Beyond Peers: Cross-Industry Competition and Strategic Financing*

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Abstract

Corporate financial leverage within competition networks is determined by both direct and indirect competitors. Using data on firms' self-reported competitors, we identify eleven stable competition communities within the U.S. economy, where firms are grouped into communities based on competitive interactions both within and across industries. We find a strong complementarity between a firm's leverage and that of its community members, consistent with strategic interactions with both immediate peers and chain effects from the propagation of shocks affecting indirect peers. To achieve identification, we employ a granular instrumental variable approach. Our results highlight that firms' financial strategies are shaped not only by direct competition but also by the broader competitive environment.

JEL classification: G31, G32, L13

Key words: capital structure, strategic competition, financial complementarity, competitor networks

1 Introduction

Understanding the determinants of corporate financial leverage has long been a central focus in finance. Traditionally, research has emphasized firm-specific factors such as profitability, asset structure, growth opportunities, and market conditions as the primary drivers of leverage decisions (Titman and Wessels 1988, Rajan and Zingales 1995). However, in increasingly interconnected markets, where firms do not operate in isolation but rather within complex networks of competitors, the strategic interactions between firms have emerged as critical determinants of financial behavior (Leary and Roberts 2014, Hoberg and Phillips 2016, Grieser et al. 2022). In this paper, we explore the role of these competitive dynamics by investigating how firms' leverage decisions are influenced by their position within what we term "competition communities."

Competition communities are groups of firms that are linked through direct and indirect competition, often spanning multiple industries. Unlike traditional industry classifications, these communities reflect the actual competitive landscape where firms face strategic interactions not just with direct competitors, but also with firms in related markets that shape the competitive environment. Leveraging data on firms' self-declared competitors, we apply a machine-learning approach to identify eleven stable competition communities in the U.S. economy. These communities provide a novel concept through which we examine how financial decisions are affected by and propagate through networks of competing firms.

Our study contributes to the literature on competition and finance by documenting novel facts about the propagation of financial shocks within these competition communities. We show that a firm's leverage decisions are influenced not only by its own characteristics but also by the characteristics and leverage choices of its direct competitors, indirect competitors, and the broader community. Remarkably, the influence of the broader community on a firm's leverage is strongly positive and economically significant, with a magnitude comparable to that of direct competitors. These findings are consistent with models of product market competition where financing decisions act as strategic complements, suggesting a potential channel through which financial shocks can be amplified across the economy due to product market interactions.

Empirically, we utilize the Factset Revere dataset, covering the period from April 2003 to August 2018, to identify firms' competitors and define competitor networks and communities and document their evolution over time. Figure 1 illustrates the competitor network within the U.S. economy for a specific year, where the colors represent different SIC industry classifications. We depict all Compustat firms matched with Factset Revere. The figure illustrates that firms compete in a complex network of direct and indirect competitive links. However, it is also apparent that traditional industry classifications do not properly capture competition networks and the groups of firms that form a community. To classify communities of firms within this network, we employ a widely accepted machine-learning approach that applies a dynamic network community detection algorithm. This method allows us to classify firms into competition communities at each point in time and track these communities over the study period. Although we observe the formation and dissipation of various communities, we consistently identify eleven permanent competition communities within the U.S. economy.

An analysis of the competition communities reveals distinct clusters of firms that are interconnected through competitive relationships across various industries. These communities range from "Innovative Chemical and Medical Services," dominated by firms in the chemicals and medical sectors with high R&D costs and growth potential, to "High-Tech Manufacturing and Services," where firms in electronics and machinery exhibit significant capital investment needs. Other communities include "Consumer Retail and Apparel," focused on consumer-driven industries with higher leverage due to inventory financing, and "Health and Professional Services," where service-oriented firms display moderate growth potential. The "Capital-Intensive Energy and Chemicals" community features firms in oil, gas, and chemical industries with high asset tangibility and leverage. Each community reflects unique financial characteristics and industrial compositions.

