goyal, 2009; Duong et al. 2015) and in corporate governance (Fairhurst and Nam 2020). However, using SIC codes is problematic due to the simultaneity/reflection problem as highlighted in Manski (1993) and more recently by Aghamolla and Thakor (2021) who look at peer effects in IPOs. As Manski (1993) notes, the reflection issue is a specific form of endogeneity that arises when the source of influencing characteristics cannot be traced back to a group or to specific entities. For example, if the relationship between the focal-firm and its peers is a feedback loop, identifying causality in the structural relationship using instrumental variables is susceptible to measurement error. Leary and Roberts (2014) concede that two-stage least squares estimation or Instrumental Variables (IVs) identification strategies remain susceptible to mis-measurement when the IVs are correlated with the omitted variables. Furthermore, Bound et al (1995) point out that if the IVs are only weakly correlated with the endogenous explanatory variable(s) biases will persist even with large samples. Our approach controls for endogeneity in two ways. First, the self-identified peers are unique to the firms. In addition, we limit our sample to uni-directional peer links, which by definition rules out the Manski (1993) reflection problem. Another problem of an industry classification approach for identifying peers is that, if the industry is large, formal identification of the linkages between firms may be intractable. Finally, even if we use a subset of firms in the industry, as in Leary and Roberts (2014), firms may consider firms outside their industry to be their key competitors, as argued by Aghamolla and Thakor (2021).

We focus on customer-connected peers, as defined by Hoberg and Phillips (2016), and hypothesize that companies actively monitor and follow a self-declared group of rival firms. Rival firms are often enunciated in the firm's financial reports, specifically in the Competition or MD&A (Management Discussion and Analysis) sections. Our analysis of self-announced and customer-connected peers differentiates itself from the vast literature of peer effects studies that focuses on firms that are in the same industry and suggests that non-announced non-customer-connected members from the same industry have no economically or statistically significant effects on a firm's financial policies. Indeed, we demonstrate that studies that use SIC classification to classify peers may not actually capture the firm's peer group that managers disclose to shareholders. We also show that peer effects are strong when firms share a common customer with their rivals.

1.3. Industry classification and peer group definition

Using SIC classifications to identify a firm's peer group has at least three limitations. First, the firm's primary industry group is not static. Figure 1.1 shows the distribution of firms in the CRSP-Compustat universe as of December 2016 according to changing SIC affiliations across age groups from their founding dates from FactSet. The stacked bars represent the number of firms in each age group. The blue shaded part shows the portion of firms with single three digit historical SIC codes. The red shading in the bars shows the part of the firms with multiple historical SIC codes. The red line shows the ratio of firms in the various age categories that have changed their primary SIC codes at least once since their establishment. The green line shows the ratio of firms in the various age categories that have changed their primary SIC codes at least twice since their establishment. The yellow line shows the ratio of firms in the various age categories that have changed their primary business segment SIC code. The blue line represents the ratio of the firms with at least two different historical SIC codes that were once utilities or financial companies, but changed their industry association, or became utilities or financial companies through time. The right vertical axis shows the number of the firms in age groups and left side vertical axis represents the percentage of firms changing their SIC codes.

[Please insert Figure 1.1 about here]

As can be seen in Figure 1.1, many firms change their primary industry of affiliation through time. In particular, as firms age, the likelihood of changing their primary SIC code tends to increase. About 12% of firms in the age category 1-10 change their SIC code. This proportion rises to over 20% in the age group 11-20. On average, across all age categories, about 17.8% of all firms undergo a change in their primary SIC classification.

Second, in studies that classify peer firms based on SIC codes, certain industries such as Utilities and financials are typically excluded. However, in the Compustat universe 7% of the firms became utility or financial companies over their history, or changed to other primary industries over their history. Ignoring these companies restricts the range of possible the peer interactions through time.

A third limitation of SIC classification of peers is that the process may allocate an intractable number of peers to firms. An industry with n members has $n-1$ peers per each member, resulting $n(n-1)$ comparison pairs per each year-industry in the study. Considering Compustat's average number of industries (265 three-digit SIC codes) and average number of firms per industry, a peer effect study on this universe between 2004-2016 has over 9.6 million pair-year observations.

Hoberg and Phillips (2010, 2014) use a text-based analysis on 10-K filings to quantify similarities between business and products descriptions of the firms. They develop a dynamic annual firm classification, which scores relationships of firms with their competitors. These scores in turn are used to form network clusters based on business and product similarity. Although this approach addresses two of the aforementioned issues given its bi-directional network structure, it fails to provide information on the direction of peer influence and learning channels.

Following Hoberg and Phillips (2010), we look for competitors specifically declared as such by managers in the company's 10-K filings. With this approach, we can form a firm-specific reference group to identify the direction of rivalry and the nature of peer influence. While the SEC's Regulation SFAS 131 requires that U.S. firms disclose the existence and names of their customers with at least 10% of their total sales, to identify customer-supplier links (e.g. Banerjee et al., 2008) there is no requirement for disclosing competitors. However, in the firm’s Annual Report to Shareholders (ARS), and 10-K filing as well as during analyst conference calls, managers typically mention the name of other companies as part of their risk related discussions, where many of these companies are explicitly designated as competitors. This information combined with complementary news and client announcement data, allows us to create networks, with source firms in the center and directed connections to customers, suppliers, and rival firms. We use SEC (Securities and Exchange Commission) Edgar firms as the base universe in this study. The relevant SEC filing and textual company data are from CapitalIQ, FactSet and Conference Call scripts. Named Entity Recognition and Relation Detection algorithms are used to identify peer firm names in the text and validate the identified relationships. Observations were manually inspected to match identifiers with the names provided in the WRDS and FactSet's name conversation tools. Furthermore, as corporate networks evolve over time due to link additions and deletions from entering or terminating agreements, we capture the history of business relationships on a yearly basis. We use companies’ disclosed information as the main source for identifying each firm’s competitors and compare this approach to the standard industry classification method.

To illustrate, consider the case of the 2011 10-K[3] filing of Silicon Laboratories Inc. (SIC:367, SLAB). The company states: “We compete with Analog Devices [SIC:367, ADI], Atmel, Broadcom [SIC:367, AVGO], Conexant, Cypress [SIC:365, 3541.TW], Epson [SIC:357, SEKEY], Freescale, IDT [SIC:481, IDT], Lantiq, LSI [SIC:364, LYTS], Vectron International, Zarlink Semiconductor and others.” In its 2014 10-K[4], the company discloses that: “We compete with Analog Devices [SIC:367, ADI], Atmel, Conexant, Cypress [SIC:365, 3541.TW], Epson

[3] https://www.sec.gov/Archives/edgar/data/1038074/000104746911000733/a2201799z10-k.htm
[4] https://www.sec.gov/Archives/edgar/data/1038074/000104746914000500/a2218058z10-k.htm

[SIC:357, SEKEY], Freescale, IDT [SIC:481, IDT]. Vectron International and others." Overall, in 2011 (2014) Silicon Laboratories Inc. (SIC:367, SLAB) discloses 20 (18) firms as competitors, 12 (11) of which were publicly traded. Table 1.1 shows the complete list of public companies that are disclosed as competitors, for illustrative purposes. We observe that in this list, four (three) of the of the disclosed firms have different SIC codes that are different from Silicon Laboratories in 2011 (2014. In addition, we observe that the composition of peers changes from year to year.

[Please insert Table 1.1 about here]

Using our method of identifying peers from company disclosures generates 187,689 pair-year observations, which is quite parsimonious, representing only 2% of the sample size needed if we were to consider all companies in the same primary SIC group as the focal firm's peers.

1.4. Empirical Model and Hypotheses Development

We begin with the following model for the empirical capital structure, based on Leary and Roberts (2014):

$$y_{ijt} = \alpha + \beta \bar{y}_{-ijt} + \lambda' X_{ijt-1} + \gamma' \bar{X}_{-ijt-1} + \delta' \mu_j + \phi' \upsilon_t + \varepsilon_{ijt} \tag{1.1}$$

where i, j, and t correspond to firm, industry, and year, respectively. The variable, y_{ijt} is a measure of corporate capital structure, such as leverage. The covariate $\bar{y}_{-ijt}$ denotes peer firms average of that measure of capital structure (excluding firm i). The vectors $\bar{X}_{-ijt-1}$ and X_{ijt-1} contain peer firm average and firm-specific characteristics and the variables μ_j and υ_t capture industry and year fixed effects. ε_{ijt} is the firm-year specific error term that is assumed to be correlated within firms and heteroskedastic. The coefficients $\lambda', \gamma', \delta'$ and ϕ', capture the firm specific fundamental characteristics from previous year, peers' average of fundamental characteristics from previous year, common industry effect, and time fixed effects, respectively. Peer effects are captured by β which measure the influence of peer firms' current financial policy on financial policy choices. The goal is to separate industry commonality in capital structure by statistically identifying the structural parameters of the model. The main challenge is with the vector $\bar{y}_{-ijt}$ as it is assumed that firm i's capital structure is a function of firm j's where firm j's capital structure can be also a function of firm i's, which means that $\bar{y}_{-ijt}$ is an endogenous regressor and that the parameters are not identified. This identification of peer effects is addressed by Manski (1993) and Leary and Roberts (2014). Manski (1993) documents three conditions that need to be distinguished in the analysis of peer effects. The first type are endogenous effects, which arise from the firm's tendency to follow the actions of its peers, such as investments (reflection). The second are so-called contextual effects, which represent the propensity of a firm to behave in some way as a function of the exogenous and environmental characteristics of its peer group. For example, a firm can spend more on investments irrespective of its own profits if it receives some positive credit space because of its peers' overall positive image. The third type are so-called correlated effects which describe circumstances in which firms in the same group tend to behave similarly because they have similar individual characteristics or have similar arrangements, i.e., firms within the same industry may react similarly due to common industry-specific or business cycle shocks. This means that there are unobservable in a group, which may have a direct effect on observed outcomes. To summarize, endogeneity, contextual, and correlational issues are all consequences of the fact that the subject firm is also member of a peer group. A solution to these issues is to clearly distinguish the firm from its peer group counterparts. One approach is to use instrumental variables in a simultaneous equation framework. The choice of the instrument variable is critical to this approach. Technically, the instrumental variable must be exogenous to the focal entity but correlated with peer level endogenous variables (see Graham 2008, Leary, and Roberts, 2014). Variation in group level information is also used as an identification strategy; Lee (2007) and Davezies et al. (2009) show that variation in group size can result in point identification. Bramoullé et al. (2009, 2020) introduce a network-based identification method and formulate sufficient conditions for point estimation of the parameters of the peer effects models. Their strategy assumes that for each connected pairs of entities, there is a triad structure that can be used to identify the parameters of the model.

We use the network-based approach, to separate focal firms and identify their rivals as depicted in Figure 1.2. We change equation (1.1) to focus on revealed peer firms, who may or may not be in the same industry grouping, to obtain the base model for our analyses:

$$y_{i,t} = \alpha + \beta \bar{y}_{g_i,t} + \gamma' \bar{X}_{g_i,t-1} + \lambda' X_{i,t-1} + \phi' \upsilon_t + \varepsilon_{i,t} \qquad (1.2)$$

where subscripts i , g_i and t correspond to firm i, firm i's disclosed peer group, and the year of the observation, respectively. Note that the firm's peer group can change from year to year in this setting. Furthermore, each firm will have a unique peer group each year (firm-specific). The variable $y_{i,t}$ is a measure of corporate capital structure, such as leverage. The variable $\bar{y}_{g_i,t}$ denotes the average of the capital structure measure of concern for a disclosed-peer-group. The vectors $\bar{X}_{g_i,t-1}$ and $X_{i,t-1}$ contain peer firm averages and firm-specific characteristics in a previous year respectively. In our data set, we identify peer-groups for each company independently, so there is no need to include a separate variable to capture group fixed-effect (μ_j, the industry fixed-effect in model (1) is eliminated). The coefficients λ', γ', and ϕ', capture the firm specific fundamental characteristics from previous year, disclosed peers' average of fundamental characteristics from previous year, and time fixed effects, respectively. Peer effects are captured by β which measure the influence of peer firms' current financial policy on the focal firm's financial policy choices. Our model provides a tractable means for identifying actual peer groups in an empirical setting that is immune to the reflection and identification issues that have not been addressed in previous studies.

Our base model is used to test several hypotheses that augment the extant literature to incorporate peer group effects on the capital structure variables $y_{i,t}$, on the left-hand side of equation (1.2). Based on theory, peer effects on capital structure can result from interactions between financial structure and product market competition, which leads to mimicking behavior of the firms. Bolton and Scharfstein (1990) present a model in which high leverage invites predatory price competition from less-levered rivals. If the expected cost of this predatory behavior is severe enough, highly levered firms will mimic the capital structures of their less-levered rivals. Similarly, in Chevalier and Scharfstein (1996), firms with high leverage underinvest during an industry downturn and lose market share to more conservatively financed competitors. This loss can motivate firms to mimic the more conservative leverage policies of their peers.

[Please insert Figure 1.2 about here]

Mimicking behavior in capital structure can also be a consequence of rational herding. Devenow and Welch (1996) show that informational cascades may explain the decisions of managers to assume debt. Without a good model of the optimal choice of debt, managers may deem it optimal to infer the best choice from the choices of peer companies. As a result, their decisions will gravitate toward those of their peers. Peer group identification is of crucial importance in the theoretical literature. Using a broad definition of industry groups leads to many methodological challenges. We believe that by employing a more refined and parsimonious peer-group formation process, peer effects can be captured meaningfully in our estimation of equation (1.2). The capital structure variables used as dependent variables include the firm's Book Leverage and Market Leverage. The independent variables are the contemporaneous peer Average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets).

Hypothesis 1: Firms monitor and mimic self-disclosed peer companies rather than industry classified peers in their capital structure decisions

Hypothesis 2: Firms monitor and mimic the choices of self-disclosed peer companies that share a common customer in terms of capital structure decisions.

We use Baltagi (2001) panel data methodology to control for individual heterogeneity, multi-collinearity, and estimation bias, and to specify the time-varying relationships between dependent and independent variables. This study uses a panel data methodology and an F-test to determine whether the fixed-effects model outperforms the pooled OLS (Ordinary Least Squares). The appropriateness of the random-effects model compared to the pooled OLS model is examined with the Breusche and Pagan Lagrange multiplier (LM) test. Hausman tests are also used to compare the fixed-effects model with the random-effects model. The results are provided the next section. To test our hypotheses, we construct four types of peer-groups as follows:

Group 1 consists of all the firms that are cited in the text of its 10-K annual filing, or announced in other media, by the source company in year t. We name group 1 as Self-Disclosed Peers (SDP). As members of this group could change over time, we use each firm-year peer group as basis to calculate capital structure values of $\bar{y}_{g_i,t}$ and $\bar{X}_{g_i,t-1}$ in equation (2). For example, a company can have four peers in year 2010 and five peers in year 2011 therefore; we use average of five companies for $\bar{y}_{g_i,t}$ and average of four companies for $\bar{X}_{g_i,t-1}$ values. As depicted in Figure 1.2, for firm A in year 2011 we construct the following peer groups[5]:

$$(\text{SDP})_{A,2011} = \{P1, P2, P4, P5, P6\}\text{ , and }(\text{SDP})_{\text{A},2010} = \{P1, P2, P4, P5\}$$

Group 2 consists of rival firms that are cited in year t that share at least one common customer with the focal company in year t. We name group 1 as Self-Disclosed Peers with Customers (SDP-C1) or rivals. For example, as depicted in Figure 1.2, we can construct the following type 2 peer groups for Firm A's year 2010 and 2011 observation:

$$(\text{SDP\_C1})_{A,2011} = \{P1, P2, P5\},\text{ and }(\text{SDP\_C1})_{A,2010} = \{P2, P4, P5\}$$

Group 3 consists of rival firms that are cited in t and t-1 who share a common customer with the focal firm only at t-1 (losing at least a customer from year t-1 to the peer in year t). We name this group Self-Disclosed Peers with Lost Customers (SDP-L1) or leaders. For example, as depicted in the Figure 1.2, we form the following type 3 peer group:

$$(\text{SDP\_L1})_{A,2011} = \{\,P4\}$$

Group 4 consists of rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years (ongoing competition). We name this group Self-Disclosed Peers with Stable Customers/Market (SDP-C2) or persistent rivals. For example, as shown in the Figure 1.2, we can form the following type 4 peer group:

$$(\text{SDP\_C2})_{A,2011} = \{P2, P5\}$$

[5] P7 was eliminate from groups because of bi-directional announced peer relationship with focal firm A.

To compare the results of using self-disclosed peers vs. the Leary and Roberts (2014) approach that uses industry classifications to select peers, we also perform the analyses using an additional *Group 5* (SIC) which consists of all firms (excluding the focal firm) from the Compustat universe with same three-digit primary SIC code as the focal firm in year t.

1.5. Variables, Data and Summary Statistics

For the sample of this study, we collected financial market and accounting data from Compustat databases. We use the levels (t) and first differences (t-1) of the following endogenous variables in the analyses: book leverage, market leverage, sales, market-to-book ratio, and profitability, and tangibility. The Compustat names and definitions for these variables are shown in Appendix A. We require at least 3 years of non-missing profitability data for each observation to calculate Earnings Volatility of each firm-year observation is the historical standard deviation of Profitability.

A corporate network can be formed by mapping all the business relationships fostered through mutual agreements between two companies as well as disclosed non-contractual relations. The main challenge is to explore all publicly available textual information to identify the business relationships. Most of previous research relies on the SEC's regulation S-K, which requires U.S. firms to disclose the existence and names of customer firms representing at least 10% of their total sales, to identify customer-supplier links (e.g. Banerjee et al., 2008). This method has two important limitations: a) when customers that fall below the 10% threshold, (which represent the majority of supply-chain relations), are not identified also there is no requirement to disclose other business counterparties and competitors. However, in most 10-K and 8-K filing's MD&A sections as well as investor presentations and analyst conferences many of these counterparties could be announced or mentioned. Moreover, with the help of other complementary business news resources one can obtain a complete list of business relationships of the firms which requires great amount of time and effort to hand-collect and verify. We use Compustat North American firm database as our base universe of companies and collected all the relevant SEC (Securities and Exchange Commission) filing and textual company data from available sources mainly from Edgar, S&P CapitalIQ (Key Development Section), FactSet's Press Release and Conference Call to create and validate the firms' relationships (corporate network). Observations were manually inspected to match identifiers with the names provided in the WRDS, and FactSet. To account for the evolution of corporate networks through time (due to link additions and deletions, as well as new as well as terminating agreements), we capture the history of business relationships in yearly basis. To the best of our knowledge, data of this degree of refinement has been never studied in the extant literature, due to the burdensome nature of the data collection process.6 The observations were recorded in following format, where firm A is the source company for collecting data: {Firm A (focal), Firm B (counterparty), year, relationship (peer or customer)}. Consistent with the literature, we applied the following filters: Firm A and Firm B must have at least 2 years of financial data (non-missing values for "Total Asset" and "Sale" variables) prior to year of the observation (3 years of financial data including the year of the observation). Firm A and Firm B should have the relationship in at least two consecutive years. Firm A and Firm B should have profitability values in the year of the observation. Bi-directional observations are removed from

[6] A number of studies use boards and directors' connections to find similarities in corporate behavior of linked firms. These studies primarily focus on corporate governance issues. For example, Guedj and Barnea (2009) use data on directors who serve on the boards of S&P firms and find evidence that firms whose directors are more central in the network, pay their CEO higher and that CEO pay is less sensitive to firm performance. Cohen, Frazzini, and Malloy (2008) study connections between mutual fund managers and corporate board members via shared education networks and find that portfolio managers place larger bets on connected firms and perform significantly better on these holdings relative to their non-connected holdings. Similarly, Hochberg et al. (2007) find that better-networked Venture Capital firms experience significantly better fund performance where they measure connections through syndication relationships

the sample (11.7% of the sample) to maintain consistent observations where only focal firm (Firm A) acknowledges the existence of the competition with the peer company. This provides a means to safeguard against endogeneity concerns.

As observations are based on calendar years, a calendarization of financial values is necessary: many companies have a regular 12-month fiscal year, but many do not; and for many of those that do, the fiscal year straddles two calendar years. Furthermore, for some firms, fiscal reporting periods do not necessarily correspond to a calendar year. In fact, the fiscal period of a corporation can start or end on any day of a calendar year and need not always have a duration of 365 days. Another reason for calendarization is to match two firms' financials in a same period where there is a year-relationship observation. To calendarize financial values of firms with fiscal periods that span calendar year boundaries, we allocate the relevant financial values proportionally to the number of days in each of the two calendar years involved. We then aggregate the amounts from all (short) fiscal periods that fall fully within the calendar year, and those that have been partially allocated to the calendar year, to get the calendarized total annual amounts. For example, when calendarizing the year 2010, if the first fiscal period ran from July 23 2009 to July 22 2010 we take the proportion of the total that fell in 2010, (i.e. the number of days of that fiscal period that fell in the calendar year divided by the total number of days in the fiscal period times the aggregate amount for the fiscal period) and add to it the similarly calculated proportion of the second fiscal period that fell within the calendar year. In rare cases where fiscal periods overlap, we give priority to the first fiscal period and reduce the prorated contribution of the second fiscal period to include only those days that fall within the calendar year but do not overlap the first period. After applying these filters on calendarized values, the sample consists of 253,679 observations. We form peer-group per year for focal firms (Firm A). Table 1.2 presents a statistical summary of the sample and Table 1.3 shows the correlation matrix of the main variables across all peer-group types.

[Please insert Tables 1.2 and 1.3 about here]

Looking at the last row of Table 1.2 (Peer-Industry Similarity), we note that only about 34% of the peers that focal firms disclose have the same SIC code as the focal firm's. In addition, only 46.4% of persistent rivals (SDP-C2) share the same SIC code as the focal firm. When we define rivals as self-identified peers that share at least one customer with the firm over a two-year time window, only look at Leary and Roberts' (2014) approach to dealing with the identification problem is to create an equity shock variable as an instrument for peers in the same industry group. When the majority of self-disclosed peers and rivals are from outside the SIC code of the firm, the Leary, and Roberts (2014) industry shock approach is clearly fraught with measurement error. The method of using self-disclosure of peers is a parsimonious way to address the identification problem that should be immune to this measurement error.

1.6. Estimation Results

1.6.1. Basic Results

In this section, we present the main findings of our study. Table 1.4 reports regressions of four capital structure measures, Book Leverage, ΔBook Leverage, Market Leverage, and ΔMarket Leverage on peer-average and firm level characteristics across the three base peer-groups SDP, SDP-C1, and SIC. OLS estimated coefficients are shown with t-statistics (in parentheses). All independent variables are lagged 1 year in the analyses.

[Please insert Table 1.4 about here]

Table 1.4 shows that the focal firm's book leverage is significantly associated with the average book leverage of its peers in group SDP-C1 (which includes self-disclosed rivals with at least one common customer in year t) which supports Hypothesis 1. Significant market leverage peer effects are also shown, across peer classifications. However, note that peer effects of changes in market leverage are only observed for groups SDP and SDP-C1, which suggests that market pricing adjustments reflect only self-disclosed peer effects, and not industry effects. This also supports Hypothesis 1.

We further analyze peer effects by estimating equation (1.2) across competition centered peer-groups of SDP-L1 and SDP-C2. The results are shown in Table 1.5, where we consider the capital structure measures of Table 1.4 as well as Debt Issuance, and Equity Issuance as dependent variables.

[Please insert Table 1.5 about here]

Table 1.5 shows that focal firm's book leverage is strongly associated with the average book leverage of its peers in group SDP-L1, which includes self-disclosed rivals for two consecutive years that had at least one common customer with the focal firm in year t-1, but not in year t. Average book leverage of peer group SDP-C2, which includes rivals that have at least one common customer in both years t-1 and t is also significant. In essence, peers matter if they have longer customer sharing with focal firms. In addition, focal firms follow the capital structure of rivals who that win over t-1 shared customers from focal firms in period t. Similar to the book leverage results, peer effects are significant for market leverage across all groups. However, changes in the focal firm's market leverage are only significant for SDP-C2.