Over the sample period, the competition communities exhibit notable stability, consis-

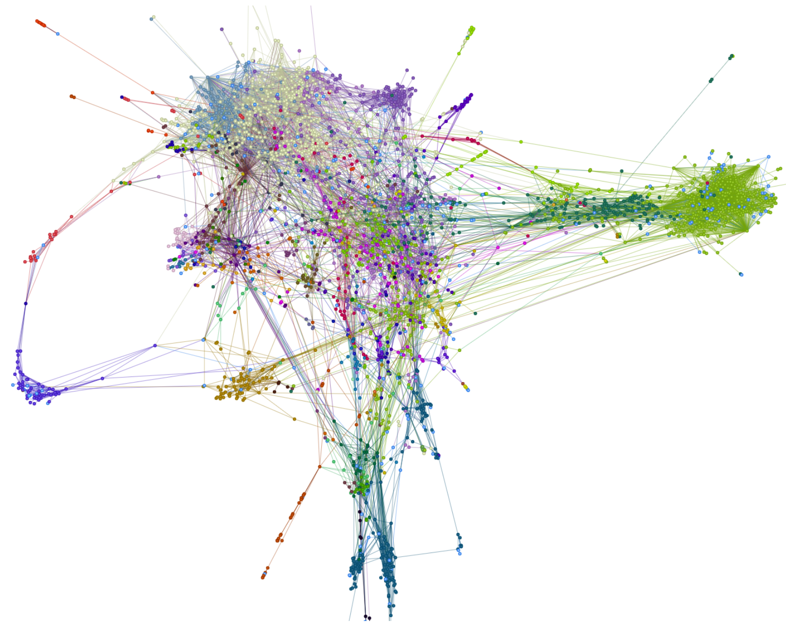

Figure 1: Competition networks and traditional industry classification
The figure documents the relation between competition network and industry classification. Firms are indicated by nodes. Every pair of nodes linked by one direct edge is a pair of direct competitors. The colors of nodes and edges indicate the SIC2 classification for each firm.

tently covering a large portion of the economy despite the dynamic nature of market entries, exits, and changing competitive links. While the overall number of communities fluctuates over time, the core composition of these major communities remains relatively constant, indicating persistent competitive structures. However, the evolution of these communities is influenced by factors such as technological innovations and market disruptions, which can lead to shifts in the composition and connectivity of firms (Hoberg and Phillips 2024).

To examine how competition communities influence firms' financial decision-making, we formulate and test three hypotheses, each designed to assess the extent to which firms' leverage choices are shaped by their internal characteristics, (in)direct competitors, and the broader competitive environment within their community. Our first hypothesis explores whether community leverage—the average leverage within a firm's competition community—affects a firm's leverage decisions. Community leverage should have little to no impact under the assumption that firms primarily focus on their immediate strategic needs and direct competitors. However, we find that community leverage does play a significant role. Both regression and IV results show that the impact of community leverage on a firm's financial decisions is strongly positive and economically significant, indicating that firms align their leverage with the broader community. A one standard deviation increase in community leverage is associated with an increase in firm leverage by 4.5 to 6.3 percentage points.

The second hypothesis addresses the relative influence of direct competitors versus the broader community. One might expect that direct competitors exert a stronger influence on a firm's leverage, given their immediate impact on market share and competitiveness. While our results confirm that direct competitors are indeed influential (Leary and Roberts 2014), they also demonstrate that the effect of the broader community on a firm's leverage is of comparable, if not larger magnitude. Based on our GIV estimates, a one standard deviation increase in competitor leverage is associated with a 2.3 percentage points increase, compared to 3.3 percentage points for the community. This suggests that firms consider both the immediate actions of their direct competitors and the overall financial behavior of their community when making leverage decisions.

The third hypothesis distinguishes between the influence of direct and indirect competitors on a firm's financial decisions. We hypothesize that direct competitors, who operate in the same market segment, are the primary drivers of leverage decisions. However, the results indicate that indirect competitors, although not directly in the same market segment, have significant impact on a firm's leverage choices. Direct and indirect peers have about the same impact. This finding highlights the importance of considering the entire competitive network, including indirect competitors in the same community.

To obtain identification of the community effect, we exploit the fact that community and overall economy are distinct concepts. Hence, our identification strategy is immune to confounding market-wide shocks. In all specifications, we include firm fixed effects and time fixed effects interacted with industry fixed effects. All confounders would have to active at the firm-quarter level. To address this alternative, we employ a granular IV approach. In the spirit of Bartik (1991) and Gabaix and Koijen (2024), we construct a granular instrumental variable that uses as 'share' (i.e., weight/importance) the network centrality within the firm's community relative to the economy and as 'shift' (i.e., shock) the idiosyncratic equity return of the firm (as in Leary and Roberts (2014)). The exclusion restriction here is that the idiosyncratic equity return is uncorrelated with the compound error, which is the share-weighted average across firms in the unexplained component of firm-level leverage and, in particular, the error term of the firm most exposed to that shock.

Our findings have important implications for understanding the propagation of financial shocks within competition networks. The significant influence of competition communities on firms' leverage decisions suggests that financial shocks can propagate more widely and deeply through the economy than previously thought, especially given the broadened scope of firms documented in Hoberg and Phillips (2024). When a financial shock affects a firm or a group of firms within a competition community, the interconnected nature of these communities means that the shock influences not just the directly affected firms but also others within the same community. Since firms tend to align their leverage with that of their community, a shock that alters the leverage decisions of key firms can ripple through the entire community, amplifying its effects. Moreover, the comparable influence of direct competitors and the broader community suggests that financial shocks can spread both through direct competitive relationships and through the broader network structure.

Literature. Peer effects on firms' financial leverage, particularly among direct competitors, have been widely studied in the finance literature. The empirical results of our paper are closest to Leary and Roberts (2014) and Grieser et al. (2022), but we extend prior work in several important ways. Leary and Roberts (2014) focus on the role of peers, which is identified via industry classification only. Grieser et al. (2022) uses text-based product description similarity to identify competitors and rely on a reduced-form spatial model to assess how direct competitors' leverage (linearly) affects firm leverage, complementing the work by Leary and Roberts (2014). Apart from using a different source of network data, we differentiate from them with our novel notion of community and by highlighting the importance of network neighbors beyond direct competitors or traditional peers.

Complementing this literature, we focus on indirect peers and identify endogenous network effects in the spirit of Manski (1993), originating in social network analysis, where the policy variable of a firm varies with the behavior of the same policy variable of its group, and distinguish these from contextual effects, where the propensity of a firm to behave varies with the exogenous characteristics of the group. To do so, we adopt and extend the exogenous firm characteristics setting of Rajan and Zingales (1995) who examines the determinants of financing decisions for a firm in isolation. Manski (1993) highlights the reflection problem in the analysis of peer effects within the economics literature (see also Bramoullé et al. (2009) and subsequent work). Our identification of community effects relies on the granular instrumental variables approach introduced by Gabaix and Koijen (2024).

Our paper also relates to the broader capital structure literature. Bradley et al. (1984) document the importance of industry classification in explaining variation in capital structure. MacKay and Phillips (2005) examine the importance of product market characteristics for firm financing within markets. Frank and Goyal (2009) examine the determinants of capital structure and highlight the role of peer effects in shaping firms' financial leverage, particularly within competitive environments. Leary and Roberts (2010) provide a comprehensive analysis of how firms adjust their financial leverage in response to the actions of peer firms, particularly in industries where competition is intense. Based on survey evidence, Graham and Harvey (2001) report that CEOs identify the behavior of competitors as an key determinant for financing decisions. Frésard and Phillips (2022) survey the literature on competition and corporate financing.

There is a large theoretical literature on strategic interactions and financing decisions pioneered by Brander and Lewis (1986) and Maksimovic (1988).[1] This research strand shows

[1]Brander and Lewis (1986) show that debt financing can commit firms to aggressive output strategies in a duopoly, thus impacting market competition. Maksimovic (1988) examines how capital structure affects

that firms take into account the leverage choices of their competitors when making capital structure decisions in stylized competitive environments. Recent contributions by Bramoullé et al. (2014) and Choné and Linnemer (2020) examine how to account for strategic interactions in a general competitive environment characterised by a network of firms. Bramoullé et al. (2020) survey the literature on peer effects in networks.

Hoberg et al. (2014), Frésard et al. (2024), and Hoberg and Phillips (2024) show the importance of measuring the competitive environment in a granular way. Hoberg and Phillips (2010, 2016) use a novel text-based approach to identify network industries and endogenous product differentiation. They present evidence that firms consider the financial policies of direct competitors when making their own capital structure decisions, reflecting strong peer effects. All these papers provide a foundation for understanding how peer effects among direct competitors influence firms' financial leverage decisions. However, they largely abstract from indirect competitors which is what our paper focuses on and which can also drive peer effects and shock propagation in corporate finance. The community detection algorithm that we employ is borrowed from the social network analysis literature in computer science.[2]

A large literature focuses on supply chain linkages and the propagation of productivity shocks (Barrot and Sauvagnat 2016, Carvalho et al. 2021, Taschereau-Dumouchel 2024, Nunez and Subramanian 2024) or trade credit (Gofman and Wu 2021). By contrast, we study competition networks and the propagation of financial shocks.

product market strategy in an oligopolistic market. Showalter (1995) investigates how Cournot vs. Bertrand competition affects strategic outcomes. Bolton and Scharfstein (1990) analyze how financial contracts can be used strategically to influence competitive outcomes in the context of predation.