Table 1.5 also shows that the average equity issuance of peers has a positive and significant effect on the focal firm's equity issuance in group SDP-L1. Focal firms in this group have higher leverage than their peers, on average. Equity issuances serve as a means to move focal firms closer to their peers' capital structures. Table 1.5 also shows that the average debt issuance of the focal firm is significantly related to the average debt issuance of its peers in group SDP-C2. In sum, the results of Table 1.5 provide consistent support for Hypothesis 2: common customers help drive peer effects in capital structure decisions of firms. The significant relationships found for Group SDP-L1 are consistent with market competition characterized by Stackelberg leader effects (see e.g. Gao et al. 2018 and Li and Chen, 2018). Rivals that win customers away from the firm can be deemed as ex post Stackelberg Leaders. The focal firm under these circumstances can be seen as a Follower, that closely mimics the capital structure decisions of the Leaders. The results for Group SDP-C2 are consistent with a more symbiotic relationship between focal firms and rivals that is driven by their longer-term joint relationships with shared customers. In other words, under market competition pressure managers make rational financial decisions, however under steady competition their decision follow more behavioral patterns or influenced by peer effects which explains why do firms follow the capital structure decision of their peers.

What drives the capital structure peer effects that we have uncovered? To explore this issue, we look at how peer effects are manifested in key traditional determinants of capital structure, the firm's profitability (EBITDA/Assets) and asset tangibility (Net PPE/Assets) Table 1.6 shows the regression estimates of equation (2) using these Profitability and Tangibility as dependent variables in the similar setting. In Table 1.6, for the profitability test, the peer effects is significant for the group SDP-L1 (when focal firm loses a common customer to the rival in year t) as well as significant negative coefficient for the peers average firm size (Log(Sales)). This suggests that peer effects are more clearly identified when we include factors influenced by the competition and the size of the competing firms. We also find a positive and significant association between the focal firm's tangibility measure and its peers' average tangibility measure across all groups.

We also explore peer effects in dividend policies and measures of firms' riskiness. Table 1.7 shows estimates of equation (1.2) using the firms' dividend payout and two measures of riskiness: earnings volatility and bankruptcy risk, measured by the firm's Altman's Z-Score.

[Please insert Tables 1.6 and 1.7 about here]

It is clear that peer effects are strongly manifested in focal firms' dividend payouts across all self-disclosed peer groups. Peer effects are shown in earnings volatility for focal firms that lose customers to rivals. Finally, peer bankruptcy risk effects are shown for firms who share customers with rivals for a longer term (two-years).

1.6.2. Robustness Tests

We conduct several robustness tests. The first tests relate peer effects to peer group size. We subdivide firms into three terciles according to the number of self-disclosed peers (SDP) they disclose: The first tercile consists of firms with up to 3 peers. The second tercile consists of firms with 4-8 peers; the third tercile consists of firms with between 9 and 26 peers. We test equation (2) for all the capital structure factors over all sub-groups. Table 1.8 shows the OLS estimated coefficient of the corresponding peer effects variable ($\hat{\beta}$) in each model. The direction and significance of peer effects are in line with our main findings.

As a second robustness test, we look at the learning behavior of the firms. Learning effects are tested by augmenting the explanatory variable vector to include the lagged peer dependent variable

($\bar{y}_{i,t-1}$). Table 1.9 show the results of the augmented "learning model." We find significant learning effects for all self-disclosed peer groups except for group SDP-L1 (when the focal firm faces with loss of a customer to peers) for the book leverage variable. In general, the significant peer effects observed in Tables 1.4 and 1.5 are robust to the incorporation of our learning factor.

[Please insert Tables 1.8 and 1.9 about here]

1.6.3. Potential Selection Bias Issues

About one-half of the firms in our initial universe actually disclose their competitors. In many cases, firms' disclosure is at the request of SEC auditors under the provisions of SFAS 131 and IFRS 8 (Königsgruber et. al, 2020). Disclosed competitors are ultimately vetted by the SEC. To allow for possible revisions in firms' disclosed competitor lists due to SEC imposed revisions, we require all the relationships in the sample have at least two-year duration. Since ultimately the SEC must approve the disclosure list, we could argue that ultimate disclosures are exogenous. However, many companies do not disclose their competitors at all, stating to the SEC the risks of possible exposure to "competitive harm." Hence, it is still possible that peer disclosure could be determined endogenously by the firm, given the nature of industry competition. In this case, there may be selection bias in the results (Heckman, 1979).

To directly address this issue, we implement a Heckman two-step test as in Ali et al. (2014) to control for the self-selection bias. In the first step, we implement a probit model that predicts the likelihood of a disclosure of the competitors by the firm. In the second stage, we use the inverse Mills ratio derived from the first stage as an explanatory variable to correct the selection bias. Our identifying selector variable in the probit for firm disclosure is the industry concentration, measured by Herfindahl-Hirschman Index (HHI) of the firms' revenue in each three-digit SIC industry. The probit regression is estimated using HHI as well as the explanatory variables of the main model.

Column (1) of Table 1.10 reports the results of the probit model that estimates the likelihood of a firm disclosing its peers. Our results show that selection bias is not apparent for the book leverage models: the inverse Mills ratio coefficients are insignificant in all cases. The results for the market leverage variables are significant for three of the five groups: SDP, SDP-C1, and SIC. In these cases, the results are qualitatively similar to the earlier findings. As in table 4, market leverage peer effects remain significant.

[Please insert Table 1.10 about here]

1.7. Conclusion

In this study, we examine how the firm's revealed peers influence its financing decisions. Our research contributes to the growing finance literature that recognizes the network of connected firms and how the competitive environment affects firm behavior. The extant literature on corporate networks typically uses the focal firm's SIC codes to construct the firm's peer reference group. We demonstrate that this approach is fraught with measurement error. Indeed, based on a large sample of firms represented in the Compustat Database, in almost 60% of focal firms self-identified peers as well as persistent rivals have different industry affiliations, based on their SIC codes.

We implement an alternative peer identification scheme that designates peer groups as those explicitly disclosed by managers to shareholders. Our approach offers a tractable way to capture peer effects in a directional network setting. The results contrast with previous studies that find only weak evidence for peer effects on capital structure. We provide new insight to the channels in which peer effects are manifested. Peer effects are particularly strong when focal firms have persistent rivals, in the sense of supplying common customers for at least two consecutive years.

While constructing the firm's actual network poses a challenge, as we demonstrate, the approach can lead to more real-world insights about firm behavior. Our disclosed network approach can also be used to address other problems in corporate finance, in which revealed product market competition plays a significant role that can help bridge the gap between classical financial theory and observed corporate policies. This remains a topic for future research

Chapter 2: Corporate Dividend Actions and Self-Disclosed Peers

In this chapter, we approach to a challenging model of peer effects on firms' dividend policy when firm-level outcomes are measured as categorical observations. We show that managers are significantly under the influence of few self-disclosed diverse competitors rather than industry peers. Our test results show that a company's dividend actions are significantly correlated with its previous dividend decision as well as with the all the dividends decisions that announced by its aspirational peers' dividend actions 180-days prior to the dividend change announcement. We investigate and report marginal effects of different endogenous and exogenous determinants on the dividend change decisions.

2.1. Introduction

Companies are constantly interacting with other firms as their customer or supplier but they interact also with peer or rival firms in strategic decision-makings situations such as strategic alliance or cooperating agreements. According to economic theories individuals and social entities often have incentives to imitate each other, e.g., Duflo and Saez (2002) find that individuals' retirement savings behaviors are highly influenced by their peers. Graham and Harvey (2001) show that corporate executives and managers consider peer firms' decisions when choosing their own firms' policies. Lieberman and Asaba (2006) present a literature review and point out information, and rivalry-based theories to explain imitation behavior of the firms, which suggests that a firm may follow other firms that are perceived to have superior information, or imitate their rivals to maintain their market and competition grounds. Similarly, Fracassi (2016) finds that managers are influenced by their social peers when making corporate policy choices.

Despite theoretical support and reported evidences, empirical research on the causal effects of peer companies on the corporate policies has been lacking mainly due to availability issue of the data on corporate level and methodological challenges in estimating peer effects models. However, after pioneering study by Leary and Roberts (2014) and their introduced research methods, few interesting studies have been published in past five years and corporate payout policy and specially dividend payments are among one of the few topics that have been in the center of the peer effect study (Adhikari and Agrawal, 2018. Grennan, 2019).

In search of a universal explanation to firm payout policy and changes in dividend payments, many theories based on rational utility maximization and behavioral decision-making assumptions have been introduced, but empirical studies demonstrate inconsistent findings and the puzzles of corporate dividend policy seems to be unsolved (Brav et al., 2005). Based on the assumption of asymmetric information between agents and shareholders, the signaling theory of dividends argues that companies use dividends to convey information about their future prospect to the markets (Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985) where managers use dividends as a communication device. Jensen et al. (1992), Nissim and Ziv (2001), and Fama and French (2001) have reported positive relationship between profitability and dividend payouts which support signaling theory's claims. In contrast, Grullon et al. (2005) find that dividend changes do not convey any information about changes in future earnings. In the other hand, some researchers believe that the individual biases and managerial overconfidence in corporate payout decision can help to explain the motives behind dividend changes. Aggarwal et al. (2012) argue that the inconsistent findings on the relationship between dividends changes and future earnings are attributed to the variation of asymmetric information across public firms. They argue that the signaling theory of dividends is more likely to be supported among firms that have high level of asymmetric information. As, the results on the association between dividend changes and earnings remain inconclusive other branch of finance theories also try to explain this phenomenon. In line with behavioral finance theory, Deangelo et al. (2009) discuss that there is evidence of managerial signaling motives behind corporate payout policy. Deshmukh et al. (2013) argue that the overconfident CEOs overestimate the value of future projects and view external finance as costly, they are more likely to pay less dividends. As the divide between two prominent rational and behavioral theories of corporate decision making continues, recent studies explore peer effects to combine findings from the applications of these conventional theories. Peer effects theory claims that managers decisions which are sought to be behavioral, can be seen as a rational process of new and strategic information from their competitors as it helps managers to learn about the best practices as well as strategic directions of business environment and make their decision accordingly. Thus, under peer influence, such mimicking behavior and changes in directions can be a rational determinant of the corporate finance policy dynamics. In this regard, Grennan (2019) finds significant evidences for peer effects and demonstrates that corporate dividend decisions are influenced by their peer group's average outcome decision.

Peer effects studies claim that they find the common ground for traditional rational-based and their often-contradicting behavioral finance theories. However, the literature suffers from two main issues; first, as the name suggests a peer effects study relies on a static, coarse-grained and simplified industry-based classification where all the firms in the group considered similar. Second, the presence of the estimation challenges - namely "identification" and "reflection" introduced by Manski (1993) - is persistent and all of the previous studies depend on finding an instrument variable(s) that can solve these issues in a two-stage least squares analysis setup. In this chapter, we argue that both of the above-mentioned issues can be addressed by applying a more transparent data about firms disclosed and business relationships, hereafter called business network, firm network, or company network interchangeably. We believe that the firm network plays important role in forming firm-specific peer groups. By putting each firm at the center of peer group, as the focal entity, we can diminish the classic group definition issues and at the same time keep information about the firm's peers. Moreover, the network represents information and influence channels and captures peer group dynamics around each firm separately. Furthermore, recent advancements in peer effects econometrics shows that under weak assumptions, a relational and firm-specific structure can solve the methodological challenges of estimating peer effect models.

In this chapter, we examine whether firms are influenced by their self-disclosed competitors' dividend announcements when making their payout announcements. Consistent with previous studies, we find that a firm's decisions on whether to increase or decrease dividends are significantly influenced by few disclosed competitors, often from different industries, rather than many industry peers. To examine the heterogeneity in peer effects, we use a longitudinal multinomial logit model with endogenous, lagged endogenous and exogenous firm and peer level explanatory variables. To overcome identification concerns, we follow Bramoulle et al. (2009, 2020) and apply a modified network-based identification technique, using competitor disclosure direction to satisfy requirements of the estimation method. To explain the motivation behind this mimicking behavior we apply explanatory variables' marginal analysis.

To our knowledge, this is the first study that attempts to identify the causal effect of peer firms on a firm's payout policies and the closest studies to ours are Adhikari and Agrawal (2018) and Grennan (2019). Our study differs from previous studies in several ways. First, we examine multiple sources of dividend announcement with detailed classifications, second, we use much smaller and firm-specific peer group, which is among the first studies to identify peer effects from firms' point of view and channels that they consider important. Third, we consider three outcomes for dividend related decisions rather than binary outcome and use logit-based models rather than linear models and OLS to explore peer effects, which enables us to explain marginal effects on both overall and decision levels. Forth, our results show that the mimicking behavior is derived by force similar to conformity theory of social interactions. The rest of the chapter is organized as follows. Section 2.2 briefly discusses the relevant literature. Section 2.3, overviews peer effects econometrical challenges and identification strategies. Section 2.4, introduces the network-based modeling and identification strategy, and presents the hypotheses and empirical methodology to study peer effects in dividend payments decision. Section 2.5 presents sample data and the main empirical findings. Section 2.6 concludes the chapter.

2.2. Literature Review

This chapter explores network-based peer effects on corporate dividend policy, which is in conjunction of three research topics that each has been in the center of theoretical and empirical studies separately in the recent years. Although it was originally introduced in sociology, peer effects have been emerged recently in finance domain as a unified approach to combine conventional and often contrasting rational and behavioral theories in explaining management decisions and corporate policies. The main assumption of peer effects studies is that entities (e.g. firms, banks, managers, individuals, and etc.) are defined in an environment (economic, business or social) setting and as interacting with other entities, they can be member of explicit or implicit groups formed along with other entities that share same interests or qualities and therefore they can learn from other co-members called peers. As long as such peer groups are identified and contextual and member-level measures collected, one can explore the group influence on the characteristics or outcome variables of these rational entities, the outcomes that often had been behavioral or irrational. In this section, we provide a short literature review on payout and dividend theories, peer effects studies, and network models in finance.

2.2.1. Dividend Policy Theories

Starting with Lintner's (1956) survey, it is known that managers may change their dividends in a smooth and gradual manner over time, towards a target payout ratio. Bhattacharya (1979) introduces a dividend signaling model where corporate cash dividends can be considered as a mechanism to reduce the asymmetric information between the agent and the shareholders and managers use dividends as a signal of future cash flow. The earlier works on the relationship between dividend changes and stock prices reveal that the stock price reacts positively (negatively) to the announcement of dividend increases (decreases) which is in line with the signaling theory (Asquith and Mullins, 1983; Kane et al., 1984; Nissim and Ziv, 2001; Gunasekarage and Power, 2002). However, the relationship between dividend changes and future earnings has not been uniform and empirical results reveal mixed conclusions. DeAngelo et al. (1996) argue that dividends are not reliable signals of future earnings which is inconsistent with the dividend signaling theory. Benartzi et al. (1997) shows that there is a high correlation between dividend and concurrent earnings changes but uncorrelated with changes in future earnings. Nissim and Ziv (2001) study the information content of dividends paid in the period of 1963 to 1998 and show that dividend changes are positively associated with future earnings changes. In more recent study, Ham et al. (2020) find that dividend changes contain predictive information about next quarter earnings, but find it difficult to strongly support the claims voiced by signaling theory mainly due to timing issue of dividend related stock returns. In the other hand and according to agency cost theory, a conflict of interests arises as a result of the separation of ownership and control due to the fact that agents do not always act in the interest of shareholders (Jensen and Meckling, 1976). It is often cited that managers distribute dividends to commit not to use firms' free cash flows in private benefits and to eliminate the over-investment problem (Jensen, 1986; Crutchley and Hansen, 1989; Jensen et al., 1992; Alli et al., 1993) where paying high dividends reduces the internal cash flow and forces firms to seek external financing from the capital markets which imposes further monitoring by the capital markets (Easterbrook, 1984). Moreover, the dividend policy can also be a source of potential conflict between shareholders and bondholders, where shareholders set a high level of dividend in order to seize wealth from bondholders which reduces the amount of funds available to bondholders (Jensen and Meckling, 1976). Several studies have attempted to provide an explanation for dividend payments through addressing agency costs and ownership concentration. Fluck (1999) shows that an increase in the external shareholders' power might encourage managers to pay higher dividends in order to commit not to waste firm's resources on private benefits. In the other hand, Grinstein and Michaely (2005) investigate the association between institutional holdings and payout policy and report that institutional holdings are not related to dividend policy, which is consistent with Brav et al. (2005) study that about 87% of executives do not agree with the use of dividend policy as a mean of imposing self-discipline. Similarly, Bartram et al. (2012) find that firms make higher payouts when they have lower ownership concentrations.

2.2.2. Channels of Peer Effects in Dividend Payments

According to Cooper and Rege, (2011) there are three channels which peer effect may work and change an entity's behavior: learning, rivalry and conformity. Group learning occurs when the information set is modified through the interactions between an entity and its reference group. Competitive rivalry refers to the positive relationship between peer group performance and the marginal utility of entity’s performance, and conformity refers to preferences over action sets resulting utility increases when the outcome is similar to the peer group’s results. Zeckhauser et al. (1991) suggest that free riding in information acquisition or relative performance evaluation for managers may lead to herd behavior in capital structure policies. Free riding in capital structure decisions can help low quality and smaller firms avoid the cost to derive firm-specific information and especially the information of those industry leaders (Bikhchandani, Hirshleifer, and Welch, 1998). However, the mimicking behavior can be observed among firms with similar qualities due to either conformity or rivalry reasons. As industry interactions indicate direct and indirect impacts on the firms, the rivalry-based theory of imitation is seen as a rational outcome to previously considered behavioral decisions. Recent studies report significant peer effects on financial policies, such as capital structure, cash holdings and dividend policy. Leary and Roberts (2014), argue that industry interactions between a firm and its peers influence the firm’s financial policy and find significant correlation between focal firm’s capital structure and their peer group’s. Adhikari and Agrawal (2018) find significant evidences for peer pressure and influences on corporate payout policies and argue that in face of product market competition and better information environments the peer effects shows higher magnitudes. Similarly, Grennan (2019) argue that dividend change decisions of peer firms are among significant determinants of dividend policy of the focal firm specially in the case of dividend increase when peer firms’ dividend increase lead to %16 increase in payout ratios of the focal firms. Gyimah et al. (2020) study peer effects on firms’ trade credit policies and find significant evidence for mimicking behavior specially in the presence of market competition and uncertain information environment. In the other hand, Kaustia and Rantala (2015) argue that firms often mistake noise for a signal and overreact to peers’ policy and outcomes and therefore the overall peer effect is not significant.

The literature on the econometrics of social interactions is vast, and this section cannot cover all important studies in this literature. We refer readers to see some of well cited reviews, and studies like Manski (2000), Glaeser and Scheinkman (2001), Scheinkman (2008), Durlauf and Ioannides (2010), Blume et al. (2011), Graham (2015), and de Paula (2017). However, we follow two recent publications on peer effects econometrics (Bramoulle et al, 2020; Kline and Tamer, 2020) as the reference and provide a short summary on novel econometrics to address the estimation challenges: reflection, and identification. As first documented by Manski (1993), the reflection issue relates to disentangling the peer effects from inter-influence between an entity[7] and its peers, and the identification issue is related to point estimation of the parameters in the regression model when there is no exclusion restriction.

2.2.3. The Linear-in-Means Model in Peer Effects (or Social Interaction) Studies

In corporate finance literature, peer effects models are often formulated as linear regression equations (Leary and Roberts, 2014 and many other studies) where financial decisions or characteristics of the focal firm is a response function, $y_{ig} = f_{ig}(d_{ig}, d_{-ig}, y_{-ig})$, that relates the outcome y_{ig} of firm i in group g to the treatment d_{ig} of firm i in group g and the outcomes, y_{-ig} , and treatments, d_{-ig}, of other firms in group g. Depending on the problem, a response function can include different variables; for example, the response function could be written in "reduced form" to depend only on the treatments but not the outcomes of the other entities in the group. In a model of infectious diseases, $f_{ig}(.)$ might be the health outcome of individual i as a function of the vaccination status of individual i, the vaccination status of the other people in individual i's reference group, and health outcomes of the other people in individual i's reference group. A

[7] The terms entity, agent, and firm will be used interchangeably, in this study.

response function can take a non-linear format, but in this section, we will focus on specific linear model known as linear-in-mean model. Most empirical models of peer effects studies are taking linear-in-mean equation form following group interactions model proposed by Manski (2009). The linear-in-means model can have many variations but they are very similar in terms of following specification:

$$y_i = \alpha + \gamma x_i + \delta\left(\sum_{j \neq i} g_{ij} x_j\right) + \beta\left(\sum_{j \neq i} g_{ij} y_j\right) + \epsilon_i \tag{2.1}$$

where y_i is the outcome of entity *i*, x_i are "exogenous" or "explanatory" variables, and ϵ_i are exogenous unobservable related to entity *i*. Similarly, x_j and y_j represent exogenous and response respectively for all other entities in the entity *i*'s peer group. Peer influence is accommodated in the model as the average of all other entities observed factors via $\delta\left(\sum_{j \neq i} g_{ij} x_j\right) + \beta\left(\sum_{j \neq i} g_{ij} y_j\right)$, with g_{ij} as the measure of the influence of entity *j* on entity *i* where usually $g_{ij} = 0$ means no influence and $g_{ij} = 1$ means there existence an influence or information channel from entity *j* to entity *i* or in other words entity *i* learns from entity *j*. The linear-in-mean equation (2.1) can also be re-written in matrix format as follows;

$$\boldsymbol{Y} = \alpha + \gamma x + \delta \boldsymbol{G} x + \beta \boldsymbol{G} \boldsymbol{Y} + \varepsilon \tag{2.1.a}$$

where $\boldsymbol{Y} = (y_1, \ldots, y_n)'$, $x = (x_1, \ldots, x_n)'$ and $\varepsilon = (\epsilon_1, \ldots, \epsilon_n)'$. Network based representation of peer effects can be written as follows:

$$\boldsymbol{Y}_N = (\boldsymbol{I} - \beta \boldsymbol{G})^{-1}(\boldsymbol{1}_{N\times\boldsymbol{1}}\alpha + X_N\gamma + \boldsymbol{G}X_N\delta + \varepsilon_N) \tag{2.1.b}$$

when the entity and peers are considered in a network (a single group). So, if network contains *N* entities, $\boldsymbol{Y}_N$ will be $N \times \boldsymbol{1}$ vector of y_i variables, and X_N is a $N \times k$ matrix that contains vectors x_i for different entities in each row, where k is the dimension of the exogenous explanatory variables. And ε_N is an $N \times \mathbf{1}$ vector that stacks the elements ϵ_i, and $\boldsymbol{G}$ be the $N \times N$ matrix of weighted links, with g_{ij} in row *i* and column *j*. The main assumption in equations (2.1), (2.1.a), and (2.1.b) is that unobservable or latent factors (ε_N), observed characteristics of the focal entity and peer group (X_N) and network relationships ($\boldsymbol{G}$) are not correlated such that $\mathbb{E}(\varepsilon_N|X_N, \boldsymbol{G}) = 0$, which is knows as the exogeneity restriction assumption.

Lemma 2.1: With $|\beta| < 1$ in equation (2.1.b), $(\boldsymbol{I} - \beta\boldsymbol{G})$ will be strictly diagonally dominant, and non-singular. Therefore, there exist a reduced form for equation (2.1.b).

Under the non-singularity and exogeneity conditions, the reduced form is achieved, as follows:

$$\mathbb{E}(\boldsymbol{Y}_N|X_N, \boldsymbol{G}) = (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}(\mathbf{1}_{N\times\mathbf{1}}.\alpha + X_N\gamma + \boldsymbol{G}X_N\delta) \tag{2.2}$$

and therefore

$$\mathbb{E}(y_i|X_N, \boldsymbol{G}) = e_i'(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}(\mathbf{1}_{N\times\mathbf{1}}.\alpha + X_N\gamma + \boldsymbol{G}X_N\delta) \tag{2.2.a}$$

where e_i is the unit vector of length N, with 1 as the *i* th element and 0 as every other element. After applying matrix calculus rules, the effect of the exogenous variables on the outcomes can be

calculated as follows;

$$\frac{\partial\mathbb{E}(y_i|X_N, \boldsymbol{G})}{\partial X_N} = \gamma e_i'(\boldsymbol{I} - \beta\boldsymbol{G})^{-1} + \delta e_i'(\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\boldsymbol{G} \tag{2.2.b}$$

$\frac{\partial\mathbb{E}(y_i|X_N, \boldsymbol{G})}{\partial X_N}$ is the marginal effect of the *k*th explanatory variable of entity *j* on the outcome of entity *i*. Equation (2.2.b) shows that the effect of X_N depends on all of the model parameters (γ, δ, β) and network relationships ($\boldsymbol{G}$), in other words X_N has at least three interrelated effects on y_i, as follows: 1) by holding the outcomes of all entities in the group fixed $(\delta = 0, \beta = 0)$ the linear-in-mean model converts to simple regression model and consequently we have $\frac{\partial \mathbb{E}(y_i|X_N, \boldsymbol{G})}{\partial x_N} = \gamma e_i'$; this means that only entity i's exogenous variables (X_N) are effecting the outcome of entity i (y_i). In case of $\delta \neq 0$ and $\beta \neq 0$, the changes in X_N will influence outcome of other entities in the group/network which leads to indirect effect(s) on y_i. 2) By holding the outcomes of other entities fixed ($\beta = 0$), we have $\frac{\partial \mathbb{E}(y_i|X_N, \boldsymbol{G})}{\partial x_N} = \gamma e_i' + \delta e_i'\boldsymbol{G}$; this means that through δ and $\boldsymbol{G}$, other entities' exogenous variables of other entities have direct effects on y_i, but if $\beta \neq 0$, then γ, δ and $\boldsymbol{G}$ can not identify the effects of the peer's exogenous variables on y_i. 3) If none of the parameters fixed, the presence of δ and $\boldsymbol{G}$ indicates that the exogenous explanatory variables of peers in the network have direct effects on their own outcome first and then the effects of peer outcomes on other entity outcomes leads to an indirect effect on y_i. In other words, it is difficult to separate the source of identification for group effect's variable, defined by average of the outcomes, and the effect of group on its members' outcomes. This is same as "reflection" issue documented first by Manski (1993). In the literature, researchers have considered many extensions of the linear-in-mean models and have introduced different identification strategies to overcome results this "reflection" issue in order to point estimate the parameters of the model. In next section we introduce few of most popular of these methods.

2.2.4. Identification Strategies of Linear-in-Means Model

Instrument Variable Strategy. From mathematical point of view, the empirical study model can be written as a system of simultaneous equations, and such system can be identified as long as it could satisfy the *exclusion restriction condition* (Wooldridge, 2010). However, in case of linear-in-mean model with group-based peer formation or fully connected network, the system of equations does not yield the exclusion restriction and therefore its parameters can not be identified separately. In such system of equations, if one can incorporate new entities that are not connected , $\exists i, j \ that \ g_{ij} = 0 \ (\sim\beta_{ij} = 0)$, the system will meet the exclusion restriction condition and therefore there exist an instrumental exogenous variable (IV) that can identify the parameters – weekly or strongly depending on the choice of IV. In this strategy, the instrument variable should be exogenous to focal entity but correlated with peer level endogenous variables. Upon finding such IV, a two-stage least squares analysis is usually carried out to separate entity level endogenous factors from group level endogenous factors and specify the model. Finding such instrumental variable(s) as the identification strategy has been the key to address the estimation challenges of the empirical peer effect studies. For example, inspired by Leary and Roberts (2014), recent studies adopt peer firms' equity shock with a lagged idiosyncratic component of the peer firms' stock returns, as the instrumental variable.

Network Strategy. Bramoulle et al. (2009) introduce a network-based identification method and formulate sufficient conditions for point estimation of the parameters in the linear-in-mean model. Their strategy assumes that for each connected pairs of entities, there is a third entity where it is connected to one of them (a triad relationship). The third entity effects the un-connected entity indirectly via its connection to the other entity of the pair, for example for three entities i, j and h, the connections are $g_{ij} = 1$, $g_{ih} = 0$, and $g_{jh} = 1$. Therefor exogenous variable x_h is not part of the linear-in-mean equation of y_i but it is relevant to y_j which is part of the linear-in-mean equation of y_i. Since $x_h$does not have direct effect on y_i, it can be used as an IV in order to specify the model. This is very similar to IV strategy, however it's commonly accepted that the fully connected network is rare and there are plenty triad structure in a network of interactions and therefore it is most likely that network has enough uncorrelated exogenous observations that are uncorrelated with the focal entity and at the same time are not part of the peer group and therefore the identification issue is almost solved by the design and structure of the peer groups in network structure. It is clear that this method relies on accuracy of structure of the network and identified relationships between entities. Bramoulle et al. (2009) have proven that in the network without isolated member, when the network is the union of all entities (transitive network), the parameters from equation (2.2.b) are linearly dependent which is sufficient conditions for identification of the linear-in-mean model.

Group Size Strategy. other studies attempted to introduce possible sources for identification of the linear-in-mean model by using a variable information in group level. For example, Davezies et al. (2009) show that variation in group size can result in point identification. The intuition for why variation in group size can solve the identification issue can be explained by the marginal effects from the linear-in-means model in Eq. (2.2.b) where different group size means that $\boldsymbol{G}$ would be different for groups of different size and therefore, the effect of the exogenous explanatory variables on outcomes is different in groups with different sizes. A size-based identification strategy works under two assumptions that the same model parameters apply to all sizes and there is sufficient variation in group sizes in order to generate valid estimators otherwise it may yield weak identification.

Utility Maximization. Kline and Tamer (2012) study partial identification of the best responses in complete information binary games. These games involve the decision between two possible actions per entity. The best response function describes the utility maximizing decision of a particular individual as a function of any counterfactual specification of decisions of the other entities. Thus, the individual's outcome is a response function, $y_i(.)$, that relates the utility maximizing of individual *i* to the outcomes $y_{-i}(.)$, of other individuals in group.

2.3. Hypotheses and Empirical Model

According to Grennan (2019), industry-influenced dividend changes are significant and can be attributed changes in the adjustment period and the target payout ratio. Our main intuition is that peer effects on corporate dividend actions take place from a smaller and more targeted group of companies that the focal firms tend to communicate them via different means rather than a large group of firms in the same industry. Our main hypothesis is that a change in a self-disclosed peer group's dividend payment is going to affect the focal firm's decision in its next announcement for any of the reason that we explained in previous section (learning, rivalry, and conformity). Since the peer group size is much smaller than industry reference groups, we hypothesis that the main motivation for mimicking behavior is conformity. A dividend decision outcome falls in three categories of "increase", "decrease" and "not-changed or affirmation". For these nominal outcomes, we want to estimate the probability of firm *i* dividend announcement that indicates one of increase (d_1), decrease (d_2) or affirmation (d_3) decisions. The probability function can be written as follows:

$$p_{it}(y_{it} = d_n) = F(\alpha + \gamma x_{it} + \delta \bar{x}_{-it} + \beta \bar{y}_{-it} + \lambda y_{i,t'} + \varepsilon_{it}) \qquad (2.3.a)$$

or

$$p_{it}^{d_n} = \frac{\exp(U_{it}^{d_n})}{\sum_d \exp(U_{-iT}^{d})} = \frac{\exp(\alpha+\gamma x_i+\delta \overline{x_{-\iota T}^{d_n}}+\beta \overline{y_{-\iota T}^{d_n}}+\lambda y_{i,t'}+\varepsilon_{it})}{\sum_d \exp(\alpha+\gamma x_i+\delta \overline{x_{-\iota T}^{d}}+\beta \overline{y_{-\iota T}^{d}}+\lambda y_{i,t'}+\varepsilon_{it})} \qquad (2.3.b)$$

$p_{it}^{d_n}$ is the expected probability of firm i's dividend related d_n action at time t and $F(.)$ is a distribution function. Time relate conscripts are t, t', and T; with t and t'denoting current and previous dividend announcement date of the focal firm, respectively, and T representing learning time window related to the focal firm's time t announcement where $T = [max(t - 180,\ t'),t)$.

$\overline{x_{-\iota t}^{d_n}}$ is the ratio of exogenous variables of peer firms who announced similar decision as the focal firm's time t during period T and $\overline{y_{-\iota t}^{d_n}}$ is the ratio of the peer firms who announced similar decision as the focal firm's decision at time t during period T, comparing to all of the focal firm's peers during time period T. Equation (2.3.b), is similar to multinomial choice model of Brock and Durlauf (2002, 2007) study but it is difference since the peer group outcomes are known to the firm at the time of the decisions. In similar model, Durlauf and Ioannides (2010) suggest that in the case of unknown peers, the non-linearity of peer outcome probability can be relaxed from the model. Brock and Durlauf (2007) demonstrate that the reflection problem does not apply in multinational choice models when the individuals have prior information about the distribution of the endogenous and latent factors, and argue that the assumption of logit error term are not strictly essential in this scenario. Figure 2.1 depicts a view of the current study's design and shows how do peer effects work?

[Please insert Figure 2.1 about here]

At this point, we are able to establish that under relatively weak assumptions the application of a network structure is sufficient to solve the identification issue. Moreover, the empirical multinomial choice model with the information flow between agents eliminates the reflection issue. Although, the multinomial choice model in Eq. (2.3.b) can be estimated by a reduced linear function but presence of time dimension leads to computational challenge of parameter estimation. As the empirical model of current study takes a form of longitudinal multinomial logit model that uses a carefully hand collected network data, one my argue that the peer group selection based on disclosed information leads to the non-random sorting of firms into groups which can lead to an estimation bias. Although this issue can be addressed technically in the model by modifying the assumptions such as imposing exclusion restrictions on the structural model (Graham and Hahn, 2005) or by introducing variance constraints on the error terms independent to the group size (Graham, 2008), but we believe that it is not a major issue in our study for these reasons: First, we believe that selection bias issue is relevant in studies that specified groups provides a real and separable interaction environments such as schools or workplaces. However, in the case of disclosed competitors, peers are identified out of sample and based on the publicly available textual information, and groups are subjective to the firm that disclosed the information. Even with subjective definition of peer groups, any major hidden or ignored common factors could be measured about the economic entities mainly because the regulated business environment where agents and companies are mainly interested in economic utility or profit maximization. Second, by eliminating pairs with mutual disclosure, we control the influence channels to be strictly uni-direct. Third, the use of non-random groups such as static or dynamic industry classification are common and accepted in the corporate finance literature. Regardless, we apply a robustness test to check existence of selection bias by applying a randomize SIC based assignment within and across groups and test a hypothesis for group-fixed effects presence. In contrast to exogeneity assumption, $\mathbb{E}(\varepsilon_N | X_N, \boldsymbol{G}) = 0$, it may seems that there is a valid argument for correlated effects by common unobserved information shocks (to the group as a whole) that may influence the outcome of the focal firm and its peers simultaneously, $\mathbb{E}(\varepsilon_N | Y_N, \boldsymbol{G}) = 0$, can prevent the point identification of the exogenous effects from the endogenous effects in the linear–in–means (Brock and Durlauf, 2001; Blume et al., 2011; Moffitt, 2001). However, we show below that even in the presence of correlated effects, if there is enough variation in the adjacency matrix across rows, it is possible to separately identify the endogenous effects from the exogenous effects. This provides an extension to Brock and Durlauf (2007)'s symmetric influence case. As they do, we do not impose the rational expectation condition between the expected behaviors and the characteristics of a group, but rather we take these vectors as known regressors.

The rest of the research method in this section follows Grennan (2019) study however we define dividend changes in three categories; increase, decrease, and affirmation (not changed) using change in indicative total dividend payout. An increase of 1% or more in respect to last paid or announced dividend constitutes an “increase” event and a decline of 1% or more is considered a “decrease” event. We relax the requirement for co-direction of the measure in the robustness analysis. We modify Eq. (2.3.b) to test our hypotheses in two test structure; Multinomial Logit Model, and Binary Logit Model:

A) Multinomial Logit Model

$$y_{i,t}^{div} = \alpha + \gamma x_{i,t} + \delta \bar{x}_{P_i^{div},T} + \beta \bar{y}_{P_i^{div},T} + \lambda y_{i,t'}^{div} + S_P + v_t + \epsilon_{i,t} \text{ ,} y_{i,t}^{div} \in \{inc,\ dec,\ aff\} \qquad (2.4)$$

where $y_{i,t}^{div}$ is the dividend decision of firm *i* in time *t* where a decision can be increase (inc), decrease (dec), or affirmation (aff) of previous paid dividend. $\bar{y}_{P_i^{div},T}$ represents peer influence, which is the ratio of firm *i*’s peers with same outcome in period of $T = [max(t\text{-}180,\ t'),t)$ where t' and t are the previous and current dividend announcement dates of the focal firm i. It should be noted that in a regular linear-in-model model peer influence is an endogenous factor, however because of time difference between the decisions, the peer influence is not an endogenous factor in our model as long as we control that $y_{i,t'}^{div}$ is not effecting $\bar{y}_{P_i^{div},T}$ with uni-directed or non-mutual disclosures . $x_{i,t}$ is a vector of the observable firm-specific exogenous factors and $\bar{x}_{P_i^{div},T}$ is vector of averages of those factors of peer firms with same decision group $\bar{x}_{P_i^{div},T}$. S_P captures fixed effect of peer group size, and v_t captures time fixed effect, and ϵ_{it} is the unobservable component of the model.

B) Logit Models

We can also decompose the multinomial logit model in equation (2.4) to binary logit models and have two separate testing model for dividend "increase" and "decrease" outcomes[8] and estimate the parameters of each model using longitudinal logistic regression methods. So. we can have two following models for decision set $div \in \{inc, dec\}$ where inc and dec indicate "increase" and "decrease" decisions respectively:

$$y_{i,t}^{inc} = \alpha + \gamma x_{i,t} + \delta \bar{x}_{P_i^{inc},T} + \beta \bar{y}_{P_i^{inc},T} + \lambda y_{i,t'}^{inc} + S_P + v_t + \epsilon_{i,t} \text{ , } y_{i,t}^{inc} \in \{0,1\} \tag{2.5.a}$$

$$y_{i,t}^{dec} = \alpha + \gamma x_{i,t} + \delta \bar{x}_{P_i^{dec},T} + \beta \bar{y}_{P_i^{dec},T} + \lambda y_{i,t'}^{dec} + S_P + v_t + \epsilon_{i,t} \text{ , } y_{i,t}^{dec} \in \{0,1\} \tag{2.5.b}$$

2.3.1. Identification Strategy

The model in the Eq. (2.4) is a fixed-effect longitudinal multinomial logit model with lagged endogenous factor and heterogeneity assumption, which to best of our knowledge there is no proposed estimation method nor programming package at time of writing this report. However, we can reconstruct Eq. (2.4) to fit in the form of a longitudinal choice model with three exclusive binary choice alternatives at each announcement date.

We also follow network-based identification strategy, since the self-disclosed peers data can be used to construct an uni-directed network of relationships. In industry-based peer group formation, a SIC code is common between members but in a uni-directed network peer groups are

[8] A third model for "affirmation" announcements is redundant due to collinearity with other two models.

firm-specific, meaning that each focal firm has a unique set of peers at time of the dividend announcements. Thus, we can relax standard industry fixed-effects from the models. Moreover, because observations are in daily basis the consideration of time fixed effect also can be relaxed. We use an improved directed network based identification strategy, where the corresponding relationship matrix, $\boldsymbol{G}$ is strictly "non-invertible" and therefore $(\boldsymbol{I} - \beta\boldsymbol{G})$ in Eq. (2.1.b) will have an invertible matrix which help us to replace equation (2.1.b) with new equation where response variable is a function of parameters, network relationship and exogenous characteristics of peer firms, as follows:

$$\boldsymbol{y} = \frac{\alpha}{1-\beta}\mathbf{1} + (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}(\gamma\boldsymbol{I} + \delta\boldsymbol{G})x + (\boldsymbol{I} - \beta\boldsymbol{G})^{-1}\varepsilon \qquad (2.6)$$

with the exogeneity assumption $\mathbb{E}(\varepsilon_i|\alpha, x, \boldsymbol{G}) = 0$, we keep characteristics x and the network $\boldsymbol{G}$ exogenous relative to outcome $\boldsymbol{y}$. With $\delta + \gamma\beta \neq 0$ assumption, the sufficient conditions for identification of equation (2.6) is if and only if $\boldsymbol{G}$ is a transitive, connected, and not-complete network - according to Bramoulle et al. (2009).

2.4. Peer group definition and Sample Data

Previous studies use three digits static SIC codes to define firms' peer reference group as the most convenient method. However, simple SIC-based group identification has few research limitations (Fort and Klimek, 2016) among those we can address following issues: first, in a static SIC code classification, company's past reference groups was ignored. It is assumed that a firm has one SIC code throughout the study and therefore the peer groups composition stays fixed in a longitudinal analysis. A simple survey on Compustat data set shows that 16% of all firms and 17% of dividend paying firms has different historical SIC codes during 1980-2018 years. We call this "temporal dynamics" of peer group formation. Second, companies have secondary SIC codes since they often have different line of businesses specially in service sectors. Table 2.1 presents a descriptive summary of changes in primary three-digit SIC code of Compustat firms between 1980-2019 years.

[Please insert Table 2.1 about here]

Using a single SIC code ignores other potential influence channels that companies may have via other SIC codes. We call this "business dynamics" of peer group formation. Third, class-based peer group formation, means that firm and its peers belong to one class (industry) and therefore each firm in that industry observe all other firms' actions. This approach, ignores the differences between influence channels that are considered by small and large firms in the same industry.

Hoberg and Phillips (2010, 2014) use a text-based analysis on 10-K filings in order to quantify similarities between business and products descriptions of the firms, and provide a dynamic annual firm classification that allows each firm to be seen in scored relationships with its competitors according to similarity between their business and product/service descriptions. Although, this approach fixes two of the above-mentioned issues, but since the overall network structure is bi-directional it fails to provide information on direction of peer influence and learning channels. In the other hand, there exist regulations for disclosure of benchmark peers in CEO compensation payments which is established after SEC's disclosure requirement in 2006[9]. We argue that the disclosed compensation peer group is not good source for specifying reference peer group that effects corporate financial policies because this practice falls in the corporate governance domain

[9] "... whether the registrant engaged in any benchmarking of total compensation, or any material element of compensation, identifying the benchmark and, if applicable, its components (including component companies)." August 29, 2006, SEC final rules 33-8732a, Item 402(b)(2)(xiv)

where it was implemented by compensation committees with independent members. Figure 2.2, shows graphical differences between previous methods and our method.

[Please insert Figure 2.2 about here]

Inspired by Hoberg and Phillips (2010), we look for competitors' that are mentioned a company's 10-K filings. With this approach, we are able to form firm specific peer group where the direction of rivalry and therefore peer influence can be specified. Previous studies rely on the SEC's SFAS 131 regulation[10] in order to identify customer-supplier relationships, but there is no requirement for disclosing the business and market competitors, however we observe that in Annual Report to Shareholders (ARS), 10-K filing as well as during analyst conference calls, managers tend to mention the name of other companies as part of their risk related discussions, where many of these companies can be identified as the competitors. We use this information and complementary news and client announcement data to create a network with the source firm in the center and directed connections to the customer, supplier and rival firms. The main text source of peer extraction of current study is the SEC Edgar filing database and other complementary sources are CapitalIQ, FactSet's Press Release and Conference Call. Different data and text mining algorithms were used in order to detect firm names in the text and validate the identified relationships (See Appendix B for more detail). Observations were manually inspected to match identifiers with the names provided in the WRDS and FactSet's name conversation tool. Also, as corporate networks evolve over time due to link additions and deletions from entering or terminating agreements, we captured history of business relationships in yearly basis. Consistent with the literature, we applied following restrictions: Firm i and j should have the relationship in

[10] which requires U.S. firms to disclose the existence and names of customer firms representing at least 10% of their total sales

at least two consecutive years to be included in the sample. Each firm must have at least one year of financial data (with non-missing values for "Total Asset" and "Sale" variables) prior to year of the observation and in the same year of the observation. Bi-directional observations (mutual disclosures) are removed from the sample in order to maintain consistent observations where only focal firm acknowledges the existence of the competition.

The base universe of the firms is based on dividend paying publicly traded U.S. firms between 2004 and 2017. The dividend announcement data is collected from two different sources. First, we collected the action-based announcement data from Key Development section of Capital IQ's NetAdvantage website where for each firm there is section that list historical corporate actions and dividend related announcements are characterized as Increase, Decrease, Special, Initiation, Cancellation events. We also used CRSP data to calculate Dividend Payout Changes. Financial and equity ownership data is from FactSet. Consistent with the literature, financial firms, utilities, and Real Estate Investment Trusts (REITs) are excluded from the sample (three-digits SIC codes of 490-499 and 600-699). Table 2.2 shows a statistical summery of different group formations.

[Please insert Table 2.2 about here]

We use 180 days window to calculate the peer group's average of increase or decrease dividend announcements in the time window. Figure 2.3 depicts a visual comparison of focal firms' average dividend increase (decrease) announcements with the peer groups average number of similar announcements. Table We also consider firm level exogeneous variables that are commonly used in the dividend payout literature such as; leverage (Myers, 1984), free cash flow (DeAngelo, et al., 2006), tangible assets (Harris and Raviv, 1991), profitability and market-to-book ratio (Fama and

French, 2002) institutional equity ownership and concentration (Grinstein and Michaely, 2005). See Appendix A for the variable definition.

[Please insert Figure 2.3 about here]

2.5. Results

In this section we present the empirical test results and evidences for influence of self-disclosed peers on dividend decisions of the focal firms. Table 2.3 presents the results of testing firms' responses to peer firms' dividend changes, testing a multinomial logit model on Self-Disclosed Peers (SDP) and industry peers (SIC) in Panel A, and testing binary logit model of dividend increase decisions in Panel B and decrease decisions in Panel C. The findings show that SDP has a significant influence on dividend decisions of the focal firms in comparison to SIC peers, especially in case of dividend increase announcements. Columns 1 and 3 show estimated coefficients of SDP and SIC peer effects without considering firm's previous dividend action. The 41% (12%) reported in column 1 (3) of Panel A is interpreted as the increase in likelihood of a focal firm is changing its dividend payments in the same direction of its SDP (SIC) peers' dividend changes measured in standard deviation unit. Statistical evidence for dividend SDP (SIC) peer effects indicates significance at the 99th (90th) percentile. Table 2.4 shows likelihood of changes in dividend actions under the SDP peer influences.

[Please insert Tables 2.3 and 2.4 about here]

Table 2.5 includes firm-specific, and peer average covariates as well as firm fixed and time fixed effects and shows the estimated results for the Eq. (2.4) using two estimation methods; 1) mixed logit choice model, and 2) Network-based estimation method. The firm-specific covariates include institutional ownership concentration and level, market-to-book, profitability, tangibility, and leverage. The peer-specific covariates include the same variables as focal firm and are computed as average values. The test results show that the dividend increasing peers' effects estimate for dividend increase decision/outcome is larger than dividend decreasing peers' effect for dividend decreases, indicating that self-disclosed peers have more influence when it comes to dividend increase decisions.

[Please insert Table 2.5 about here]

Table 2.6 presents the details of firm-specific coefficient estimates from Table 2.5 for dividend increases and decrease outcome in two separate binary logit models from Eq. (2.5.a) and Eq. (2.5.b). We report several important findings in Table 2.6; first, peer effect does not change other dividend firm-specific determinants where firm-specific variables such as institutional ownership, market-to-book, tangibility, and book leverage can be found statistically significant. Second, Table 2.6 – also Table 2.5 - shows where peer influence ranks relative to other firm-specific and peer-specific covariates in each outcome scenarios. For example, in column 4 (the binary outcome of dividend increase), dividend increasing peers' dividend action effects and institutional ownership has coefficients of 0.603 and -1.03 respectively, dividend decreasing peers' profitability has a coefficient of 9.934, and firm-specific covariates of institutional ownership, tangibility and book leverage have coefficients of -1.028, 0.815, -1.525 respectively. In terms of economic importance, these are the six most influential factors on dividend increase announcements. All other coefficient estimates for the SDP peer average and firm-specific covariates further also show the peer influence ranks relative to the type of focal firm's dividend related announcements. Third and in contrast to previous studies, we find additional peer-firm-average characteristics to be statistically significant in determining the dividend change outcome of the focal firms.

[Please insert Table 2.6 about here]

2.6. Conclusion

Our study has developed a spatial model of peer decision making based on the network identification strategy and has applied this econometric model to a unique data set of firms and their self-disclosed peers. We have developed both binary and multinomial logit versions of the dividend change action models incorporating standard firm-specific and peer-firm-average dividend determinants used in this literature. Our results clearly point to the importance of specific set of benchmark firms that the focal firm disclose in their public filings and communications, and that have statistically distinguishable outcome and contextual effects on the focal firm. We show that utilizing new benchmark of self-disclosed peers improves our understanding of the determinants of corporate dividend decisions both in terms of magnitudes and in terms of directions of effects.