[2]Girvan and Newman (2002) has pioneered network community detection. Since then, community detection methods on static networks have grown in different directions. Led by Newman and Girvan (2004) and Clauset (2005), one stream involves defining and maximizing a quality function that scores a partition. The classic quality function that we apply is modularity (Newman and Girvan 2004), which was shown to be NP-hard by Brandes et al. (2006). Consequently, a series of fast approximation algorithms has been proposed, with Blondel et al. (2008) being one of the most successful static methods. Perturbations in the network topology due to the dynamic evolution of nodes and edges present challenges and have given rise to a dynamic community detection literature. Aynaud and Guillaume (2010) extend the well-accepted method by Blondel et al. (2008), and this is the approach we apply to our dynamic firm networks.

2 Motivation and Hypotheses

While the empirical literature has focused on direct peer effects in firms' capital structure decisions, theoretical network models of product market competition and financial decisions highlight that competition takes places in networks comprising direct and indirect peers, giving rise to competition communities. This section provides a motivation for our empirical analysis and formulates several testable hypotheses.

2.1 Motivation

Competition networks emerge from the interactions between firms operating within the same or related markets. These networks represent the interconnected relationships of competition where firms influence and are influenced by each other's product market and financial strategies. In markets where products are similar, firms compete more directly, fostering dense competition networks. Conversely, when products are differentiated, competition networks become more sparse and segmented due to some firms being more specialized while others operate in multiple segments.

Competition networks, through their interconnected nature, lead to the formation of *communities* where firms are related in terms of market focus, competition, and strategic interactions. Understanding these communities is crucial for analyzing product markets and financial conditions and exploring the propagation of shocks. It is therefore important to identify how many competition communities exist in the economy, how they are comprised of firms that are direct or indirect competitors, and whether there is complementarity or substitutability between a firm's leverage and the leverage of its community members. In the former case, strategic interactions with immediate peers can lead to chain effects from the propagation of productivity and financial shocks.

To give an illustration, start with companies (A, B, and C) that compete directly within the same industry, such as the automotive industry. These firms form a simple competition network where each company is linked through their rivalry in producing cars. As more companies enter the network, but operate in a different yet related industry, such as auto loan financing (D, E, and F) or, alternatively, electric vehicle components (F, G, and H), the network expands and diversifies. Industry 1 consists of companies A, B, and C, which are closely connected by their competition within the traditional automotive sector. Industry 2 (3) includes D, E, F (F, G, H), which are more closely connected by their competition in the lending and electrical components industry.[3] Despite operating in different industries, there are cross-industry links, as they share the same competitors A-C and, in addition, there may be competition on customers or technology development. These cross-industry interactions create a broader competition network, but across this network, a single community emerges that encompasses all firms A through H.

Competition communities can significantly influence firms' financial choices because the competitive environment affects not only product market strategies but also the optimal use of financial resources. When firms operate within a competitive community, they are not only influenced by their own goals but also by the actions and strategies of their peers. This interconnectedness can lead to either a convergence or divergence of financial strategies, as firms are pressured to predate or accommodate the financial decisions of their competitors to maintain competitive parity. For instance, if one firm in the community increases its leverage to commit itself to an aggressive product market strategy or to finance expansion or innovation, others may follow suit to avoid falling behind, even if it involves greater financial risk. To the extent that firm A competes directly with firms D and H, while D and H are not direct competitors, the joint consideration of firm A's product market and financial policies can lead D and H to pursue similar leverage decisions—creating a chain of propagation of productivity and financial shocks within competition networks.

[3] Note that company F is active in both segments.

2.2 Hypotheses

To explore how productivity and financial shocks propagate within competition networks, we formulate several hypotheses on the determinants of firms' leverage choices.