The statistically significance of self-disclosed peers' average characteristics in the studies models shows that: 1) unlike industry peer-firm-average factors coefficients that are usually statistically insignificant to the firm's corporate policy, self-disclosed peers' contextual characteristics can be enlightening factors in determining likelihood of a firm's behaviour to be similar to its disclosed or aspirational peers that are often do not share same industry classification codes, and, 2) self-disclosed peer effects work not only on dividend payments but also can be associated with other financial policies. Taken together, this is obvious that self-disclosed peers effects work on the dividend policy not only via dividend change announcement, but also through set of fundamental financial factors that the focal firms' managers consider important and actively monitor them in their aspirational peers.

Chapter 3: Intangible Value of the Firm Network

We introduce a new asset pricing factor based on the firm's positional value in the corporate network. We argue that the network value of the firms can be used as proxy for the intangible value of firms' capital stock. By integrating firms' centrality metrics in to the Fama and French (1992, 1993) value factor, we show that the network based HML portfolio provides a higher return and captures stock price variations better than the conventional value factor over the period 2004 and 2017.

3.1. Introduction

One of most cited asset pricing factors, the Fama and French (1992, 1993)'s value factor has underperformed for past two decades. Most researchers believe that this is due to insufficient information provided by the accounting metrics on which the value of the firm has been measured. In particular the focus of many papers has shifted to looking at different types of intangible assets studies the role of intangibles in the valuation of companies. Corrado et al. (2009) estimate the value of three key categories of intangibles: computerized knowledge, R&D, and economic competencies. Similarly, Zhang (2020), Falato et al. (2021), and Peters and Taylor (2017) use sale and general administrative costs (SG&A) to measure intangible assets. Eisfeldt and Papanikolaou (2014) show that companies with higher knowledge capitals outperform companies with lower values. Moreover, Eisfeldt et al. (2021) argue that human resources and brand value are also sources for intangible value of the firms. Many of these metrics are recorded as costs and therefore do not appear in balance sheets, therefor Eisfeldt et al. (2021) introduce a new value factor using an augmented book-assets value.

In this study, we use a similar approach as Eisfeldt et al. (2021) and introduce an enriched book-asset values as estimates of the true value of the firm's capital stock, that recognizes the firm's network connections as a source of underlying value. We follow Fama and French (1992, 1993) and construct an updated HML portfolio based on the network-centric book value of assets of the firms (HMLNET). We find that the network-centric value factors are distinct from the traditional HML, and outperform the traditional HML in terms of providing lower pricing errors. The average returns of HMLNET factor portfolio is 0.18% monthly, with a standard deviation of 1.77 comparing to traditional value factor portfolio with average monthly return of 0.01% a standard deviation of 2.51 between 2004 and 2017. We observe that after 2008 financial crisis, HMLNET shows better performance over the traditional HML. In addition, HMLNET shows less mispricing, based on model alphas, for most asset classes.

We also document a robust performance of the network-centric value factors, and extend the analysis to study another type of network value factor which is based on a portfolio sorted Book-to-Market ratio where book value of the assets is replaced by the centrality metrics of the firms , Pure HMLNET (HMLNET-P) with average monthly returns of 0.24% monthly and standard deviation of 1.90. Finally, we consider different test asset classes and find that models with HMLNET or HMLNET-P replacing HML generate lower alphas and better performance metrics.

There is a growing literature that has attempted to address the deficiencies of the conventional value factor. One approach is to try to uncover the firm's true value using its intangible capital stock, or other hidden fundamental measures; our approach is in this spirit. Our study contributes to the literature by demonstrating that firms' network centrality metrics can improve the measurement of the value of the firm by capturing the hidden component of the firm's capital stock. The novelty of our approach is that it provides a measure of the intangible value that is associated with the firm centric measures that are derived from a macro and economy level construct. In this regard, our approach is one of the first studies that introduces semi-macro traded factors for asset pricing models. Our approach can be of great interest to portfolio managers and active fund managers who employ longer term as well short-term active value strategies. In our analyses, we show that network centric value factors can capture the value effect while providing higher average returns and lower volatility. We also highlight the differences between Fama and French (1992,1993,2015)'s HML factor and network centric value factors when tested on portfolios that are sorted on Profitability, Momentum, Investment as well as dual sorted size Book-to-Market 25 portfolio.

The remainder of the paper is as follows: In Section 2, we describe the network metric and sample data sources and methodology of construction the network value factor. In Section 3, we illustrate the relationship among the conventional and the network value factors, as well as the performance of the network value factor in pricing the standard momentum, investment, and profitability portfolios. In Section 4 we discuss the enablers of the performance difference between the network centric value and conventional value factors, and Section 5 concludes the study.

3.2. Data and Sample Description

Our sample is based on the universe of U.S. firms on the CRSP and Compustat databases, which provide our basic market and accounting data. We require at least 2 years of non-missing and positive book value of assets data for each firm in the analyses. For the network data, we manually collected business relationships (supply chain, strategic alliance, and licensing) data from relevant SEC (Securities and Exchange Commission) filing and textual company data accessed via Edgar and S&P CapitalIQ (Key Development Section). Observations were inspected to match identifiers with the names provided in the Compustat database. To account for the evolution of corporate networks through time (due to link additions and deletions, as well as new as well as terminating agreements), we capture the history of business relationships in yearly basis. We keep the relationships with span of at least two consecutive years. From the base universe we kept firms that have network data between years 2004 and 2017. In total the sample of the sample has 3214 firms with average of 3.7 links per each firm-year observation.

To capture the network value of each firm we use a widely used metric called "Betweenness". Betweenness centrality counts the number of times a firm occurs on the shortest paths between other firms, and therefore it is considered as a measure of the control that a firm has over the communication flow among the rest of the network. In this sense, the firm that have high betweenness are the gatekeepers of information, because of their relative location in the network. The formula for firm $\boldsymbol{u}$'s betweenness centrality is $\boldsymbol{C_b(u)} = \sum_{\substack{s \neq u \neq t \in N \\ s \neq t}} \frac{\sigma_{st}(u)}{\sigma_{st}}$ where $\boldsymbol{\sigma_{st}}$ is the number of shortest paths between two other firms in the network, $\boldsymbol{s}$ and $\boldsymbol{t}$, and $\boldsymbol{\sigma_{st}(u)}$ is the number of shortest paths from $\boldsymbol{s}$ to $\boldsymbol{t}$ that pass through firm $\boldsymbol{u}$. Since the network centrality measures has different scale than the book equity value, we rescaled both values using the range values (uniform transformation). To construct our network centric value factors, we add the multiplied network centrality metric of each firm to its annual book equity value and use the new value as the basis to calculate the HMLNET factor. We use different coefficients to add transformed network metrics to the transformed book equity values, baseline coefficients set is {0.1, 0.3, 0.5, 0.7, 0.9}. The new Book Equity value is calculated using following formula:

$$Firm\ Value\ (BE\_NET) = Scaled\ Book\ Equity + \delta * Scaled\ Centrality\ Measure \quad (3.1)$$

We followed Fama and French (1992, 1993) methodology to construct HML portfolio based on the BE-NET values of the firms. Other conventional asset pricing factors and test asset classes' monthly returns are obtained from Ken French's website[11].

3.3. Network Value Factors and Asset Pricing Errors

This section examines the performance of the network value factors (HMLNET) and Fama and French's value factor (HML) in predicting out test portfolios. Figure 3.1 shows that there is a lot of commonality between the monthly returns of HML and network value portfolios. To explore pricing capability of network value factors, we construct another network centric value portfolio by sorting companies only based on betweenness centrality metrics of the firm relative to market equity values, and call it pure network value factor.

[Please insert Figure 3.1 about here]

We begin by descriptive statistics of the asset pricing factors (Table 3.1) and the correlation analysis of the monthly returns of the HMLNET portfolios and other factor portfolios (Table 3.2). Table 3.2 shows that HMLNET factors and HML are moderately correlated, with a full sample correlation coefficient estimate of (12% to 36%). We show that this correlation is enough for network value to explain the "value effect", but low enough to allow network value to offer better asset pricing output.

[Please insert Tables 3.1 and 3.2 about here]

Table 3.3 presents the baseline asset pricing test results. For each portfolio class, the columns (1) and (2) present the results for the Fama and French (1992, 1993) three factor plus momentum asset pricing model, in column (1) the original value factor, and in column (2) the network value

[11] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

factor. The test assets for these models are 25 dual sorted size and book-to-market portfolio, and 10 momentum portfolios. As can be seen in the table, the network value factor reduces the alpha for 25 Size-BM portfolio class by 60%, and 53% for the 10 Momentum portfolio class. The changes in the root mean squared error is negligible, -1%. Columns (3) and (4) show the results for the Fama and French (2015) five-factor with momentum asset pricing model, which adds two factors to the model, the conservative minus aggressive (CMA) investment factor, and the robust minus weak (RMW) profitability factor. For this six-factor model, we separately test it on 10 investment portfolios and 10 profitability portfolios in addition to 25 Size-BM and 10 momentum portfolios. The estimated coefficient for HML value factor is significant only when tested on 25 Size-BM portfolios but becomes insignificant in all other test portfolio classes. In the other hand, pure network value factor shows better performance, while its estimated parameter is not significant but it shows significant risk-premium (significant Fama-Macbeth t-Value) at the 5% level. The changes in root mean squared errors are very small. Except 10 Profitability portfolios, the network value factor reduced the monthly alpha of the models by at least 42%. The Fama-Macbeth t-values show that network value factor has significant risk permia in most of the tested asset classes while HML only appears to have significant risk premia in 10 Investment portfolio class while generating higher Sharpe squared value. Hence, we can state that the network value factor has a better performance in the three plus momentum and five plus momentum asset pricing model.

[Please insert Table 3.3 about here]

Table 3.4 presents the estimated parameters for three-factor plus momentum pricing model using 25 size-BM and 10 momentum standard portfolios. Similarly, Table 3.5 presents the estimated parameters for five-factor plus momentum pricing model using 25 size-BM, 10 momentum, 10 investment, and 10 profitability standard portfolios. As can be seen in column 2 of Table 3.4, adding pure network value factor (HMLNET-P) to the three-factor model plus momentum improves the performance of the model for 25 size-BM (10 momentum) portfolios by reducing the alpha by 17.5% (13.8%) without changing the root mean squared error of the model (column 1). In Table 3.5, we see a similar improvement in performance of five-factor plus momentum model (column 4); adding pure network value factor, column 5, reduces the alpha at least 20% without reducing the root mean squared error of the model. In column 3, of Table 3.4 and column 6, of Table 3.5, pure network value factor replaces the traditional value factor. Although columns 3 and 6 do not show complete out-performance in terms of alpha reduction however they yield higher Sh^2 (squared Sharpe ratio) values.

[Please insert Tables 3.4 and 3.5 about here]

In this section we document that the network value factor prices standard portfolios in the three and five factor models, plus momentum, with lower errors than the traditional value factor, except in 25 Size-BM portfolio class since they are formed based on the book-to-market measure. We also provide evidence that when the network value is reduced to its pure form (without combining with book value of equity) asset pricing models using HMLNET-P (sorting firms only based on the Betweenness centrality metrics relative to market equity values into three high, medium and low sub-portfolios), produce smaller pricing errors than traditional models with HML factor. Thus, we can conclude that the centrality metrics and network value factor have the capability to capture the anomaly of the valuation of the firms better than accounting book value of the assets and conventional value factor (HML), which is consistent with the idea that accounting book value of the firms falls short in representing the anomalies in the value anchor of the firms.

3.4. Performance and Selection of the Asset Pricing Model

Table 3.2 and Figure 3.1 show that the traditional and network value factors are moderately correlated, and we also reported superior pricing error performance for the model with network value as well as its pure form. In this section, we show that there is enough independent variation to allow for a consistent performance of the network value factors. Table 3.6 documents the outperformance of network value relative to traditional value using single factor HML models. Panel A shows the results from a model of HMLNET regressed on the HML factor. We present results for the full sample, and for subsamples covering the pre-crisis from 2004-2008, and the post-crisis era from 2009 to 2017. The alpha of HMLNET over HML is significant and 0.24% (2.92% annual) in the full sample. This is sizable, given the apparent close relationship between the two factors. However, it is also reasonable, as the α/RMSE is 0.15% (1.77% annual). The alpha is almost stable over the time period of the sample data, and is significant in post-crisis subsample. Similarly, panel B of Table 3.6 shows the results from a model of HMLNET-P regressed on the HML factor. The alpha of HMLNET-P over HML is significant and 0.28% (3.32% annual) in the full sample. However, the alpha is not stable over the time period of the sample data, and is significant in post-crisis subsample, 0.425% (5.1% annual). One reason for the inconsistency of the pre-crisis sample can be due to availability and the quality of disclosed information before 2008. Panel B also exhibits the outperformance of the pure network value factor, and as expected, the factor portfolio that isolate the network-centrality effects captures the variation of the asset prices more independently, as we report much smaller R^2 compared to Panel A. Panel C of Table 3.6 shows the results for the converse model in which HML is regressed on the HMLNET factor, we see that the alpha is negative, and insignificant for the full sample and weekly significant for the post-crisis subsample only. Column 3 of panel C shows that the underperformance of HML in comparison to HMLNET which is consistent with the previous studies which reported under-performance for the traditional value strategy after 2008 crisis. Overall, we see observe that the alpha is larger for the portfolio that sorts firms based on the network value of the firms relative to market equity. The alpha for HMLNET-P is larger than HMLNET in each subsample, however it has a significant alpha over the traditional value only in the most recent period, post financial crisis.

[Please insert Table 3.6 about here]

In a study, Eisfeldt et al. (2021) use SG&A as the of measure of firms' organization capital and introduce an intangible value factor (HMLINT). They show that firms with more intangible assets relative to physical capital earn positive excess returns. However, our network value is different from the intangible factor, which should not be surprising given that the SG&A is also an internal accounting metric while the network metrics is a market-driven measure which value the position and relationships of the firms in a macro setting. Table 3.7 clearly shows that the network value factor is different from the intangible value factor In the full sample, the R^2 in a regression of the network value factor on the intangible factor (HMLINT) is 0.01%. Similarly, for traditional value factor, the R^2 in the analogous regression is 0.02%. Thus, we can conclude that the network value factor is different from intangible and the organization capital factors both in terms of measurement dimension and capturing return anomalies.

[Please insert Table 3.7 about here]

We also investigate the explanatory power of the new factor models on the variation of test assets' monthly returns by looking at average returns, volatility, range, information ratio, the GRS

(Gibbons et al., 1989) test statistics[12] and the maximum squared Sharpe ratio for factors, Sh^2 (Barillas and Shanken, 2017). According to Barillas and Shanken (2017) the best model is the one that provides the highest Sh^2. Table 3.8 displays performance statistics for HMLFF, HMLNET, and HMLNET-P factors. We show results for average returns, volatility, range, information, Sh^2, and GRS ratios. Panel A tabulates the performance statistics of the three-factor plus momentum model on 25 Size-BM and 10 momentum portfolios and shows that the network value factors have higher and positive returns. We see that although the range of the returns are larger for HMLNET and HMLNET-P but they still outperform HML considering the higher information and Sh^2 ratios. Similarly, Panel B shows the performance statistics of the five-factor plus momentum model on 25 Size-BM and 10 momentum portfolios and shows that the network value factors have higher and positive returns. We see that although the range of the returns are larger for HMLNET and HMLNET-P but they still outperform HML considering the higher information and Sh^2 ratios.

[Please insert Table 3.8 about here]

Figure 3.2 also depicts the superiority of the network-centric value factors over the traditional value factors. It illustrates one-dollar investment growth on each of factor portfolios and clearly shows HMLNET and HMLNET-P has higher cumulative returns over HML. Over the sample, we observe that the network value factors are very similar in magnitude to the RMV, or profitability factor, and are superior to almost all other factors in the Fama and French (2015) five factor model.

[Please insert Figure 3.2 about here]

[12] GRS tests whether the regression intercepts are jointly equal to zero

3.5. Conclusion

The conventional value investing strategy using firms' book value of assets as the fundamental measure of the firm value has been performing poorly after 2008 financial crisis. There is a growing research trend to uncover the hidden value of the firms and many recent studies focused on the importance of intangible assets such as knowledge capital, goodwill and SG&A that are not considered in the traditional measure and valuation of the firms. In this study we show that a value portfolio that adds network value to book assets prior to sorting provides much stronger performance relative to HML. The network value factor also prices standard test assets with similar pricing errors as the traditional value factor. We also find that long-short strategies just based on the ratio of the network centrality over market value without incorporating book value of assets continue to price standard test assets and yield positive and significant alphas. In summary, our results show that asset pricing studies should consider incorporating firm-specific systemic tradable fundamentals pricing factors such as one explored in this study and accompany test assets to incorporate network based firm factors. Investors and managers can also use the network value factor to implement a profitable relative value strategy, especially in recent years when traditional value has underperformed.

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Figure 1.1. Percentage of firms changing SIC codes since their founding date
This figure shows the distribution of firms in the CRSP-Compustat Universe as of December 2016 according to changing SIC affiliations across age groups from their founding dates. The stacked bars are the number of firms in each age group. The blue shaded part shows the part of firms with single three digit historical SIC codes. The red shading in the bars shows the part of the firms with multiple historical SIC codes. The red line shows the ratio of firms in the various age categories that have changed their primary SIC codes at least once since their establishment. The green line shows the ratio of firms in the various age categories that have changed their primary SIC codes at least twice since their establishment. The yellow line shows the ratio of firms in the various age categories that have changed their primary business segment SIC code. The blue line is the ratio of the firms with at least two different historical SIC codes that were once utilities or financial companies, but changed their industry association, or became utilities or financial companies through time. The right vertical axis shows the number of the firms in age groups and left side vertical axis is the percentage of firms changing their SIC codes.

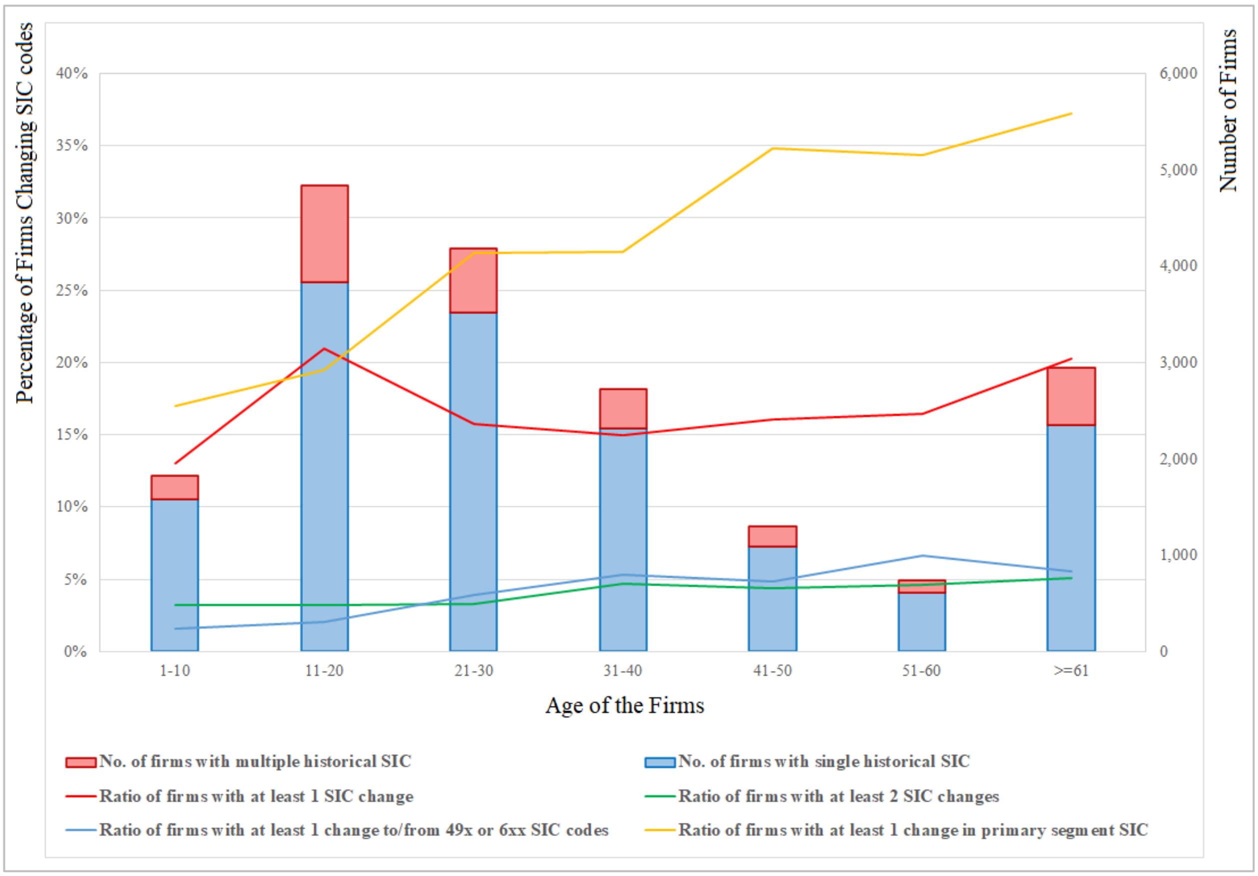

Figure 1.2. Schematic representation of peer group formation

This table shows different peer groups formation. *Group 1* (SDP) consists of all of firms that are cited by the focal company in the current year *t*. *Group 2* (SDP-C1) includes rival firms that are cited in year *t* that share at least one common customer in year *t* with the focal company in year *t*. *Group 3* (SDP-L1) includes those firms that are cited in *t* and *t-1* who share a common customer with the focal firm in year *t-1* and not in year *t* (i.e. the focal firm loses the customer to the rival in year *t*); *Group 4* (SDP-C2) includes rival firms that are cited in *t* and *t-1* who share a common customer with the focal firm in years *t* and *t-1*.

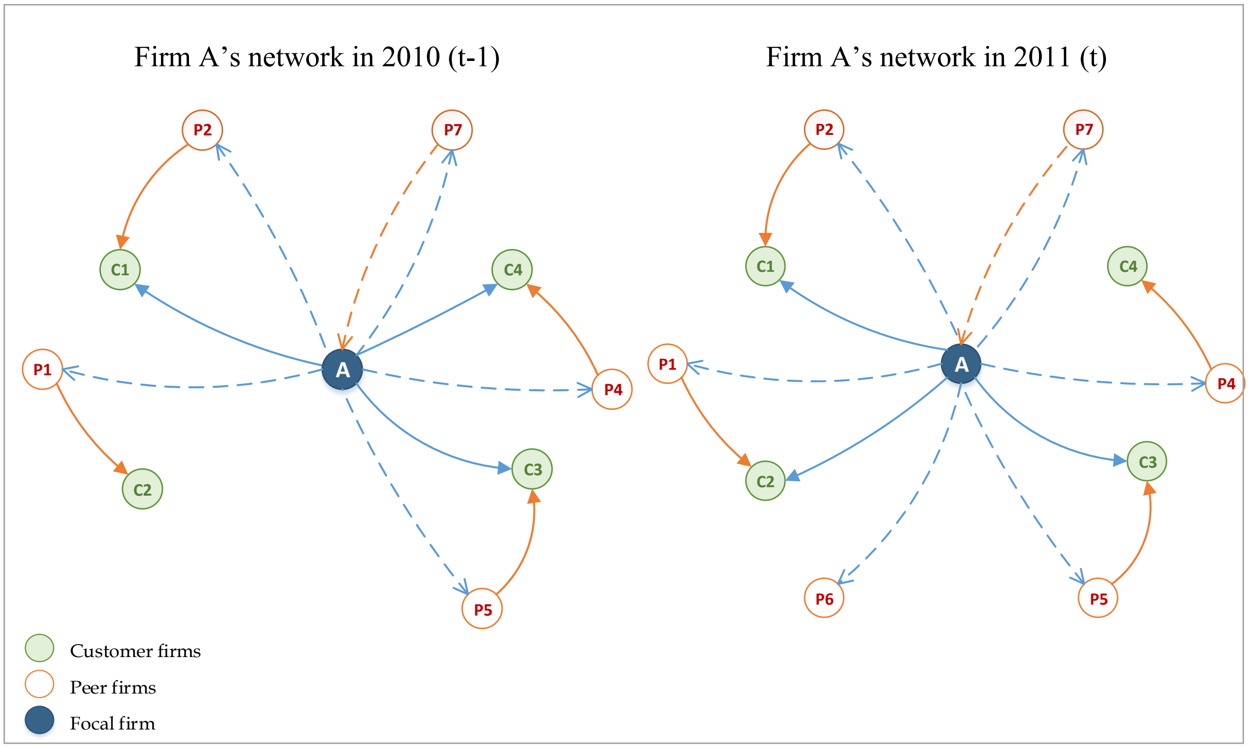

Figure 2.1. Peer Group Formation Methods

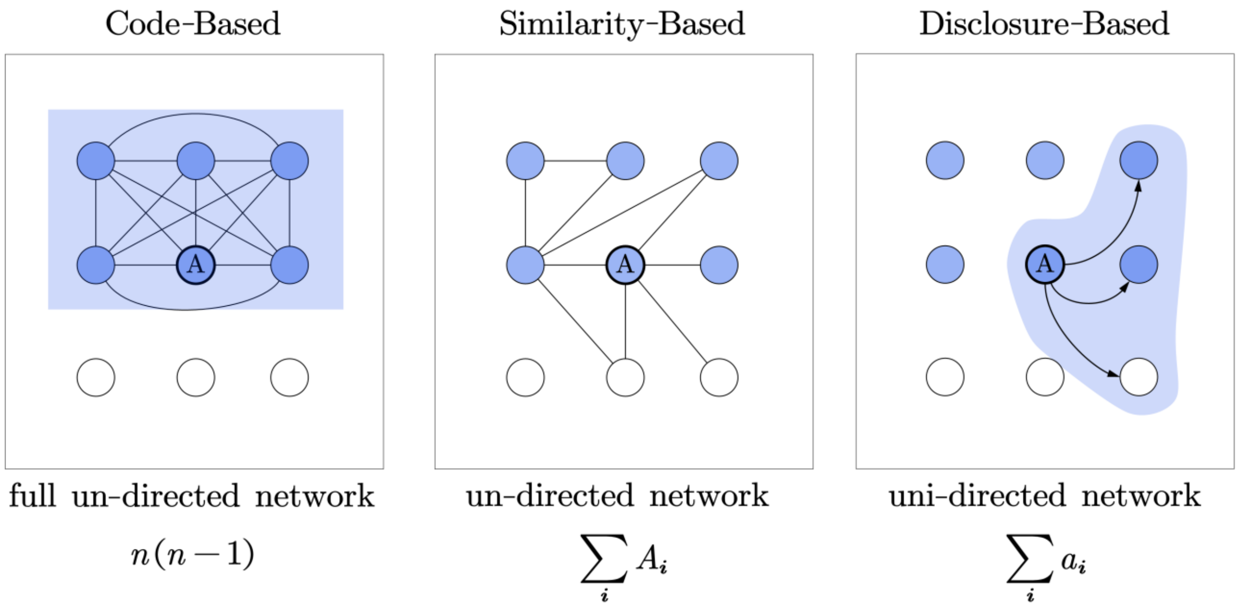

Figure 2.2. Dividend Peer Effects Mechanism Design

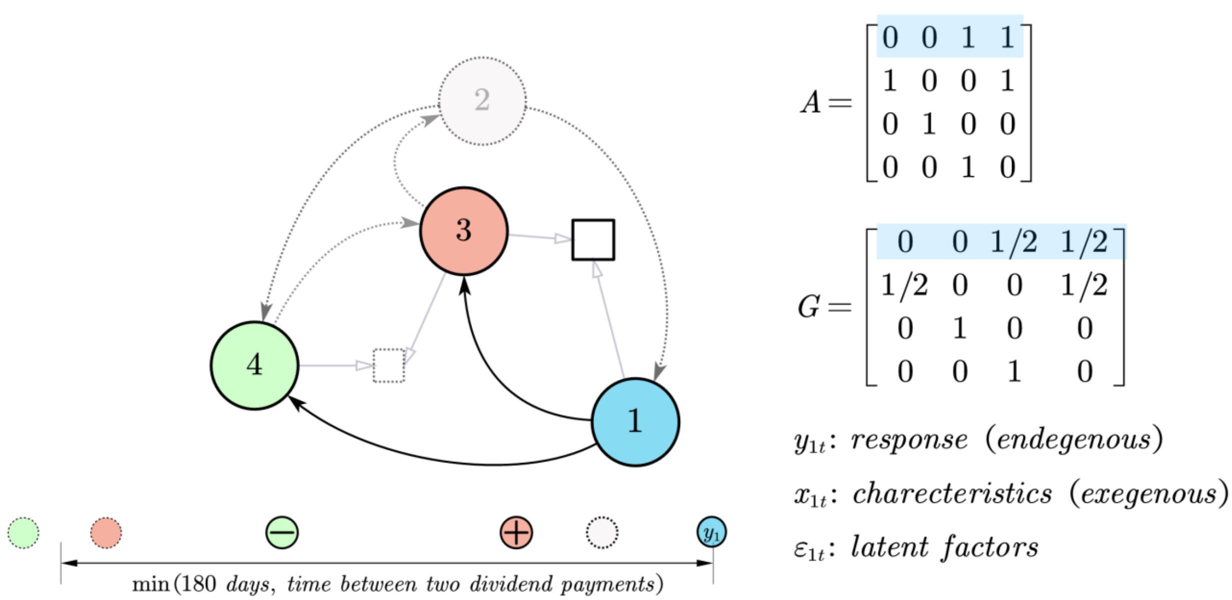

Figure 2.3. Dividend Peer Effects Mechanism Design

Figure 3.1. Monthly Returns of Traditional and Network-Based Value Factor

This figure plots the monthly returns for conventional value factor (HML), network centric value factor (HMLNET) and pure network centric value factor (HMLNET-P) from 2004 to 2017. The HML portfolio mimics the risk factor in returns related to book-to-market equity, and is calculated as the difference between the returns on high-B/M portfolios and the returns on low-B/M portfolios. HMNET adds network metric of betweenness to the scaled book equity term of the book-to-market equity ratio and conduct portfolio sorts. HMNET-P is based on sorted portfolios where the betweenness measure of the firms replaces book equity term in the book-to-market equity ratio before the sort.

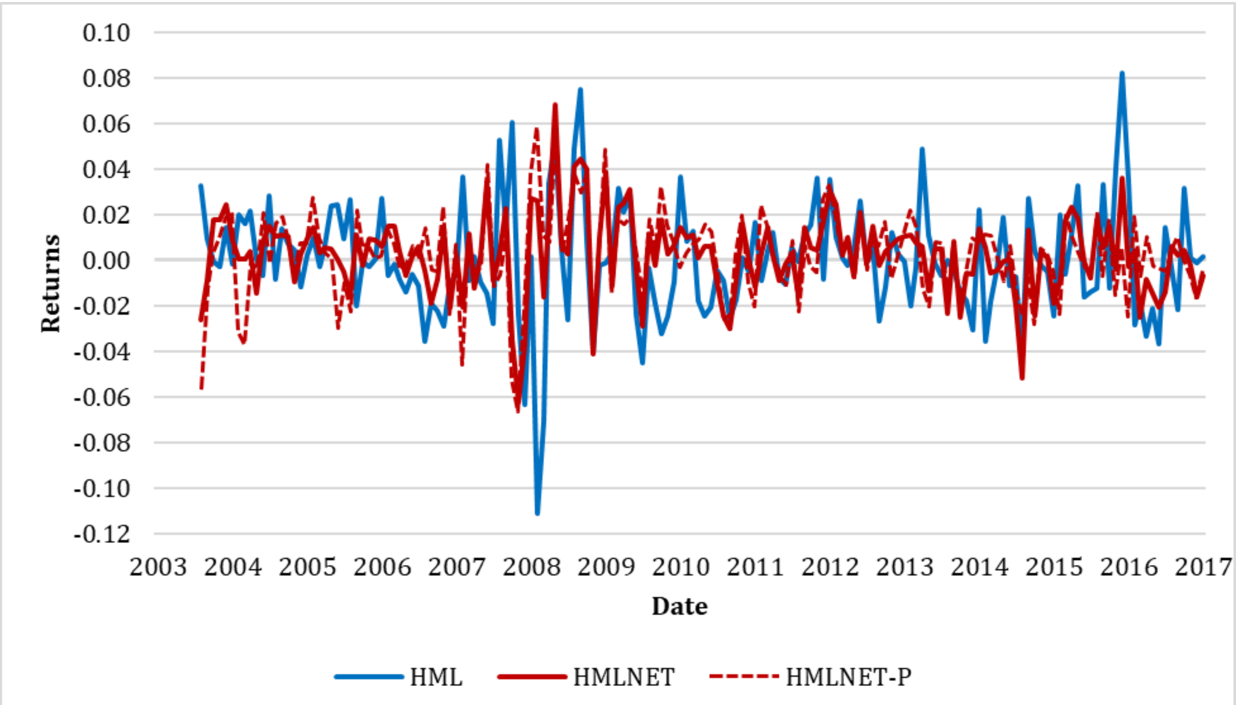

Figure 3.2. Monthly Cumulative Returns of Factor Portfolios

This figure plots the cumulative returns for several long short strategies for the full sample and for the monthly observation starting in July, 2004 till December 2017. The cumulative returns of investing one dollar in either HML, HMLNET, HMLNET-P and other factors clearly show the superior returns of HMLNET (red line) and HMLNET-P (dotted red line) over HML (blue line). Over the sample, the network value factor's performance is of a very similar magnitude to the RMV, or profitability factor, and are superior to almost all other factors in the Fama and French (2015) five factor model.

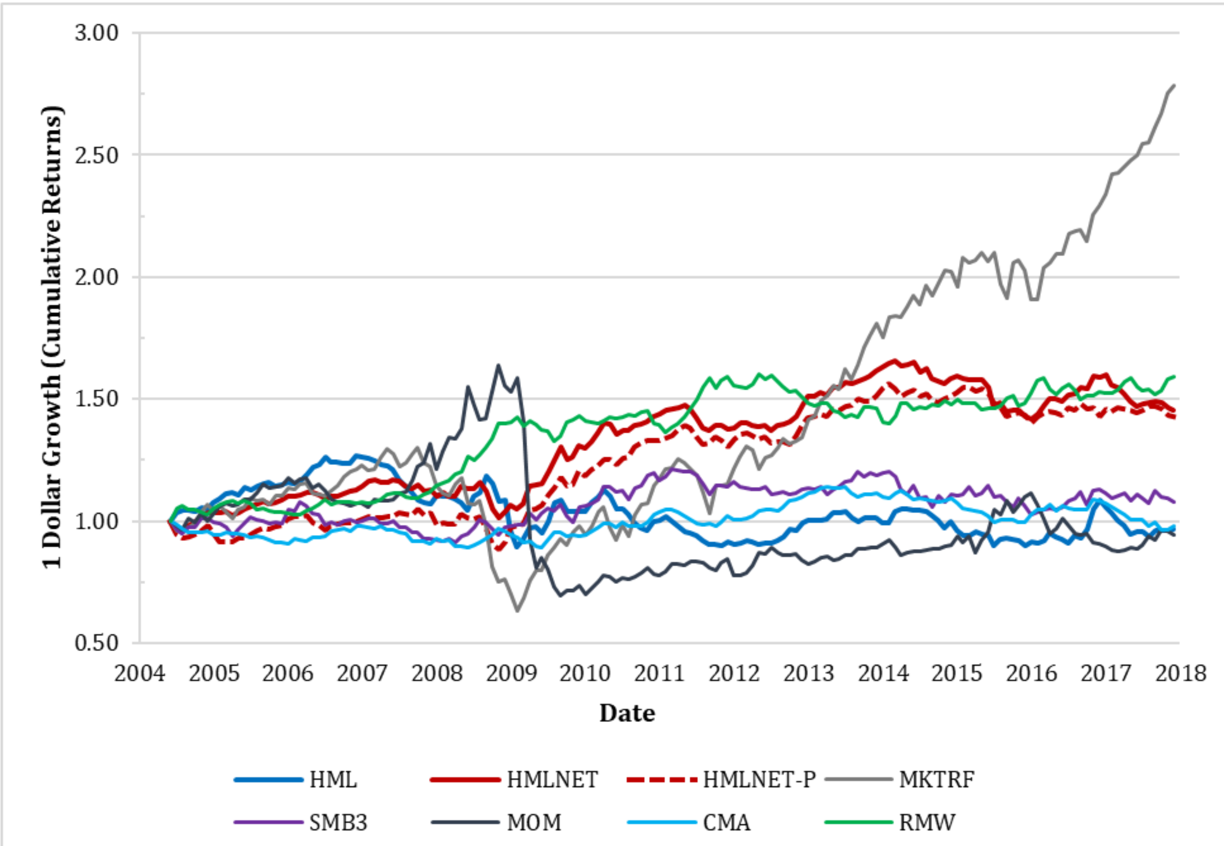

Table 1.1. Silicon Laboratories Inc.'s list of competitors based on annual 10-K filings

Year	Disclosing Firm	Disclosing Firm's SIC	Disclosed Peer Firm	Disclosed Peer Firm's SIC
2011	Silicon Laboratories Inc. (SLAB)	367	Analog Devices, Inc. (ADI)	367
			Broadcom Inc. (AVGO)	367
			Cypress Technology Co. Ltd. (3541.TW)	365*
			IDT Corporation (IDT)	481*
			LSI Industries Inc. (LYTS)	364*
			Maxim Integrated Products, Inc. (MXIM)	367
			Microchip Technology Incorporated (MCHP)	367
			NXP Semiconductors NV (NXPI)	367
			Renesas Electronics Corporation (RNECY)	367
			Seiko Epson Corp. (SEKEY)	357*
			STMicroelectronics NV (STM)	367
			Texas Instruments Incorporated (TXN)	367
2014	Silicon Laboratories Inc. (SLAB)	367	Analog Devices, Inc. (ADI)	367
			Cypress Technology Co. Ltd. (3541.TW)	365*
			IDT Corporation (IDT)	481*
			Maxim Integrated Products, Inc. (MXIM)	367
			MaxLinear Inc. (MXL)	367
			Microchip Technology Incorporated (MCHP)	367
			NXP Semiconductors NV (NXPI)	367
			Renesas Electronics Corporation (RNECY)	367
			Seiko Epson Corp. (SEKEY)	357*
			STMicroelectronics NV (STM)	367
			Texas Instruments Incorporated (TXN)	367

Table 1.2. Sample Data Summary Statistics

This table presents means, standard deviations (SD), and medians for the capital structure indicators (book and market leverage) and four factors (Size (Log(Sales)), Valuation (Market to Book), Profitability (EBTDA/Total Assets), and Asset Tangibility (Net PPE/Assets) for focal firm and peer group classes. Peer group SDP consists of all of firms that are cited in the text of the focal firm's 10-K annual filing, or announced in other media, by the focal company in the current year t. Peer group SDP-C1 includes rival firms that are cited in year t that share at least one common customer in year t with the focal company in year t. Group SDP-L1 includes those firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t); Group SDP-C2 includes rival firms that are cited in t and t-1 who share a common customer with the focal firm in years t and t-1. Group SIC includes all firms, excluding the focal firms, with same three-digit SIC code as the focal firm's. The sample consists of US firms, with the identified self-disclosed peers and at least three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A).

		Focal Firm	**SDP**	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SIC**
Book Leverage	Mean	0.254	0.254	0.257	0.232	0.240	2.245
	Median	0.156	0.226	0.225	0.204	0.209	0.282
	SD	0.856	0.515	0.617	0.192	0.203	38.897
Market Leverage	Mean	0.225	0.264	0.272	0.210	0.215	0.264
	Median	0.131	0.220	0.227	0.160	0.170	0.232
	SD	0.292	0.198	0.209	0.201	0.188	0.143
Log(Sales)	Mean	5.797	8.448	8.540	8.054	8.073	5.280
	Median	5.963	8.537	8.674	8.152	8.177	5.180
	SD	2.384	1.459	1.589	1.981	1.758	1.090
Market-to-Book	Mean	1.841	2.002	2.203	1.713	1.631	26.564
	Median	1.231	1.357	1.319	1.418	1.394	1.855
	SD	2.923	70.017	97.549	1.167	0.980	580
EBITDA/Assets	Mean	-0.002	0.090	0.082	0.100	0.101	-1.875
	Median	0.088	0.117	0.117	0.114	0.116	0.018
	SD	0.649	1.425	1.984	0.147	0.138	33.996
Net PPE/Assets	Mean	0.204	0.218	0.222	0.187	0.188	0.228
	Median	0.118	0.162	0.171	0.123	0.127	0.183
	SD	0.220	0.177	0.177	0.182	0.177	0.140
Number of Focal Firms		4,582	4,582	4,495	2,430	2,311	4,581
Number of Firm-Year Observations		23,347	23,347	22,389	6,621	9,445	23,344
Number of Firm-Year-Peer Observations			187,689	144,846	14,123	28,720	9,568,720
Average Peer Group Size			8.04	6.47	2.13	3.04	409.90
Average Peer Industry Similarity			34.1%	45.8%	46.0%	46.4%	100%

Table 1.3. Correlation Matrix of Main Variables

Group	Time	Level	Variable	Time= *t*								Time= *t-1*							
				Firm				Peers				Firm				Peers			
				Book Leverage	Market Leverage	EBITDA /Assets	Net PPE /Assets	Book Leverage	Market Leverage	EBITDA /Assets	Net PPE /Assets	EBITDA /Assets	Net PPE /Assets	Market-to-Book	Log (Sales)	EBITDA /Assets	Net PPE /Assets	Market-to-Book	Log (Sales)
SDP	*t*	Firm	Book Leverage	1															
			Market Leverage	0.088	1														
			EBITDA/Assets	-0.614	0.003	1													
			Net PPE/Assets	0.059	0.131	0.095	1	`											
		Peers	Book Leverage	0.072	0.102	-0.009	0.246	1											
			Market Leverage	0.042	0.160	0.053	0.215	0.502	1										
			EBITDA/Assets	-0.018	-0.007	0.106	0.061	-0.177	-0.126	1									
			Net PPE/Assets	0.048	0.137	0.071	0.715	0.280	0.191	0.104	1								
	t-1	Firm	EBITDA/Assets	-0.399	0.008	0.603	0.119	-0.011	0.058	0.115	0.076	1							
			Net PPE/Assets	0.060	0.132	0.102	0.967	0.246	0.213	0.064	0.715	0.106	1						
			Market-to-Book	0.171	-0.066	-0.257	-0.097	-0.011	-0.092	-0.015	-0.069	-0.537	-0.090	1					
			Log(Sales)	-0.037	0.088	0.326	0.222	0.049	0.156	0.141	0.183	0.370	0.226	-0.21	1				
		Peers	EBITDA/Assets	-0.012	-0.006	0.077	0.051	-0.171	-0.101	0.579	0.095	0.093	0.074	-0.104	0.075	1			
			Net PPE/Assets	0.049	0.137	0.070	0.716	0.280	0.189	0.104	0.986	0.049	0.719	-0.164	-0.027	0.087	1		
			Market-to-Book	-0.001	-0.108	-0.096	-0.159	-0.028	-0.396	0.210	-0.106	-0.013	-0.068	0.138	-0.031	-0.019	-0.104	1	
			Log(Sales)	-0.013	0.028	0.075	-0.024	-0.025	0.079	0.207	-0.027	0.121	0.180	-0.213	0.313	0.193	-0.033	-0.187	1
SDP-C1	*t*	Firm	Book Leverage	1															
			Market Leverage	0.300	1														
			EBITDA/Assets	-0.383	0.004	1													
			Net PPE/Assets	0.175	0.363	0.105	1												
		Peers	Book Leverage	0.118	0.133	-0.023	0.281	1											
			Market Leverage	0.145	0.286	0.025	0.282	0.597	1										
			EBITDA/Assets	0.008	0.020	0.182	0.075	-0.175	-0.082	1									
			Net PPE/Assets	0.196	0.300	0.071	0.762	0.282	0.293	0.149	1								
	t-1	Firm	EBITDA/Assets	0.006	0.031	0.641	0.142	-0.101	0.062	0.336	0.145	1							
			Net PPE/Assets	0.222	0.368	0.094	0.980	0.275	0.278	0.077	0.760	0.144	1						
			Market-to-Book	-0.064	-0.308	-0.051	-0.191	-0.030	-0.177	-0.024	-0.155	-0.080	-0.188	1					
			Log(Sales)	0.051	0.225	0.392	0.207	0.058	0.208	0.189	0.199	0.537	0.208	-0.25	1				
		Peers	EBITDA/Assets	0.013	0.024	0.189	0.084	-0.175	-0.133	0.777	0.143	0.355	0.136	-0.142	0.265	1			
			Net PPE/Assets	0.189	0.302	0.074	0.756	0.279	0.286	0.151	0.986	0.083	0.757	-0.162	0.023	0.150	1		
			Market-to-Book	-0.056	-0.204	-0.105	-0.162	-0.048	-0.431	0.060	-0.128	-0.011	-0.155	0.249	-0.088	0.068	-0.129	1	
			Log(Sales)	-0.005	0.089	0.179	0.030	0.031	0.147	0.379	0.068	0.195	0.193	-0.283	0.517	0.400	0.064	-0.193	1
SDP-C2	*t*	Firm	Book Leverage	1															
			Market Leverage	0.578	1														
			EBITDA/Assets	-0.067	0.067	1													
			Net PPE/Assets	0.198	0.398	0.119	1												
		Peers	Book Leverage	0.089	0.156	0.034	0.160	1											
			Market Leverage	0.115	0.320	0.059	0.308	0.723	1										
			EBITDA/Assets	0.019	0.022	0.176	0.059	0.044	-0.068	1									
			Net PPE/Assets	0.187	0.350	0.082	0.698	0.256	0.415	0.099	1								
	t-1	Firm	EBITDA/Assets	-0.068	0.119	0.602	0.160	0.050	0.119	0.195	0.108	1							
			Net PPE/Assets	0.230	0.402	0.118	0.960	0.169	0.307	0.064	0.703	0.150	1						
			Market-to-Book	0.145	-0.294	-0.168	-0.172	-0.054	-0.174	0.021	-0.135	-0.344	-0.168	1					
			Log(Sales)	0.100	0.244	0.390	0.212	-0.033	0.059	0.226	0.134	0.537	0.204	-0.230	1				
		Peers	EBITDA/Assets	0.023	0.038	0.171	0.084	0.042	-0.045	0.850	0.123	0.205	0.102	-0.127	0.167	1			
			Net PPE/Assets	0.186	0.345	0.080	0.698	0.269	0.420	0.103	0.980	0.088	0.704	-0.174	0.03	0.113	1		
			Market-to-Book	-0.023	-0.192	-0.085	-0.174	0.001	-0.325	0.058	-0.173	0.025	-0.133	0.239	0.003	0.025	-0.169	1	
			Log(Sales)	0.145	0.125	0.154	0.025	-0.030	-0.019	0.469	0.016	0.246	0.131	-0.199	0.404	0.495	0.002	-0.117	1
SDP-L1	*t*	Firm	Book Leverage	1															
			Market Leverage	0.708	1														
			EBITDA/Assets	0.074	0.006	1													
			Net PPE/Assets	0.422	0.310	0.180	1												
		Peers	Book Leverage	0.240	0.124	-0.128	0.200	1											
			Market Leverage	0.303	0.325	0.006	0.317	0.654	1										
			EBITDA/Assets	0.033	-0.001	0.381	0.235	-0.143	-0.156	1									
			Net PPE/Assets	0.308	0.314	0.183	0.688	0.253	0.266	0.210	1								
	t-1	Firm	EBITDA/Assets	0.026	-0.032	0.817	0.221	-0.216	-0.052	0.435	0.173	1							
			Net PPE/Assets	0.435	0.306	0.199	0.975	0.208	0.309	0.237	0.694	0.213	1						
			Market-to-Book	-0.214	-0.377	0.301	-0.102	-0.034	-0.171	0.139	-0.224	0.218	-0.106	1					
			Log(Sales)	0.254	0.264	0.477	0.333	-0.079	0.073	0.327	0.338	0.586	0.336	-0.09	1				
		Peers	EBITDA/Assets	0.023	-0.052	0.329	0.230	-0.157	-0.166	0.852	0.206	0.470	0.181	-0.437	0.280	1			
			Net PPE/Assets	0.324	0.317	0.197	0.702	0.223	0.275	0.200	0.970	0.231	0.708	-0.099	0.161	0.239	1		
			Market-to-Book	0.011	-0.128	-0.375	-0.103	0.121	-0.235	0.177	-0.112	0.092	-0.233	0.148	0.032	0.145	-0.114	1	
			Log(Sales)	0.166	0.118	0.288	0.169	-0.008	0.098	0.379	0.039	0.324	0.334	-0.209	0.429	0.418	0.061	-0.100	1
SIC	*t*	Firm	Book Leverage	1															
			Market Leverage	0.007	1														
			EBITDA/Assets	-0.309	-0.007	1													
			Net PPE/Assets	-0.005	0.081	0.005	1												
		Peers	Book Leverage	0.000	0.001	0.000	-0.005	1											
			Market Leverage	0.001	0.141	0.006	0.140	0.009	1										
			EBITDA/Assets	0.000	0.002	0.000	0.005	-0.143	0.000	1									
			Net PPE/Assets	-0.003	0.063	0.006	0.730	-0.007	0.197	0.007	1								
	t-1	Firm	EBITDA/Assets	-0.219	-0.005	0.091	0.005	0.000	0.007	0.002	0.006	1							
			Net PPE/Assets	-0.005	0.086	0.006	0.950	-0.003	0.140	0.012	0.726	0.006	1						
			Market-to-Book	0.001	-0.003	-0.014	-0.002	0.021	-0.001	-0.045	0.001	-0.026	-0.007	1					
			Log(Sales)	-0.025	0.060	0.075	0.182	0.012	0.083	-0.006	0.160	0.005	0.181	-0.02	1				
		Peers	EBITDA/Assets	0.000	0.003	0.001	0.005	-0.153	0.013	0.029	0.014	0.000	0.006	-0.033	-0.004	1			
			Net PPE/Assets	-0.002	0.064	0.006	0.727	-0.006	0.201	0.007	0.991	0.005	0.728	0.003	0.232	0.007	1		
			Market-to-Book	0.037	-0.002	-0.063	0.002	0.080	-0.007	-0.030	0.001	-0.009	0.001	0.001	0.001	-0.046	0.002	1	
			Log(Sales)	0.009	0.056	-0.003	0.238	0.022	0.168	-0.009	0.304	-0.006	0.155	0.002	0.459	-0.009	0.296	0.004	1