Our first hypothesis is grounded in the traditional view that a firm's financial decisions, particularly regarding leverage, are primarily driven by its own strategic needs, direct competitors, and internal factors such as profitability, risk tolerance, and growth opportunities. If a firm focuses on these internal and immediate competitive pressures, the average leverage within its broader community might have little to no impact on its own leverage decisions. This could occur if the firm perceives its situation as unique or if the community's influence is diluted across a diverse group of firms with varying strategies.

The alternative is that community leverage affects a firm's leverage. This alternate hypothesis suggests that firms are influenced by the financial behavior of their community as a whole. In this novel view, firms align their leverage with community averages due to shared economic conditions or the desire to maintain competitive parity within the broader industry network. This leads to a convergence of financial strategies within the community, but not the overall economy.

Hypothesis 1. *Community leverage does not affect a firm's leverage.*

Our second hypothesis posits that direct competitors exert a stronger influence on a firm's financial choices than the broader community does (Leary and Roberts 2014, Grieser et al. 2022). The reason may be that firms are more likely to monitor and react to the actions of their direct competitors, who have a more immediate impact on market share, pricing strategies, and overall competitiveness. Direct competitors are often operating in the same market, facing similar customer demands and cost structures, making their financial strategies particularly relevant.

The alternative is that community leverage matters as much or even more than competitors' leverage for a firm's leverage. This alternative hypothesis suggests that the broader community's financial behavior might provide a valuable signal of strategic interactions in competition networks and a signal for firms, especially if the community represents a comprehensive picture of the competitive environment. In this case, firms might prioritize aligning with the community average to commit to product market strategies, mitigate risk, or maintain industry standards.

Hypothesis 2. *Competitors' leverage matters more than the community leverage for a firm's leverage.*

Our third hypothesis is based on the idea that direct competitors, who compete in the same market segment, product lines, or geographical areas, have the most significant impact on a firm's financial decisions. The rationale is that these competitors are more visible and their financial strategies, such as leverage decisions, directly influence a firm's market position. Firms may feel more immediate competitive pressure to match or counter the leverage levels of these direct rivals to protect or enhance their market share (Brander and Lewis 1986).

The alternative is that indirect competitors are equally or more important than direct competitors in determining a firm's leverage. This alternative hypothesis suggests that indirect competitors, though not directly competing in the same market segment, might still significantly influence a firm's financial decisions for strategic reasons.

Hypothesis 3. *Direct competitors are more important than indirect competitors in determining a firm's leverage.*

Each of these hypotheses reflects different perspectives on how firms in competition communities prioritize various sources of influence when making financial decisions, particularly regarding leverage. By testing these hypotheses, we provide insights into the relative importance of direct competitors versus the broader competitive environment in shaping corporate financial strategies. Before doing so, we introduce the data and provide evidence on cross-industry competition networks in the U.S. economy.

3 Evidence on Cross-Industry Competition Networks

In this section, we provide novel empirical evidence on competition networks within the U.S. economy. Using granular data on firms' self-declared competitors, we map out competition networks among all publicly listed firms that extend both within and across industry. We also document the prevalence of cross-industry interactions among clusters of competitors, which extend beyond standard industry classifications and traditional peers.

3.1 Data

Our main data source is the FactSet Revere Supply Chain Relationships database over the period from April 2003 to August 2018, which provides monthly updated information about the business relationships and interconnections between firms. We merge the Revere data with the Compustat North America dataset by CUSIP identifier to obtain quarterly fundamental variables for each firm.

The Revere dataset classifies the firm-level relationships into four types: competitor, partner, customer, and supplier. It covers the most comprehensive relationship network that is currently available to practitioners. It includes relationships disclosed by either one of the two firms in a relationship (or by both), with the start and end monthly dates for each relationship. FactSet's analysts collect and monitor information from firms' public financial filings (e.g., 10-K, 10-Q, and 8-K reports), financial statements, investor presentations, websites, corporate action announcements, and press releases. Importantly for our analysis, if firm A reports firm B as its competitor, a mutual competitor relationship is identified and we treat the competition relationship symmetrically.[4]

To clean the Revere dataset, we remove uninformative relationships where either the source or target firm is missing. We combine multiple same-class relationships between the same pair of firms over different time periods into one continuous relationship if the

[4]Similarly, if firm A reports firm B as its supplier, firm A is naturally identified as firm B's customer. We do not use this customer-supplier data for the purpose of this study.

time gap between two consecutive relationships is not longer than 4 quarters. We drop duplicate relationships when the valid period falls within the time period of a longer same-class relationship between the same pair of firms, and remove firms that are private or for which fundamental data is not available from Compustat North America for the period relevant for measuring relationships.

In the Compustat data, we exclude utilities firms (SIC code 4000–4999), financial firms (SIC code 6000–6999), and international affairs non-operating establishments (SIC code >9000) as well as any firm with missing SIC code. We exclude very small firms with total assets that are less than 5 millions or sales are zero. We exclude observations with missing or invalid (negative) total asset, sales, and total liabilities. Last, we exclude observations with missing data required to calculate market-to-book ratio, return on asset, market leverage, and tangibility. Data are winsorized for each quarter at the 1% and 99% level. Table 1 reports the definitions of the variables used in the analysis.

Our merged Revere-Compustat sample has 5,126 firms of which 4,762 report at least one competitor, and it covers 72,508 competitor relationships over 62 quarters for a total of 120,256 observations. Table 2 reports summary statistics on the competitor network and all relevant variables used in the empirical analysis. Panel A provides summary statistics of the variables used in the empirical analysis. The community variables are the average of the winsorized firm-level variables of the firms in each community. The competitors variables are the weighted average (according to adjacency matrices) of the winsorized firm-level variables of the competitor firms. No further winsorization is done on the derived variables.

Table 2, Panel B provides features of the network used in the regression analysis. The number of communities excludes the communities of less than four firms. Nodes in community measures the average number of firms (over time) in each community. We report its average, standard deviation, and other distributional statistics across communities.

Table 2, Panel C reports the number of firms and links in the Revere data, only involving the firms with data available in Compustat after all cleaning steps. The number of competition links rises from 6,241 in 2003 to 21,464 in 2017, and then declines to 19,205 by the end of our sample. The second column shows that the number of firms rises from 1,765 in 2003 to 3,580 in 2017, and then declines to 3,378 by the end of our sample.

3.2 Identifying competition networks and communities

We focus our analysis on the notion of *competition community*, borrowing the concept from the social network literature in computer science. In this field, large networks are decomposed into sub-units to help discover unknown functional modules in complex networks. In our context, we define a competition community as a group of firms that exhibit dense connections among their members while maintaining relatively sparse connections with companies outside their group. Consequently, the notion of community is not constrained to merely the set of directly related competitors of a firm, let alone to standard industry classifications. For example, two firms sharing the same industry classification but only distantly or sparsely connected would not be classified into the same community. Furthermore, two firms that directly compete with each other but are more densely connected and interact with other sets of firms may be identified as belonging to separate communities.

In addition, as firms enter and exit the market both the competition links among firms and the number of existing nodes in the competition network change over time. Consequently, classifying firms based on static graphs for separate time periods cannot identify persistent communities present in the U.S. economy. In our context, communities may merge, split, appear, or disappear in response to the dynamic changes in nodes and links. Using static methods, we cannot determine whether the community in one time period is the same community in a subsequent period.

To identify competition communities in our data, we borrow from the machine-learning literature and apply a dynamic community detection framework that modifies a well-accepted static community detection algorithm (Blondel et al. 2008) to track network evolution over time using a rolling window approach (Aynaud and Guillaume 2010). In this setup, the algorithm seeks a proper partition of the nodes, meaning no overlapping communities and no node belonging to more than one community[5]. A quality function is defined to assign a score to each partition, with the best partition being the one that maximizes this quality function. The function we use is modularity, which was introduced conceptually by Newman and Girvan (2004) and is defined below for each graph.

$$Q = \frac{1}{2m} \sum_{i=1}^{N} \sum_{j=1}^{N} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j),$$

where N is the total number of nodes in the graph, A_{ij} represents the edge strength (weight) between nodes i and j as defined in the adjacency matrix[6], k_i denotes the sum of the weights of the edges attached to node i, c_i represents the community to which node i belongs, the Kronecker delta function $\delta(c_i, c_j)$ equals 1 if nodes i and j are in the same community ($c_i = c_j$) and 0 otherwise, and $m = \frac{1}{2}\sum_{ij} A_{ij}$. The modularity value of a partition ranges from -1 to 1. Given a partition of the network, this quantity calculates the actual fraction of edges that connect two nodes of the same community (i.e., the probability that two nodes classified into the same community by the partition are connected) minus the expected fraction of edges that would connect the two nodes when connections between them are random (i.e., the expected probability of connection). Essentially, it quantifies the ratio of the density of links within communities relative to the density of links between communities.