Table 1.4. Self-Disclosed Peer Effects on Capital Structure

This table shows the results of OLS regressions of the firm's Book Leverage, ΔBook Leverage, Market Leverage, and ΔMarket Leverage on peer-average and firm level characteristics for three peer-group classes: a) Self disclosed peers (SDP); b) Self-Disclosed peers with a shared customer in year t (SDP-C1); and c) all firms, excluding the focal firm, with the same primary SIC code as the focal firm's. The independent variables are the contemporaneous peer average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Book Leverage			ΔBook Leverage			Market Leverage			ΔMarket Leverage		
	SDP	SDP-C1	SIC	SDP	SDP-C1	SIC	SDP	SDP-C1	SIC	SDP	SDP-C1	SIC
Peers Average of Dependent Variable in year t												
$\bar{y}_{g_i,t}$	0.015	0.021*	0.000	0.004	0.002	0.000	0.367**	0.315**	0.422**	0.035**	0.029**	0.026
	(1.56)	(2.07)	(0.81)	(0.38)	(0.19)	(0.17)	(38.85)	(34.28)	(28.86)	(4.24)	(3.55)	(1.95)
Peers Average of Characteristics in year t-1												
EBITDA/Assets	0.086**	0.040*	0.000	0.020	0.010	0.000	-0.012	-0.006	0.000	0.007	0.004	0.000
	(3.39)	(2.25)	(-0.52)	(0.90)	(0.60)	(0.14)	(-1.32)	(-1.00)	(-0.35)	(0.94)	(0.79)	(-0.37)
Net PPE/Assets	0.179**	0.171**	0.236**	0.017	0.010	0.077	0.095**	0.088**	0.037	0.012	0.010	0.006
	(4.14)	(3.90)	(4.69)	(0.43)	(0.25)	(1.72)	(6.07)	(5.55)	(1.95)	(0.90)	(0.72)	(0.35)
Market-to-Book	0.002**	0.001*	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000	-
	(3.33)	(2.20)	(-0.90)	(0.93)	(0.62)	(0.00)	(-1.23)	(-0.91)	-	(0.91)	(0.76)	-
Log(Sales)	-0.005	-0.005	0.011*	0.005	0.004	-0.013**	0.003*	0.002	0.004	0.001	0.000	0.000
	(-1.44)	(-1.58)	(1.98)	(1.78)	(1.25)	(-2.60)	(2.36)	(1.86)	(1.84)	(0.79)	(0.11)	(0.25)
Focal Firm Characteristics in year t-1												
EBITDA/Assets	-0.891**	-0.894**	-0.887**	0.034**	0.034**	0.034**	-0.080**	-0.080**	-0.080**	0.003	0.003	0.003
	(-82.12)	(-80.33)	(-81.89)	(3.54)	(3.42)	(3.57)	(-20.59)	(-20.18)	(-20.27)	(0.79)	(0.84)	(0.88)
Net PPE/Assets	0.261**	0.269**	0.261**	-0.021	-0.018	-0.031	0.213**	0.234**	0.252**	0.009	0.012	0.013
	(7.47)	(7.60)	(8.49)	(-0.67)	(-0.56)	(-1.15)	(16.88)	(18.36)	(22.52)	(0.79)	(1.06)	(1.39)
Market-to-Book	0.023**	0.024**	0.023**	-0.023**	-0.023**	-0.023**	-0.016**	-0.016**	-0.016**	0.001	0.001*	0.001*
	(11.95)	(12.09)	(12.32)	(-13.55)	(-13.33)	(-13.66)	(-23.58)	(-23.22)	(-23.61)	(1.96)	(1.98)	(2.05)
Log(Sales)	0.061**	0.062**	0.059**	-0.021**	-0.021**	-0.018**	0.015**	0.015**	0.014**	-0.002*	-0.002*	-0.002
	(25.95)	(25.49)	(23.73)	(-10.14)	(-9.62)	(-8.18)	(17.87)	(17.56)	(15.59)	(-2.25)	(-2.04)	(-1.92)
Intercept	-0.180**	-0.178**	-0.266**	0.128**	0.143**	0.214**	-0.002	0.012	0.004	-0.005	0.000	0.000
	(-5.41)	(-5.33)	(-8.75)	(4.37)	(4.83)	(7.96)	(-0.17)	(0.98)	(0.38)	(-0.51)	(0.01)	(-0.01)
R-Square	0.290	0.293	0.290	0.014	0.014	0.014	0.208	0.193	0.188	0.030	0.029	0.029
Year Fixed Effects	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	4526	4412	4518	4524	4410	4516	4524	4410	4516	4522	4408	4514
Number of Years	12	12	12	12	12	12	12	12	12	12	12	12

Table 1.5. Market Competitors' Persistent Peer Effects on Capital Structure

This table shows the results of OLS regressions of the firm's Book Leverage, ΔBook Leverage, Market Leverage, and ΔMarket Leverage, Debt Issuance and Equity Issuance on peer-average and firm level characteristics for two peer group classes: a) includes those firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)); b) rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2). The independent variables are the contemporaneous peer average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/.Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Book Leverage		**ΔBook Leverage**		**Market Leverage**		**ΔMarket Leverage**		**Debt Issuance**		**Equity Issuance**	
	SDP-L1	**SDP-C2**	**SDP-L1**	**SDP-C2**	**SDP-L1**	**SDP-C2**	**SDP-L1**	**SDP-C2**	**SDP-L1**	**SDP-C2**	**SDP-L1**	**SDP-C2**
Peers Average of Dependent Variable in year t												
$\bar{y}_{g_i,t}$	0.158**	0.377**	0.020	0.049	0.155**	0.279**	0.011	0.098**	0.031	0.114**	0.127**	0.010
	(3.89)	(11.52)	(1.01)	(1.79)	(7.52)	(16.36)	(0.98)	(7.41)	(1.33)	(4.41)	(5.15)	(0.21)
Peers Average of Characteristics in year t-1												
EBITDA/Assets	0.086	0.285**	0.015	-0.069	0.072*	0.066**	0.010	-0.006	0.004	-0.046	0.254**	-0.085*
	(1.36)	(4.99)	(0.40)	(-1.90)	(2.38)	(2.99)	(0.49)	(-0.39)	(0.10)	(-1.65)	(4.40)	(-2.06)
Net PPE/Assets	0.112	0.045	0.055	0.009	0.143**	0.073**	0.025	-0.009	0.054	0.020	0.058	0.074
	(1.62)	(0.78)	(1.31)	(0.23)	(4.37)	(3.12)	(1.11)	(-0.60)	(1.38)	(0.69)	(0.93)	(1.87)
Market-to-Book	-0.004	-0.019**	-0.003	0.008	-0.009*	-0.001	0.000	-0.001	-0.003	0.003	-0.010	0.006
	(-0.56)	(-2.59)	(-0.66)	(1.58)	(-2.38)	(-0.29)	(0.11)	(-0.71)	(-0.69)	(0.70)	(-1.40)	(1.16)
Log(Sales)	0.008	0.002	0.005	0.013**	0.000	-0.004*	0.004*	0.002*	0.003	0.007**	-0.008	-0.004
	(1.59)	(0.54)	(1.65)	(4.38)	(0.09)	(-2.13)	(2.41)	(2.17)	(1.12)	(3.11)	(-1.73)	(-1.25)
Focal Firm Characteristics in year t-1												
EBITDA/Assets	-0.248**	-0.670**	-0.053**	0.100**	-0.061**	-0.110**	0.006	-0.004	-0.032*	0.116**	-0.874**	-0.494**
	(-9.87)	(-34.49)	(-3.51)	(7.87)	(-5.13)	(-14.28)	(0.66)	(-0.85)	(-2.19)	(11.84)	(-37.21)	(-36.50)
Net PPE/Assets	0.287**	0.329**	-0.005	-0.002	0.330**	0.329**	0.013	0.010	0.003	-0.002	-0.004	0.040
	(4.64)	(6.65)	(-0.13)	(-0.05)	(11.17)	(16.83)	(0.64)	(0.79)	(0.07)	(-0.08)	(-0.07)	(1.18)
Market-to-Book	0.007*	0.052**	-0.001	-0.002	-0.012**	-0.021**	0.001	0.002*	0.004*	0.007**	0.019**	0.014**
	(2.30)	(14.78)	(-0.59)	(-1.02)	(-8.12)	(-14.97)	(0.88)	(2.31)	(2.17)	(3.69)	(6.68)	(5.85)
Log(Sales)	0.022**	0.048**	-0.001	-0.020**	0.016**	0.018**	-0.002	-0.001	0.003	-0.010**	0.013**	-0.009**
	(5.02)	(13.68)	(-0.52)	(-8.68)	(7.82)	(13.20)	(-1.22)	(-1.55)	(1.01)	(-5.61)	(3.34)	(-3.87)
Intercept	-0.057	-0.286**	-0.024	0.024	0.033	0.040*	-0.033	-0.019	-0.032	0.013	-0.010	0.092**
	(-0.99)	(-5.87)	(-0.69)	(0.76)	(1.19)	(2.04)	(-1.72)	(-1.49)	(-0.97)	(0.51)	(-0.19)	(2.71)
R-Square	0.0824	0.2629	0.0108	0.0215	0.3051	0.2899	0.0367	0.0846	0.0117	0.0292	0.4213	0.2766
Year Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes	No	Yes	No	No
Number of Firms	1281	1756	1280	1756	1281	1756	1280	1756	1279	1756	1274	1755
Number of Years	11	10	11	10	11	10	11	10	11	10	11	10

Table 1.6. Self-Disclosed Peers and Firm Profitability and Tangibility

This table shows the results of OLS regressions of the focal firm's Profitability (EBITDA/Assets) and Tangibility (Net PPE/Assets) on peer-average and firm level characteristics across all of the peer-group classes: a) Self disclosed peers (SDP); b) Self-Disclosed peers with a shared customer in year t (SDP-C1); c) firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)); d) Rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2); and e) all firms, excluding the focal firm, with the same primary SIC code as the focal firm's. The independent variables are the contemporaneous peer average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Profitability					Tangibility				
	SDP	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SIC**	**SDP**	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SIC**
Peers Average of Dependent Variable in year t										
$\bar{y}_{g_i,t}$	0.001	0.001	0.082**	0.012	0.000	0.064**	0.039**	0.041**	0.067**	0.136**
	(0.48)	(0.45)	(2.65)	(0.32)	(-0.18)	(7.07)	(5.08)	(5.35)	(6.86)	(5.45)
Peers Average of Characteristics in year t-1										
EBITDA/Assets	0.023	0.007	0.064	0.104**	0.000	0.001	0.001	0.004	0.000	0.000
	(1.45)	(0.62)	(1.82)	(2.63)	(-0.33)	(0.50)	(0.82)	(0.66)	(0.00)	(0.26)
Net PPE/Assets	-0.075**	-0.061*	-0.043	-0.091**	-0.122**	0.012	0.030**	0.026**	-0.009	-0.072**
	(-2.68)	(-2.13)	(-1.09)	(-2.65)	(-3.54)	(1.34)	(3.85)	(3.22)	(-0.93)	(-2.92)
Market-to-Book	0.001	0.000	-0.007	-0.006	0.000	0.000	0.000	0.002*	-0.001	-
	(1.42)	(0.60)	(-1.69)	(-1.38)	(-0.99)	(0.55)	(0.88)	(2.19)	(-1.13)	-
Log(Sales)	-0.004	-0.003	-0.009**	-0.008**	0.007	0.000	0.000	0.000	0.000	0.001
	(-1.75)	(-1.17)	(-3.23)	(-3.19)	(1.91)	(-0.63)	(-0.57)	(0.32)	(0.04)	(1.54)
Focal Firm Characteristics in year t-1										
EBITDA/Assets	0.762**	0.762**	0.429**	0.680**	0.762**	0.005**	0.005**	0.013**	0.004**	0.006**
	(114.54)	(111.16)	(31.05)	(61.28)	(114.77)	(6.67)	(6.47)	(4.95)	(2.63)	(6.82)
Net PPE/Assets	0.098**	0.090**	0.047	0.070*	0.096**	0.928**	0.933**	0.939**	0.940**	0.944**
	(4.45)	(4.02)	(1.32)	(2.39)	(4.81)	(343.10)	(343.21)	(126.85)	(211.24)	(387.07)
Market-to-Book	0.007**	0.007**	-0.001	-0.002	0.007**	0.000	0.000	0.000	0.000	0.000
	(6.04)	(5.86)	(-0.50)	(-1.20)	(6.20)	(1.04)	(0.81)	(-0.67)	(-0.22)	(0.97)
Log(Sales)	0.031**	0.031**	0.042**	0.028**	0.029**	-0.001**	-0.001**	-0.001	0.000	-0.001**
	(20.95)	(20.54)	(17.25)	(13.83)	(19.13)	(-3.16)	(-3.36)	(-1.77)	(-0.44)	(-4.04)
Intercept	-0.194**	-0.210**	-0.191**	-0.105**	-0.241**	0.004	0.004	0.001	0.004	-0.001
	(-9.29)	(-9.95)	(-5.94)	(-3.68)	(-12.73)	(1.46)	(1.49)	(0.15)	(0.92)	(-0.27)
R-Square	0.515	0.514	0.517	0.533	0.515	0.938	0.936	0.945	0.944	0.937
Year Fixed Effects	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	3777	3677	1208	1654	3767	3775	3675	1208	1653	3765
Number of Years	12	12	11	10	12	12	12	11	10	12

Table 1.7. Self-Disclosed Competitors and Firm Dividend Payout and Riskiness

This table shows the results of OLS regressions of the focal firm's dividend payout, earning volatility, and Altman's Z-Score measures on peer-average and firm level characteristics across three competition-based peer groups: a) those rival firms that are cited in year t that share at least one common customer in year t with the focal company in year t (SDP-C1); b) rival firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)); and c) rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2). The independent variables are the contemporaneous peer average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Common Dividends			Earning Volatility			Altman's Z-Score		
	SDP-C1	**SDP-L1**	**SDP-C2**	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SDP-C1**	**SDP-L1**	**SDP-C2**
Peers Average of Dependent Variable in year t									
$\bar{y}_{g_i,t}$	0.073**	0.013*	0.021**	0.000	0.064*	-0.002	0.007	0.054	0.077*
	(20.62)	(2.55)	(4.79)	(0.12)	(2.12)	(-0.04)	(1.28)	(1.00)	(2.170)
Peers Average of Characteristics in year t-1									
EBITDA/Assets	-22.102	-211.761**	-64.011	0.010	-0.013	0.018	-1.253	-1.256	-2.246
	(-1.72)	(-3.09)	(-1.45)	(1.69)	(-0.70)	(1.01)	(-1.18)	(-0.57)	(-1.270)
Net PPE/Assets	-138.324**	70.831	5.280	0.043**	0.018	0.040*	6.683*	5.828*	2.072
	(-4.07)	(0.93)	(0.11)	(2.67)	(0.86)	(2.15)	(2.32)	(2.29)	(1.140)
Market-to-Book	-0.444	29.567**	29.798**	0.000	-0.001	-0.006*	-0.025	0.124	0.670**
	(-1.70)	(3.64)	(4.95)	(1.67)	(-0.38)	(-2.56)	(-1.16)	(0.47)	(3.040)
Log(Sales)	-9.690**	14.718**	0.798	0.001	0.001	0.001	0.077	-0.060	0.064
	(-3.40)	(2.81)	(0.20)	(0.45)	(0.40)	(0.58)	(0.37)	(-0.35)	(0.480)
Focal Firm Characteristics in year t-1									
EBITDA/Assets	-72.320**	-135.438**	-74.349**	-0.371**	-0.347**	-0.413**	35.945**	14.974**	32.186**
	(-8.95)	(-4.97)	(-4.86)	(-97.60)	(-47.12)	(-69.37)	(53.93)	(17.13)	(57.150)
Net PPE/Assets	53.931*	-110.756	-45.266	-0.027*	-0.004	-0.013	-8.256**	-7.809**	-4.599**
	(2.03)	(-1.63)	(-1.13)	(-2.13)	(-0.20)	(-0.86)	(-3.68)	(-3.47)	(-3.020)
Market-to-Book	1.270	4.399	2.329	0.008**	0.005**	0.018**	0.698**	1.204**	0.399**
	(0.90)	(1.34)	(0.85)	(12.37)	(5.63)	(16.79)	(6.04)	(11.40)	(3.920)
Log(Sales)	75.747**	78.334**	65.586**	-0.007**	-0.001	0.003*	-1.321**	-0.256	-1.013**
	(41.26)	(16.84)	(23.03)	(-7.88)	(-1.00)	(2.48)	(-8.88)	(-1.69)	(-9.660)
Intercept	-278.689**	-553.204**	-384.953**	0.096**	0.065**	0.019	7.772**	2.216	5.459**
	(-10.82)	(-8.89)	(-9.52)	(8.17)	(3.75)	(1.24)	(3.75)	(1.10)	(3.700)
R-Square	0.109	0.111	0.089	0.462	0.569	0.572	0.157	0.153	0.394
Year Fixed Effects	No	No	No	Yes	No	Yes	No	No	No
Number of Firms	3648	1183	1640	3677	1208	1654	3561	1155	1602
Number of Years	12	11	10	12	11	10	12	11	10

Table 1.8. Peer Effects and Peer Group Sizes

This table shows the results of OLS estimates of the peer effects coefficients, β of equation (2). The dependent variables in Panel A are the focal firm's Book Leverage, ΔBook Leverage, Market Leverage, ΔMarket Leverage across all peer groups. The dependent variables in Panel B are Debt Issuance, and Equity Issuance. Peer group classes in Panel A are: Self disclosed peers (SDP), Self-Disclosed peers with a shared customer in year t (SDP-C1), firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)), Rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2), and firms, excluding the focal firm, with the same primary SIC code as the focal firm's. The peer groups in Panel B are the three competition-based peer groups: SDP-C1, SDP-L1, and SDP-C2. The results are shown for three different peer group size strata: a) up to 3 peer firms (Small); b) four to eight peer firms (Medium); and 9-26 peer firms (Large). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses; * and **, denotes statistical significance at the 5% and 1% levels, respectively.

Panel A

	Small ($n \leq 3$)					Medium ($4 \leq n \leq 8$)					Large ($9 \leq n \leq 26$)				
$\hat{\beta}$	SDP	SDP-C1	SDP-L1	SDP-C2	SIC	SDP	SDP-C1	SDP-L1	SDP-C2	SIC	SDP	SDP-C1	SDP-L1	SDP-C2	SIC
Book Leverage	0.015	0.006	0.152**	0.380**	0.081	0.269**	0.144**	0.202*	0.270**	0.158	-0.002	-0.003	2.324*	0.449**	0.000
	(1.89)	(0.71)	(3.49)	(9.40)	(0.49)	(6.86)	(4.55)	(2.04)	(6.03)	(1.66)	(-0.09)	(-0.16)	(2.80)	(3.38)	(1.34)
ΔBook Leverage	-0.001	0.000	0.015	0.048	0.013	-0.051	-0.032	0.017	0.034	0.034	0.007	0.004	0.980*	-0.326**	0.000
	(-0.06)	(-0.01)	(0.71)	(1.34)	(0.09)	(-1.63)	(-1.19)	(0.46)	(1.32)	(0.59)	(0.36)	(0.23)	(2.30)	(-2.63)	(0.77)
Market Leverage	0.222**	0.194**	0.150**	0.240**	0.350**	0.513**	0.515**	0.189*	0.543**	0.038	0.478**	0.413**	0.936	0.698**	0.318**
	(17.36)	(17.47)	(7.02)	(12.75)	(3.03)	(26.91)	(29.64)	(2.04)	(11.51)	(1.14)	(19.03)	(13.76)	(1.70)	(4.32)	(6.49)
ΔMarket Leverage	0.024**	0.021**	0.010	0.083**	0.151	0.055**	0.053**	0.029	0.143**	-0.011	0.062	0.037	0.268	0.318**	0.029
	(2.75)	(2.76)	(0.86)	(5.74)	(1.52)	(4.02)	(3.58)	(0.58)	(4.44)	(-0.68)	(1.73)	(0.90)	(0.94)	(2.90)	(0.40)

Panel B

	Small ($n \leq 3$)			Medium ($4 \leq n \leq 8$)			Large ($9 \leq n \leq 26$)		
$\hat{\beta}$	SDP-C1	SDP-L1	SDP-C2	SDP-C1	SDP-L1	SDP-C2	SDP-C1	SDP-L1	SDP-C2
Debt Issuance	0.007	0.035	0.108**	0.050*	0.046	0.122*	0.125**	1.227	0.440*
	(0.39)	(1.45)	(3.47)	(2.32)	(0.41)	(2.31)	(2.73)	(1.51)	(2.09)
Equity Issuance	-0.003	0.124**	-0.024	0.000	0.255*	0.109	0.201**	0.308	-0.399
	(-0.20)	(4.78)	(-0.40)	(0.41)	(2.20)	(1.81)	(5.65)	(0.67)	(-1.05)

Table 1.9. Peer Effects and Learning (Augmented Model)

This table shows the results of OLS regressions of the focal firm's Book Leverage and Market Leverage on peer-average and firm level characteristics across all of the peer-group classes: a) Self disclosed peers (SDP); b) Self-Disclosed peers with a shared customer in year t (SDP-C1); c) firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)); d) Rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2); and e) all firms, excluding the focal firm with the same primary SIC code as the focal firm's. The independent variables are the contemporaneous peer average of the dependent variable, the one-year lagged values of the peer average of the dependent variable (learning factor) and one year lags of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2004 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Book Leverage					Market Leverage				
	SDP	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SIC**	**SDP**	**SDP-C1**	**SDP-L1**	**SDP-C2**	**SIC**
Peers Average of Dependent Variable in years t and t-1										
$\bar{y}_{g_i,t}$	-0.029*	-0.015	0.150**	0.260**	0.000	0.303**	0.251**	0.142**	0.200**	0.268**
	(-2.24)	(-1.51)	(3.66)	(6.01)	(0.80)	(24.70)	(21.24)	(6.94)	(9.07)	(15.46)
$\bar{y}_{g_i,t-1}$	0.131**	0.070**	0.086	0.215**	0.000	0.081**	0.083**	0.167**	0.128**	0.294**
	(4.77)	(3.07)	(1.85)	(4.16)	(-0.12)	(8.18)	(8.46)	(6.68)	(5.53)	(16.14)
Peers Average of Characteristics in year t-1										
EBITDA/Assets	0.136**	0.069**	0.103	0.315**	0.000	-0.009	-0.004	0.089**	0.078**	0.000
	(4.95)	(3.43)	(1.61)	(5.48)	(-0.33)	(-0.95)	(-0.69)	(2.98)	(3.53)	(-0.23)
Net PPE/Assets	0.160**	0.161**	0.087	0.005	0.236**	0.095**	0.088**	0.100**	0.051*	-0.005
	(3.68)	(3.65)	(1.24)	(0.09)	(4.69)	(6.06)	(5.58)	(3.03)	(2.18)	(-0.25)
Market-to-Book	0.002**	0.001**	-0.005	-0.021**	0.000	0.000	0.000	0.000	0.003	-
	(4.10)	(2.89)	(-0.67)	(-2.86)	(-0.89)	(-0.87)	(-0.60)	(0.08)	(1.07)	-
Log(Sales)	-0.006	-0.006	0.007	0.001	0.011*	0.003*	0.002	-0.001	-0.004*	-0.002
	(-1.66)	(-1.68)	(1.37)	(0.18)	(1.98)	(2.12)	(1.64)	(-0.41)	(-2.45)	(-0.94)
Focal Firm Characteristics in year t-1										
EBITDA/Assets	-0.893**	-0.895**	-0.246**	-0.670**	-0.887**	-0.080**	-0.080**	-0.063**	-0.110**	-0.079**
	(-82.28)	(-80.44)	(-9.81)	(-34.54)	(-81.89)	(-20.59)	(-20.17)	(-5.31)	(-14.36)	(-20.12)
Net PPE/Assets	0.252**	0.263**	0.279**	0.322**	0.261**	0.210**	0.230**	0.308**	0.328**	0.251**
	(7.21)	(7.42)	(4.51)	(6.53)	(8.49)	(16.67)	(18.10)	(10.43)	(16.81)	(22.58)
Market-to-Book	0.022**	0.024**	0.007*	0.052**	0.023**	-0.016**	-0.016**	-0.012**	-0.021**	-0.016**
	(11.82)	(11.99)	(2.32)	(14.76)	(12.32)	(-23.39)	(-23.01)	(-7.91)	(-15.05)	(-22.91)
Log(Sales)	0.061**	0.062**	0.022**	0.048**	0.059**	0.015**	0.015**	0.016**	0.018**	0.014**
	(25.94)	(25.49)	(5.07)	(13.69)	(23.72)	(17.78)	(17.46)	(7.97)	(13.28)	(15.78)
Intercept	-0.196**	-0.189**	-0.067	-0.291**	-0.266**	-0.004	0.009	-0.005	0.027	0.004
	(-5.86)	(-5.59)	(-1.15)	(-5.98)	(-8.75)	(-0.31)	(0.78)	(-0.18)	(1.37)	(0.38)
R-Square	0.291	0.293	0.084	0.265	0.29	0.21	0.196	0.316	0.293	0.197
Year Fixed Effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Number of Firms	4526	4412	1281	1756	4518	4524	4410	1281	1756	4516
Number of Years	12	12	11	10	12	12	12	11	10	12

Table 1.10. Two-stage Regression for Self-Disclosed Peer Effects on Capital Structure

This Table reports the Heckman (1979) two-stage regression for self-disclosed peer effects on capital structure. The dependent variable of the column (1) is a dummy that takes one if a company in Compustat universe discloses its competitors and zero otherwise. The column (1) is a probit model that predicts the likelihood of the peer-disclosure. The columns (2) are OLS regressions of the firm's current Book Leverage, and Market Leverage on the Inverse Mills Ratio derived in first stage, current peer average of the capital structure sa,e as the dependent variable, peer-average and firm level characteristics from previous year for all of the peer-group classes: a) Self disclosed peers (SDP); b) Self-Disclosed peers with a shared customer in year t (SDP-C1); c) firms that are cited in t and t-1 who share a common customer with the focal firm in year t-1 and not in year t (i.e. the focal firm loses the customer to the rival in year t (SDP-L1)); d) Rival firms that are cited in t and t-1 who share a common customer with the focal firm in both years t and t-1 (SDP-C2); and e) all firms, excluding the focal firm, with the same primary SIC code as the focal firm's. The independent variables are the segment revenue concentration in each three-digit SIC industry measured by Herfindahl-Hirschman Index (HHI), Inverse Mills Ratio derived from first stage, the contemporaneous peer average of the dependent variable, and one-year lagged values of four factors (for the focal firm and for the peer class average (that excludes the focal firm)): Size (Log(Sales)), Valuation (Market to Book), Profitability (EBITDA/Assets), and Asset Tangibility (Net PPE/Assets). The sample consists of US firms with identified self-disclosed peers and three years of financial data in the annual Compustat database between 2014 and 2016 with non-missing data for all analysis variables (see Appendix A). t-statistics are in parentheses. * and **, denotes statistical significance at the 5% and 1% levels, respectively.

	Firm's Book Leverage (t)						Firm's Market Leverage (t)					
	Probit	SDP	SDP-C1	SDP-C2	SDP-L1	SIC	Probit	SDP	SDP-C1	SDP-C2	SDP-L1	SIC
	(1)	(2)	(2)	(2)	(2)	(2)	(1)	(2)	(2)	(2)	(2)	(2)
Industry Concentration (HHI)	0.202**						0.073					
	(3.96)						(1.40)					
Inverse Mills Ratio		-0.164	-0.056	-0.254	-0.774	-0.155		0.155**	0.192**	0.090	-0.020	0.145**
		(-1.35)	(-0.06)	(-0.57)	(-1.36)	(-0.60)		(9.24)	(3.54)	(1.53)	(-0.08)	(4.83)
Peers' Book Leverage (t)	0.017	0.237**	0.432	0.304**	0.061	0.023						
	(0.66)	(4.18)	(1.38)	(2.37)	(0.32)	(1.38)						
Peers' Market Leverage (t)							-2.212**	0.051**	0.132**	0.355**	-0.178	0.162**
							(-21.89)	(4.04)	(3.50)	(5.92)	(-0.69)	(3.84)
Peers' Average of Characteristics at (t-1)												
EBITDA/Assets	-0.040**	0.011	0.049	-0.372	-0.970	0.006	-0.032**	-0.048	0.063	0.055	-1.227	-0.003**
	(-8.92)	(0.08)	(0.11)	(-0.98)	(-1.28)	(0.82)	(-6.96)	(-1.15)	(0.96)	(0.32)	(-1.64)	(-3.39)
Net PPE/Assets	-0.150	0.078	0.386	0.167	0.132	0.478**	0.571**	0.116**	0.112	0.025	0.126	0.111**
	(-1.40)	(0.96)	(0.84)	(0.70)	(0.44)	(5.58)	(5.10)	(3.92)	(1.44)	(0.23)	(0.43)	(4.23)
Market-to-Book	0.000	-0.005	-0.044	-0.015	0.006	0.000	-0.001	-0.013**	-0.002	0.000	0.013	0.000
	(-0.55)	(-0.46)	(-1.15)	(-0.88)	(0.29)	(-0.49)	(-1.63)	(-3.88)	(-0.29)	(-0.03)	(0.71)	(-0.24)
Log(Sales)	-0.056**	-0.012*	-0.033	0.034*	-0.012	0.008	-0.029**	0.000	-0.007	0.005	-0.005	0.001
	(-5.01)	(-1.71)	(-0.81)	(1.83)	(-0.42)	(0.68)	(-2.59)	(0.03)	(-1.10)	(0.53)	(-0.19)	(0.22)
Focal Firm's Characteristics at (t-1)												
EBITDA/Assets	-0.025**	-0.690**	-0.132	-0.146	-0.077	-0.105**	-0.017*	-0.014**	-0.068	-0.012	0.255	-0.004**
	(-2.29)	(-44.05)	(-0.28)	(-1.14)	(-0.19)	(-16.01)	(-1.79)	(-3.21)	(-1.04)	(-0.21)	(0.66)	(-2.81)
Net PPE/Assets	-0.227**	0.420**	0.473	0.233	0.922**	0.090	-0.207**	0.187**	0.305**	0.221**	0.652**	0.083**
	(-2.91)	(5.82)	(0.97)	(0.99)	(3.61)	(1.29)	(-2.59)	(7.33)	(4.12)	(2.08)	(2.69)	(5.40)
Market-to-Book	0.002**	-0.021**	-0.012	0.043**	-0.003	0.012**	0.001	-0.002**	-0.024**	-0.014**	-0.019	0.000
	(1.99)	(-10.39)	(-0.34)	(3.54)	(-0.16)	(18.25)	(0.90)	(-3.67)	(-4.46)	(-2.55)	(-1.00)	(-0.24)
Log(Sales)	0.066**	0.038**	-0.029	-0.011	0.018	-0.020	0.064**	0.015**	0.013*	0.007	0.015	0.012**
	(10.46)	(6.36)	(-0.58)	(-0.49)	(0.55)	(-1.63)	(10.13)	(7.35)	(1.86)	(0.95)	(0.69)	(5.78)
Intercept	-0.165**	0.174	0.650	0.134	0.782	0.341	0.168**	-0.043	-0.023	-0.038	0.143	-0.025
	(-2.83)	(1.21)	(0.60)	(0.26)	(1.19)	(1.43)	(2.81)	(-1.39)	(-0.30)	(-0.38)	(0.48)	(-0.90)
R-Square	0.020	0.436	0.053	0.271	0.655	0.093	0.059	0.259	0.480	0.332	0.520	0.185
Year Fixed Effects	-	No	No	No	No	No	-	No	No	No	No	No
Number of Observations	9357	4015	439	295	42	9331	9357	4015	439	295	42	9331
Number of Firms		1766	261	158	27	3516		1766	261	158	27	3516

Table 2.1. Changes in Historical three-digit SIC codes

Panel A) Compustat-NA Firms with Changed Primary SIC code in 3-Year Time Spans

Time Period	Number of Firms	Changed SIC	Change Percentage
1980-1989	13643	2621	19.21%
1990-1999	18277	4294	23.49%
2000-2009	17420	2894	16.61%
2010-2019	15799	1458	9.23%

Panel B) Compustat-NA Dividend Paying Firms with Changed Primary SIC code in 3-Year Time Spans

Time Period	Number of Firms	Changed SIC	Change Percentage
1980-1989	6545	1352	20.66%
1990-1999	8331	2029	24.35%
2000-2009	6662	1210	18.16%
2010-2019	5578	510	9.14%

Table 2.2. Peer group formation methods and number of peer effect channels

	SIC-code Universe (COMPUSTAT-NA)			Text-Based Networks (Hoberg and Phillips 2010)			Self-Disclosure Peers		
Year	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
2005	26.33	10	66.76	134.02	44	194.29	4.16	2	5.17
2006	26.4	9	68.43	138.24	43	198.84	4.25	2	5.33
2007	26.5	9	72.65	134.8	44	187.02	4.15	2	5.2
2008	26.42	8	75.28	129.71	41	184.49	4.16	2	5.11
2009	26.37	9	76.83	119.28	36	171.52	4.04	2	5.05
2010	26.83	8	83.21	117.42	34	170.18	3.72	2	4.55
2011	27.56	8	92.6	118.33	36	166.24	3.86	2	4.89
2012	29.17	8	101.15	111.28	34	155.45	3.94	2	4.96
2013	29.43	8	103.74	122.37	40	163.07	3.9	2	4.91
2014	29.49	8	110.13	135.05	44	171.53	3.94	2	5.1
2015	29.55	8	118.31	132.72	41	172.03	3.98	2	5.35
2016	29.4	8	126.04	128.82	38	167.58	3.95	2	5.38
Number of focal firms	20,737			7,631			4,574		
Number of channels	6,311,540			3,375,720			110,779		

Table 2.3. Peer effects on dividend actions without exogenous variables

This table presents details on the coefficient estimates from models in equations 2.4, 2.5.a, and 2.5.b, under assumption that coefficients of exogenous variables are zero. Equation $y_{i,t}^{div} = \alpha + \beta \bar{y}_{P_i^{div},T} + \lambda y_{i,t'}^{div} + S_P + v_t + \epsilon_{i,t}$ is used for estimation of parameters in columns 1-2 with self-disclosed peers and columns 3-4 with industry peers as common three-digit SIC codes, and equation $y_{i,t}^{inc} = \alpha + \beta \bar{y}_{P_i^{inc},T} + \lambda y_{i,t'}^{inc} + S_P + v_t + \epsilon_{i,t}$ for columns 5-8 with self-disclosed peers and columns 9-12 with industry peers as common three-digit SIC codes, and $y_{i,t}^{dec} = \alpha + \beta \bar{y}_{P_i^{dec},T} + \lambda y_{i,t'}^{dec} + S_P + v_t + \epsilon_{i,t}$ for columns 13-16 with self-disclosed peers and columns 17-20 with industry peers as common three-digit SIC codes. The table shows estimated coefficients for peer influence and previous action on current dividend action of the focal firm. *t*-statistics are in parentheses, and ***, **, and indicate p-values of 1%, 5%, and 10%, respectively.

Panel A)

	MLM-SDP		MLM-SIC	
	(1)	(2)	(3)	(4)
$\bar{y}_{P_iT}$	0.417***	0.387***	0.115*	0.049
	(21.61)	(19.81)	(1.69)	(1.39)
$y_{i,t'}$		0.352***		0.358***
		(24.22)		(24.57)
Decrease Alt. Const.	-1.049***	-0.917***	-1.054***	-0.961***
	(-56.04)	(-46.95)	(-33.12)	(-29.75)
Increase Alt. Const.	-0.572***	-0.478***	-0.578***	-0.507***
	(-37.25)	(-30.08)	(-26.16)	(-22.66)
No. of observations	69,354	69,354	68,559	68,559
No. of focal firms	1,508	15,08	1,495	1,495
Log likelihood	-22,779	-22,493	-22,721	-22,427
Fixed-effects	No	No	No	No

Panel B)

	Logit Model (Dividend Increase) SDP				Logit Model (Dividend Increase) SIC			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\bar{y}_{P_iT}$	0.484***	0.499***	0.362***	0.373***	-0.049	0.059	-0.314***	-0.085
	(10.04)	(10.15)	(5.63)	(5.79)	(-0.53)	(.62)	(-2.92)	(.77)
$y_{i,t'}$		-0.591***		-0.186***		-0.599***		-0.842***
		(-14.55)		(-3.96)		(-14.64)		(-20.62)
Model Constant	-0.979***	-0.810***	-	-	-0.798***	-0.663	-	-
	(-26.70)	(-19.30)	-	-	(-16.86)	(-12.79)	-	-
No. of observations	23,118	23,118	21,783	20,223	22,853	22,853	21,578	21,578
No. of focal firms	1,508	1,508	1,127	983	1,495	1,495	1,118	1,118
Log likelihood	-13,106	-12,994	-7,341	-7,333	-13,015	-12,902	-9800	-9567
Fixed-effects	No	No	Yes	Yes	No	No	Yes	Yes

Panel C)

	Logit Model (Dividend Decrease) SDP				Logit Model (Dividend Decrease) SIC			
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
$\bar{y}_{P_iT}$	0.483***	0.477***	0.273***	0.261***	0.631**	0.612**	0.164	0.200
	(7.79)	(7.72)	(5.63)	(5.79)	(3.09)	(3.01)	(0.72)	(0.88)
$y_{i,t'}$		0.148***		-0.186***		0.153**		-0.175***
		(3.04)		(-3.96)		(3.15)		(-3.73)
Model Constant	-1.834***	-1.852***	-	-	-1.769***	-1.787***	-	-
	(-47.52)	(-48.31)	-	-	(-44.56)	(-45.38)	-	-
No. of observations	23,118	23,118	20,223	20,223	22,853	22,853	20,042	20,042
No. of focal firms	1,508	15,08	983	983	1,495	1,495	975	975
Log likelihood	-10,047	-10,042	-7,341	-7,333	-9,991	-9,986	-7,303	-7,296
Fixed-effects	No	No	Yes	Yes	No	No	Yes	Yes

Table 2.4. Dividend Payment Changes Conditional on Self-Disclosed Peer (SDP) Activity

Likelihood of a dividend increase	23.4%
Likelihood of a dividend increase after at least 1 SDP increases its dividend pays	36.2%
Likelihood of a dividend decrease	15.6%
Likelihood of a dividend decrease after at least 1 SDP decreases its dividend pays	27.3%

Table 2.5. SDP Peer Effects on Dividend Actions - Multinomial Logit Model

This table presents additional details of the coefficient estimates for dividend change actions, where the endogenous peer effects variables are decomposed to the dividend action types. Standard errors are reported in parentheses. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

		Panel Mixed Choice Model		Network Panel Logit Model	
		$y_{i,t}^{dec}$	$y_{i,t}^{Inc}$	$y_{i,t}^{dec}$	$y_{i,t}^{Inc}$
Level	Variable	(1)	(2)	(3)	(4)
Focal Firm's Previous Action	$y_{i,t'}^{dec}$	1.096***	0.828***	0.785***	0.760***
		(0.15)	(0.14)	(0.17)	(0.15)
	$y_{i,t'}^{Inc}$	0.613***	0.183*	0.571***	-0.348***
		(0.13)	(0.11)	(0.14)	(0.14)
Focal Firm	HHI of Inst. Ownership	0.673	-1.017	0.971	-0.944
		(0.68)	(0.65)	(0.82)	(0.86)
	Institutional Ownership	0.429	-0.856***	0.469	-0.978***
		(0.27)	(0.22)	(0.35)	(0.32)
	Market-to-Book	0.076	0.267***	0.082	0.265***
		(0.08)	(0.07)	(0.10)	(0.10)
	Profitability	-1.594	-2.695	-3.025	-1.148
		(3.06)	(2.75)	(3.51)	(3.15)
	Tangibility	0.094	0.853**	0.034	0.833*
		(0.44)	(0.34)	(0.55)	(0.49)
	Book Leverage	0.946**	-0.827***	1.102**	-1.320***
		(0.38)	(0.32)	(0.46)	(0.43)
Div. Decreased Peers' Averages	Peer Effects	0.701**	0.166	0.653*	0.107
		(0.39)	(0.33)	(0.45)	(0.40)
	HHI of Inst. Ownership	4.936***	2.672*	4.764**	2.223
		(1.75)	(1.58)	(2.00)	(1.81)
	Institutional Ownership	-0.243	0.251	-0.305	0.088
		(0.45)	(0.36)	(0.51)	(0.44)
	Market-to-Book	-0.035	-0.412***	-0.078	-0.458***
		(0.12)	(0.11)	(0.14)	(0.13)
	Profitability	-2.057	8.506**	-1.304	9.531**
		(4.36)	(3.48)	(5.09)	(4.16)
	Tangibility	0.425	-0.291	0.628	-0.172
		(0.46)	(0.37)	(0.53)	(0.45)
	Book Leverage	-0.361	-0.537*	-0.386	-0.370
		(0.39)	(0.32)	(0.45)	(0.39)
Div. Increased Peers' Averages	Peer Effects	0.395	0.756***	0.247	0.820**
		(0.38)	(0.30)	(0.43)	(0.36)
	HHI of Inst. Ownership	-0.203	-1.177	-0.524	-1.066
		(1.14)	(1.18)	(1.26)	(1.40)
	Institutional Ownership	0.208	-0.988***	0.254	-0.969**
		(0.43)	(0.33)	(0.49)	(0.41)
	Market-to-Book	-0.232*	0.206**	-0.270*	0.188*
		(0.12)	(0.09)	(0.14)	(0.11)
	Profitability	2.206	-1.572	3.660	2.808
		(4.48)	(4.06)	(5.13)	(4.71)
	Tangibility	-1.086**	0.441	-1.079*	0.447
		(0.51)	(0.40)	(0.57)	(0.49)
	Book Leverage	-0.464	0.483	-0.467	0.357
		(0.43)	(0.36)	(0.49)	(0.44)
No. of Observations		2,855		2,855	
No. of Focal Firms		593		593	
Fixed Effects		Yes		No	
Log likelihood		-2563.7		-2500.3	
BIC		5127.4		5000.6	

Table 2.6. SDP Peer Effects on Dividend Actions - Binary Logit Models

This table presents details of the coefficient estimates for dividend change actions, where response variable is 0,1 for increase and decrease actions in two separate models. The endogenous peer effects are decomposed to the dividend increase and decrease action types. Standard errors are reported in parentheses. ***, ** and * indicate p-values of 1%, 5%, and 10%, respectively.

		Panel Logit Model for $y_{i,t}^{dec}$		Panel Logit Model for $y_{i,t}^{Inc}$	
		Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Level	Variable	(1)	(2)	(3)	(4)
Focal Firm's Previous Action	$y_{i,t'}^{dec}$	-0.248	0.532***	0.385**	0.508***
		(0.17)	(0.16)	(0.16)	(0.14)
	$y_{i,t'}^{Inc}$	0.582***	0.584***	-1.147***	-0.445***
		(0.16)	(0.14)	(0.15)	(0.13)
Focal Firm	HHI of Inst. Ownership	1.569	1.185	-0.624	-1.149
		(1.89)	(0.79)	(1.73)	(0.83)
	Institutional Ownership	-0.001	0.793**	-0.495	-1.028***
		(1.06)	(0.33)	(0.83)	(0.31)
	Market-to-Book	-0.202	-0.015	0.124	0.243***
		(0.18)	(0.10)	(0.15)	(0.09)
	Profitability	-5.529	-2.357	0.196	-0.608
		(4.18)	(3.29)	(3.46)	(3.00)
	Tangibility	1.192	-0.322	-1.213	0.815*
		(2.04)	(0.52)	(1.33)	(0.47)
	Book Leverage	1.727*	1.331***	-4.237***	-1.525***
		(0.99)	(0.44)	(0.81)	(0.42)
Div. Decreased Peers' Averages	Peer Effects	0.498*	0.405**	0.589	-0.078
		(0.57)	(0.43)	(0.50)	(0.39)
	HHI of Inst. Ownership	1.223	3.820**	1.062	0.861
		(2.55)	(1.75)	(2.02)	(1.61)
	Institutional Ownership	-0.631	-0.376	0.556	0.157
		(0.67)	(0.49)	(0.55)	(0.42)
	Market-to-Book	-0.067	0.060	-0.332**	-0.438***
		(0.17)	(0.13)	(0.14)	(0.12)
	Profitability	-2.120	-4.001	10.908**	9.934**
		(6.93)	(4.81)	(4.92)	(4.04)
	Tangibility	0.924	0.703	-0.435	-0.292
		(0.78)	(0.51)	(0.63)	(0.44)
	Book Leverage	-0.581	-0.212	-0.201	-0.277
		(0.60)	(0.43)	(0.52)	(0.38)
Div. Increased Peers' Averages	Peer Effects	-0.346	-0.005	0.555**	0.603*
		(0.52)	(0.41)	(0.42)	(0.35)
	HHI of Inst. Ownership	-1.777	-0.161	0.263	-0.997
		(1.66)	(1.22)	(1.95)	(1.36)
	Institutional Ownership	-0.052	0.592	-0.335	-1.030***
		(0.71)	(0.47)	(0.54)	(0.40)
	Market-to-Book	-0.315*	-0.327**	0.063	0.246**
		(0.18)	(0.13)	(0.13)	(0.11)
	Profitability	1.680	4.155	14.777***	2.165
		(6.71)	(4.91)	(5.48)	(4.56)
	Tangibility	-0.256	-1.259**	-0.469	0.673
		(0.80)	(0.55)	(0.67)	(0.47)
	Book Leverage	-1.053	-0.609	0.377	0.465
		(0.68)	(0.47)	(0.60)	(0.43)
No. of Observations		1660	2855	2059	2855
No. of Focal Firms		205	593	261	593
Fixed Effects		Yes	No	Yes	No
Log likelihood		-549.9	-1141.3	-763.9	-1515.2
BIC		1285.1	2481.4	1718.6	3229.4

Table 3.1. Descriptive statistics of the factor portfolios

This table shows the base formula of the quasi book value component of Book-to-Market ratio that is used to form monthly returns of new HML portfolio using Fama and French (1992, 1993) methods, along with descriptive statistics of the Fama and French (2015) five factor portfolios plus momentum portfolio's monthly returns between 2004 and 2017.

Factors	Proxy Variable for Book Value of Equity	Mean	Std. Dev.	Min	Max
HMLNET	$Scaled\ Book\ Equity + 0.7 * Scaled\ Betweenness$	0.18	1.77	-6.20	6.84
	$Scaled\ Book\ Equity + 0.3 * Scaled\ In\text{-}Closeness$	0.08	6.26	-23.46	16.65
	$Scaled\ Book\ Equity + 0.1 * Scaled\ Out\text{-}Closeness$	-0.23	4.30	-13.21	15.20
HMLNET-P	$Betweenness$	0.24	1.90	-6.65	5.87
	$In\text{-}Closeness$	0.41	6.27	-22.57	18.50
	$Out\text{-}Closeness$	-0.58	7.43	-30.55	42.94
MKT-RF	-	0.72	4.04	-17.23	11.35
HML	Book Value of Equity[13]	0.01	2.51	-11.12	8.22
SMB	-	0.07	2.27	-4.43	6.13
MOM	-	0.07	4.48	-34.39	12.54
CMA	-	0.00	1.38	-3.35	3.78
RMW	-	0.30	1.62	-3.93	5.07

Table 3.2. Correlations between variables

This table shows the Pearson correlation coefficients between the network centric value factors and Fama and French (2015) five factors plus momentum portfolios measured in the sample between years 2004 and 2017.

Factors	Proxy variable for Book Value of Equity	HML	MKT-RF	SMB	MOM	RMW	CMA
HMLNET	$Scaled\ Book\ Equity + 0.7 * Scaled\ Betweenness$	0.36	0.58	0.60	-0.40	-0.41	0.20
	$Scaled\ Book\ Equity + 0.3 * Scaled\ In\text{-}Closeness$	0.12	0.18	0.26	0.03	-0.25	-0.22
	$Scaled\ Book\ Equity + 0.1 * Scaled\ Out\text{-}Closeness$	0.25	0.26	0.30	-0.22	-0.24	0.15
HMLNET-P	$Betweenness$	-0.12	0.52	0.57	-0.24	-0.46	-0.03
	$In\text{-}Closeness$	-0.09	0.16	0.25	0.10	-0.26	-0.27
	$Out\text{-}Closeness$	-0.10	0.08	0.13	-0.05	-0.11	-0.06

[13] Book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock (if available).

Table 3.3. Pricing Errors: Network Value vs. Traditional Value

This table represents pricing results for the Fama and French (1992, 1993, 2015) three-factor and five-factor models plus momentum. Test assets for three factors plus momentum models are 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Test assets for five-factor plus momentum models are 25 portfolios double-sorted on size and book-to-market, 10 momentum, 10 investment and 10 profitability portfolios. Column 1 (3) shows the estimated coefficients of the traditional three (five) factors plus momentum model, and column 2 (4) shows the estimated coefficients of the traditional three (five) factors plus momentum model when HML factor was replaced by the HMLNET. *, ** and *** denotes statistical significance of the first stage (OLS) statements of the models at the 10%, 5% and 1% levels, respectively. Second stage (Fama and MacBeth, 1973) t-statistics are reported in parentheses. The sample is monthly from August 2004 to December 2017. All coefficients are reported in percentage per month (per year coefficient can be obtained by monthly percentages multiplied by twelve).

	Three-factor model				Six-factor model							
	25 Size-BM Portfolios		10 Momentum Portfolios		25 Size-BM Portfolios		10 Momentum Portfolios		10 Investment Portfolios		10 Profitability Portfolios	
	(1)	(2)	(1)	(2)	(3)	(4)	(3)	(4)	(3)	(4)	(3)	(4)
α (%)	1.54	-0.62	2.17	1.01	2.86	1.67	2.81	1.34	0.29	0.15	-0.04	-0.53
	(4.21)	(2.74)	(3.60)	(0.52)	(4.86)	(3.49)	(2.56)	(0.85)	(1.52)	(0.92)	(-0.24)	(-2.64)
MKT-RF	1.02***	1.02***	1.06***	1.04***	1.00***	1.01***	1.05***	1.04***	1.01***	1.00***	1.01***	1.01***
	(-1.44)	(-1.03)	(-1.25)	(0.71)	(-1.83)	(-1.47)	(-1.93)	(-0.43)	(-0.35)	(1.41)	(1.19)	(-1.46)
SMB	0.57***	0.54***	0.08**	0.06	0.56***	0.56***	0.09**	0.06	0.03*	0.02	0.05**	0.04*
	(0.43)	(0.47)	(0.28)	(1.18)	(0.79)	(0.72)	(-1.23)	(-0.28)	(-2.72)	(-0.88)	(0.24)	(-1.67)
MOM	-0.02**	-0.04**	-0.19**	-0.18**	-0.01	-0.03**	-0.19**	-0.18**	-0.01	0.00	-0.01	-0.01
	(0.50)	(0.57)	(0.23)	(0.53)	(-0.69)	(-0.18)	(0.39)	(0.56)	(0.40)	(-0.15)	(-2.60)	(-0.37)
CMA					-0.04*	0.04*	-0.06	-0.06	0.07**	0.06**	-0.03	-0.03
					(-0.71)	(-1.19)	(-1.64)	(-0.86)	(-1.07)	(-1.71)	(-2.41)	(-0.68)
RMW					-0.06**	-0.07**	-0.02	-0.01	-0.02	-0.01	-0.13**	-0.13**
					(2.34)	(2.02)	(-0.77)	(-0.66)	(-1.32)	(1.11)	(0.86)	(1.40)
HML	0.20***		0.02		0.13***		0.02		-0.02		0.02	
	(-0.69)		(-0.64)		(-0.69)		(-1.51)		(-1.98)		(0.06)	
HMLNET		0.11***		0.09		0.05**		0.09		0.01		0.03
		(0.20)		(-2.63)		(0.07)		(-1.90)		(2.17)		(-0.04)
Adj R^2	0.86	0.85	0.73	0.73	0.86	0.86	0.73	0.73	0.89	0.89	0.87	0.87
RMSE	1.99	2.01	2.88	2.88	1.98	2.00	2.88	2.88	1.43	1.43	1.61	1.61
Sh^2	0.02	0.03	0.02	0.03	0.04	0.05	0.04	0.05	0.04	0.05	0.04	0.05
GRS	2.43	2.55	2.04	2.49	2.03	2.04	1.42	1.98	0.81	0.74	0.80	1.01

Table 3.4. Four Factor Model Pricing Errors: Network Centrality Metric to Market Equity

This table represents pricing results for the Fama and French (1992, 1993) three-factor model plus momentum. Test assets are 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Column 1 shows the estimated coefficients of the traditional three factors plus momentum model, and column 2 shows the estimated coefficients of the traditional three factors plus momentum and HMLNET-P factors model, and column 3 shows the estimated coefficients of the traditional three factors plus momentum when HML factor was replaced by the HMLNET-P. *, ** and *** denotes statistical significance of the first stage (OLS) statements of the models at the 10%, 5% and 1% levels, respectively. Second stage (Fama and MacBeth, 1973) t-statistics are reported in parentheses. The sample is monthly from August 2004 to December 2017. All coefficients are reported in percentage per month (per year coefficient can be obtained by monthly percentages multiplied by twelve).

	25 Size-BM Portfolios			10 Momentum Portfolios		
	(1)	(2)	(3)	(1)	(2)	(3)
α (%)	1.54	1.27	2.04	2.17	1.87	1.97
	(4.21)	(3.31)	(3.74)	(3.60)	(2.81)	(2.74)
MKT-RF	1.02***	1.01***	1.05***	1.06***	1.05***	1.05***
	(-1.44)	(-1.07)	(-1.33)	(-1.25)	(-0.73)	(-0.86)
SMB	0.57***	0.56***	0.62***	0.08**	0.07*	0.08**
	(0.43)	(0.46)	(0.38)	(0.28)	(0.21)	(0.01)
MOM	-0.02**	-0.01	-0.06**	-0.19**	-0.19**	-0.19**
	(0.50)	(0.54)	(0.58)	(0.23)	(0.39)	(0.28)
HML	0.20**	0.20**		0.02	0.03	
	(-0.69)	(-0.69)		(-0.64)	(-0.85)	
HMLNET-P		0.03	-0.12**		0.03	0.01
		(-0.30)	(0.06)		(-0.67)	(-0.24)
Adj R^2	0.86	0.86	0.85	0.73	0.73	0.71
RMSE	1.99	1.99	2.00	2.88	2.88	2.65
Sh^2	0.02	0.02	0.03	0.02	0.02	0.03
GRS	2.43	2.49	2.48	2.04	2.23	2.25

Table 3.5. Six Factor Model Pricing Errors, Network Centrality Metric to Market Equity

This table represents pricing results for the Fama and French (2015) five-factor model plus momentum. Test assets are 25 portfolios double-sorted on size and book-to-market, 10 momentum, 10 investment and 10 profitability portfolios. Column 4 shows the estimated coefficients of the traditional five-factors plus momentum model. Column 5 shows the estimated coefficients of the traditional five-factors plus momentum and HMLNET-P factors, and column 6 shows the estimated coefficients of the five-factors plus momentum when HML factor was replaced by the HMLNET-P. *, ** and *** denotes statistical significance of the first stage (OLS) statements of the models at the 10%, 5% and 1% levels, respectively. Second stage (Fama and MacBeth, 1973) t-statistics are reported in parentheses. The sample is monthly from August 2004 to December 2017. All coefficients are reported in percentage per month (per year coefficient can be obtained by monthly percentages multiplied by twelve).

	25 Size-BM Portfolios			10 Momentum Portfolios			10 Investment Portfolios			10 Profitability Portfolios		
	(4)	(5)	(6)	(4)	(5)	(6)	(4)	(5)	(6)	(4)	(5)	(6)
α (%)	2.86	2.30	2.99	2.81	2.10	2.53	0.29	0.12	-0.04	-0.04	-0.52	-0.18
	(4.86)	(3.33)	(4.33)	(2.56)	(1.77)	(2.01)	(2.06)	(1.47)	(-2.78)	(2.18)	(0.94)	(-0.27)
MKT-RF	1.00**	1.00**	1.02**	1.05**	1.04**	1.05**	1.01**	1.00**	1.00**	1.01**	1.01**	1.01**
	(-1.83)	(-1.55)	(-1.55)	(-1.93)	(-1.44)	(-1.62)	(-2.25)	(-2.69)	(1.23)	(-1.55)	(0.81)	(0.67)
SMB	0.56**	0.55**	0.60**	0.09**	0.08*	0.09**	0.03*	0.03	0.02	0.05**	0.04*	0.05**
	(0.79)	(0.77)	(0.68)	(-1.23)	(-0.99)	(-1.36)	(-0.08)	(0.36)	(-0.91)	(0.42)	(0.17)	(2.48)
MOM	-0.01	-0.01	-0.04**	-0.19**	-0.18**	-0.19**	-0.01	-0.01	0.00	-0.01	-0.01	-0.01
	(-0.69)	(-0.63)	(-0.42)	(0.39)	(0.41)	(0.39)	(-1.78)	(2.05)	(1.03)	(-1.31)	(-1.48)	(2.39)
CMA	-0.04*	-0.05*	0.05**	-0.06	-0.07	-0.04	0.07**	0.07**	0.06**	-0.03	-0.04	-0.02
	(-0.71)	(-0.41)	(-0.99)	(-1.64)	(-1.39)	(-1.69)	(-2.84)	(-0.28)	(0.58)	(1.43)	(1.01)	(2.39)
RMW	-0.06**	-0.06**	-0.09***	-0.02	-0.01	-0.01	-0.02	-0.01	-0.01	-0.13**	-0.13**	-0.13**
	(2.34)	(2.28)	(2.23)	(-0.77)	(-0.69)	(-1.11)	(-1.32)	(-2.00)	(0.20)	(1.91)	(-2.72)	(2.25)
HML	0.13**	0.14**		0.02	0.04		-0.02	-0.01		0.02	0.03	
	(-0.69)	(-0.64)		(-1.51)	(-1.27)		(-1.06)	(1.84)		(2.01)	(1.39)	
HMLNET-P		0.03	-0.07**		0.04	0.01		0.01	0.02		0.03	0.02
		(0.04)	(0.13)		(-1.19)	(-0.91)		(2.31)	(-1.68)		(-1.91)	(2.03)
Adj R^2	0.86	0.86	0.87	0.73	0.73	0.73	0.89	0.89	0.89	0.87	0.87	0.86
RMSE	1.98	1.98	1.92	2.88	2.88	2.74	1.43	1.43	1.44	1.61	1.61	1.59
Sh^2	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.05
GRS	2.03	2.03	1.98	1.42	1.74	1.71	0.81	0.74	0.71	0.80	1.03	0.99

Table 3.6. Single Factor Models for Network Value and Traditional Value Factors

In this table, we study the relative performance of the HML, HMLNET, and HMLNET-P factors. We report alphas and betas of a regression of each return on the other, for the full sample as well as for sub-periods before and after 2008 financial crisis. The data are monthly and the sample period is 2004 to 2018. We include *t*-statistics that adjust for heteroskedasticity in parentheses. All coefficients are reported in percentage per month (per year coefficient can be obtained by monthly percentages multiplied by twelve).

	2004-2017 (1)	2004-2008 (2)	2009-2017 (3)
A) $\boldsymbol{HML_t^{NET} = \alpha + \beta_{HML_t^{FF}} HML_t^{FF} + \epsilon_t}$			
α (%)	0.244	0.078	0.351
	(1.88)	(0.33)	(2.31)
$\beta_{HML^{FF}}$	0.254	0.039	0.325
	(4.91)	(0.36)	(5.71)
Adj. R	0.126	0.002	0.228
RMSE	0.017	0.017	0.016
α /RMSE	0.148	0.045	0.222
B) $\boldsymbol{HML_t^{NET-P} = \alpha + \beta_{HML_t^{FF}} HML_t^{FF} + \epsilon_t}$			
α (%)	0.279	-0.082	0.425
	(1.71)	(-0.28)	(2.57)
$\beta_{HML^{FF}}$	-0.093	-0.321	-0.015
	(-1.56)	(-2.36)	(-0.24)
Adj. R^2	0.009	0.079	0.001
RMSE	0.019	0.021	0.017
α /RMSE	0.126	-0.040	0.250
C) $\boldsymbol{HML_t^{FF} = \alpha + \beta_{HML_t^{NET}} HML_t^{NET} + \epsilon_t}$			
α (%)	-0.118	0.166	-0.309
	(-0.63)	(0.57)	(-1.54)
$\beta_{HML^{NET}}$	0.515	0.062	0.724
	(4.91)	(0.36)	(5.71)
Adj. R^2	0.126	0.002	0.228
RMSE	0.023	0.216	0.024
α /RMSE	-0.050	0.008	-0.131

Table 3.7. Single Factor Models for Intangible Value and Network Value Factor

In this table, we report alphas and betas of a regression of HMLNET and HML factors on the HMLINT factor (Eisfeldt et al., 2021), for the full sample as well as for sub-periods around the 2008 financial crisis. The data are monthly and the sample period is 2004 to 2017. We include *t*-statistics that adjust for heteroskedasticity in parentheses. All factors are annualized in percent per year.

	2004-2017	2004-2008	2009-2017
	(1)	(2)	(3)
A) $\boldsymbol{HML_t^{NET} = \alpha + \beta_{INT} HML_t^{INT} + \epsilon_t}$			
α (%)	0.010	0.240	-0.116
	(0.10)	(0.80)	(-0.45)
β_{INT}	-0.142	-0.103	-0.190
	(-1.67)	(-0.88)	(-1.61)
Adj. R^2	0.011	0.002	0.015
RMSE	0.025	0.021	0.027
α /RMSE			
B) $\boldsymbol{HML_t = \alpha + \beta_{INT} HML_t^{INT} + \epsilon_t}$			
α (%)	0.256	0.181	0.298
	(1.87)	(0.77)	(1.73)
β_{INT}	-0.138	-0.144	-0.127
	(-2.35)	(-1.57)	(-1.61)
Adj. R^2	0.027	0.027	0.015
RMSE	0.017	0.017	0.018
α /RMSE			

Table 3.8. Performance Statistics: Intangible Value vs. Traditional Value

This table summarizes the risk and return associated with HML, HMLINT and HMLNET-P. The numbers in parentheses are t-statistics for the test that the average return, $E[R]$, is different from zero. The underlying data are monthly and the full sample period is 2004 to 2017. The information ratio is given by $E[R_P - R_B]/\sigma[R_P - R_B]$, where R_P is the portfolio return and R_B is the Market return as the benchmark. GRS is the F-statistics for null hypothesis test whether the regression intercepts are jointly equal to zero, and Sh^2 is the maximum squared Sharpe ratio for factors. Panel A, shows performance metrics for three-factor plus momentum model with test assets of 25 portfolios double-sorted on size and book-to-market and 10 portfolios sorted on momentum. Panel B shows the performance statistics for five-factor plus momentum models with test assets of 25 portfolios double-sorted on size and book-to-market, 10 momentum, 10 investment and 10 profitability portfolios.

A) Three-Factor + Momentum		25 Size-BM Portfolios	10 Momentum Portfolios	10 Investment Portfolios	10 Profitability Portfolios
	$E[R]$	0.804	0.814		
	σ	5.299	5.324		
HML	[Min, Max]	[-23.90,22.33]	[-29.47,47.43]		
	Information	0.015	0.016		
	Sh^2	0.020	0.020		
	GRS	2.430	2.040		
	$E[R]$	0.838	0.824		
	σ	5.143	5.310		
HMLNET	[Min, Max]	[-24.23,23.11]	[-30.36,47.38]		
	Information	0.033	0.020		
	Sh^2	0.030	0.030		
	GRS	2.480	2.250		
	$E[R]$	0.816	0.814		
	σ	5.208	5.320		
HMLNET-P	[Min, Max]	[-24.45,23.18]	[-30.14,47.35]		
	Information	0.022	0.016		
	Sh^2	0.021	0.021		
	GRS	2.490	2.230		
B) Five-Factor + Momentum					
	$E[R]$	0.784	0.790	0.740	0.711
	σ	5.191	5.338	4.254	4.445
HML	[Min, Max]	[-23.77,21.06]	[-29.78,45.68]	[-20.09,14.92]	[-22.95,15.83]
	Information	0.024	0.021	0.007	-0.020
	Sh^2	0.040	0.040	0.040	0.040
	GRS	2.030	1.420	0.810	0.800
	$E[R]$	0.831	0.808	0.744	0.726
	σ	5.129	5.322	4.249	4.439
HMLNET	[Min, Max]	[-24.16,22.49]	[-30.57,45.76]	[-21.19,14.88]	[-23.89,16.06]
	Information	0.049	0.028	0.012	-0.007
	Sh^2	0.050	0.050	0.050	0.050
	GRS	1.980	1.710	0.710	0.990
	$E[R]$	0.797	0.778	0.746	0.725
	σ	5.146	5.326	4.252	4.439
HMLNET-P	[Min, Max]	[-23.96,21.19]	[-29.90,44.68]	[-21.61,15.05]	[-23.68,15.81]
	Information	0.031	0.017	0.013	-0.008
	Sh^2	0.043	0.043	0.043	0.043
	GRS	2.030	1.740	0.740	1.030

Appendix A. Variable Definitions

Our sample consists of firm-year observations for the period 2004 to 2016, Compustat firms with at least three years of accounting data. The analysis begins in 2004 because of the availability of online text data on corporate filings and as well as news data. To maintain consistency with previous empirical studies and to avoid capital structures dictated by regulatory considerations, we include firms with headquarters in the US that are listed on US stock exchanges. ADRs are therefore not included. Focal firm-year observations are excluded if they have missing data for the levels and first differences of the following variables: net equity issuances, net debt issuances, book leverage, market leverage, sales, market-to-book ratio, profitability, and tangibility. Variable definitions are below. Compustat variable names are denoted by their WRDS variable name in bold.

Table 1.A-1: Model Variables and Calculation Method

Capital Structure Factors	
Book Leverage	(**dltt** + **dlc**)/**at**
Market Leverage	(**dltt** + **dlc**)/(**prcc_f** * **cshpri** + **dlc** + **dltt** + **pstkl** − **txditc**)
Net Debt Issuances	[(**dltt**(t) + **dlc**(t)) − (**dltt**(t-1) + **dlc**(t-1))]/**at**(t-1)
Net Equity Issuances	(**sstk**(t) − **prstkc**(t))/**at**(t-1)
Firm Characteristics	
Firm Size	Log(**sale**)
EBITDA/Assets (Profitability)	**oibdp**/**at**
Net PPE/Assets (Tangibility)	**ppent**/**at**
Market-to-Book Ratio	(**prcc_f** * **cshpri** + **dlc** + **dltt** + **pstkl** − **txditc**)/**at**
Common Dividends	**dvc**
Altman's (1968) Z-Score	(3.3 * **pi** + **sale** + 1.4 * **re** + 1.2 * (**act** − **lct**))/**at**
Earnings Volatility	Standard Deviation of [(**oibdp**/**at**)(t), (**oibdp**/**at**)(t-1), (**oibdp**/**at**)(t-2)]
Payout Variables	
Regular Cash Dividends (**rcd**)	**div_amt*shrout** when **distcd** starts with 120, 121, 122, 123, 124, 125, 126,128,130, 131, 132, 133, 134, 135, 136, or 138
Dividend Payout Change (**dpc**)	$(\mathbf{rcd}_t - \mathbf{rcd}_{t-1}) / \mathbf{rcd}_{t-1}$
Dividend Decrease	an indicator variable equal to 1, if **dpc** <= -0.01
Dividend Increase	an indicator variable equal to 1, if **dpc** >= 0.01
Institutional Ownership	**io** from FactSet
Herfindahl-Hirschman index of **io**	**herf** from FactSet

Appendix B. Aspirational Peer Disclosure and Name Detection

To identify revealed peer companies within company filings, I begin with list of all companies that can be identified in the WRDS platform using web scraping on WRDS' "Find Companies" page. These names are matched with generic identifiers such as CIK, CUSIP and ISIN using Factset's Company Lookup excel add-in. Manual quality control steps are also taken to get a clean linking table between companies short and long names with generic identifiers such as: Removing spaces between two single letter names. Removing "THE" if it is the first word of the company name. Removing common ending words such as Corp., Co. Replacing abbreviated common terms such as Ltd., Co. and Srvs with their complete form. Converting names recorded as web domain to short names such as Twitter.com to Twitter Matching common and short names with long and principle company names using WRDS CapitalIQ Identifiers datasets. If two or more firms in a file/text have the same short or long names, expand the short or long names so that the peers could be distinguished from one another. When this is not possible or involves large name expansions (and hence likely false negative mentions), then these peers are dropped from the sample. When the focal firm and disclosed firm have the same short or long names, then the focal-peer observation is also dropped from the sample.

After controlling discrepancies between names of companies that appear in different databases but with unique generic identifier, I then match the new names with old names of the companies to get a clean list of short and long names with their unique generic identifiers. This list is used to detect company names in the text with one of the following approaches: The first approach searches through the text looking for an exact match of the short or long names. To count as a hit, the company names in the file should be in proper-case or upper-case format. This approach works well provided the name keyword assumptions hold. For example, false negatives are possible when the case assumption is wrong (e.g., “eBay” would be missed) or short/long names are too long. The second approach is to use a machine learning technique called named entity recognition (NER) which classifies named entities in a textual file into different categories. There are pre-build codes and programs that can do NER with reliable accuracy such as a software named spaCy (available at https://spacy.io/). After running the NER model on the company filings and public text files, we get a list of identified entity names with the type and number of the hits in the file. The output NER result should be manually inspected and matched with the list of the names from fist stage. This inspection is necessary since NER output could include many unrelated entity names for example common entity names such as “Board of Directors”, “Securities and Exchange Commission”, “General Counsel” and abbreviations such as “EPS”, “GAAP”, etc. should be cleaned. The cleaned NER output then should be matched with the short/long using fuzzy matching techniques. After combining the results from two approaches, we can create a list of company names and number of hits per each text file. To determine the accuracy of the identified list, we manually checked more than 1000 focal-peer observations in filings of 100 randomly selected companies.