The exact optimization of modularity is NP-hard (computationally intractable), so only fast approximation algorithms can provide feasible solutions. We refer readers to the original paper by Blondel et al. (2008) for a complete explanation of their hierarchical greedy algorithm (Louvain Method) for solving this optimization, where the computational complexity is close to linear in data size. Appendix A provides a brief description of the algorithm.

[5] In the real world, a community might not disappear instantaneously but could be slowly absorbed by others. This type of transformation remains a challenge for the literature, and the method we apply in this paper does not yet address this issue.

[6] In our work, edges are assumed to be equal-weighted due to the lack of precise information about the strength of competition. Hence, A_{ij} equals one if i and j are directly linked and zero otherwise.

Figure 2: Competition network, industry classification, and cross-industry communities
The figure documents the relation between competition network and cross-industry firm communities. Firms are indicated by nodes. Every pair of nodes linked by one direct edge is a pair of direct competitors. The colors of nodes and edges indicate the cross-industry firm communities.

3.3 Competition communities in the U.S. economy

Over the sample period from April 2003 to August 2018, we identify a combined total of over 150 competition communities. Among those, many communities exhibit a short lifespan because of newly formed or broken links between firms dynamically and the entry and exit of firms. We identify eleven stable communities over time that cover the majority of firms throughout our sample. These communities group firms across industries and thus constitute a more general and flexible notion of "industry" to characterize a competitive environment.

Figures 1 and 2 provide a graphical illustration of our results. In the figures, firms are represented by nodes, and competitive relationships are indicated by edges connecting pairs of nodes. We apply a force-directed graph drawing algorithm to position the nodes. Nodes are drawn closer together if there is a larger number of direct and indirect linkages between them. Also, a central-hub node with a higher node degree is assigned greater gravitational force, which attracts other nodes closer to it. In Figure 1 we depict the competition network and highlight the standard industry classifications. Here, the colors of nodes and edges correspond to the SIC2 classification for each firm. The figure shows that SIC2 industries are quite distinct from actual competition networks as the colors are quite mixed throughout each cluster of firms.

Figure 2 shows that the communities are only weakly related to the SIC industries depicted in Figure 1. The plot illustrates the cross-industry communities of firms that emerge from the competition network classification based on our community detection algorithm. Firms within the same cross-industry community are denoted by the same color of nodes and edges. Although firms are competitors within an SIC industry, they often compete across SIC industries as well. Additionally, not all firms are directly or indirectly in competition with one another, leading to several distinct communities of firms. By comparing the middle areas of the two plots, we can observe that a community is not merely a naïve superset or subset of an industry concept.

Characteristics of competition communities. Table 3 summarizes several characteristics of the eleven stable competition communities that we identify using the Louvian method. We characterize each community by the (average) number of firms comprising it, their operating and financial characteristics, and the industries they operate in. We include average leverage (L), return on assets (ROA), firm size (Size), asset tangibility (Tang), and market-to-book ratio (MB). The last column lists the SIC codes of the industries that are most represented within each community, with percentages indicating the proportion of firms from those industries.

Table 3 shows that there is a sizeable variation in average leverage across the communities, with Community 1 having the lowest average leverage (0.195) and Community 11 the highest (0.428). This suggests differing financial strategies regarding debt usage. The return on assets varies slightly across communities, with some communities like Community 5 showing higher profitability (0.023) compared to others like Community 1 (-0.056). Larger firms with higher asset tangibility, like those in Community 11 (Size: 6.988, Tang: 0.280), have different financing needs compared to smaller or less asset-heavy firms. Communities with higher MB ratios, such as Community 1 (3.411), are in industries with high growth potential and market expectations, compared to those with lower MB ratios like Community 11 (1.611).

The next section explores the extent to which financing policies are substitutes or complements within competition communities in the U.S. economy.

4 Financial Leverage in Competition Networks

In this section, we provide a framework and empirical evidence showing that competition communities serve as a useful concept from social network analysis to study the influence on financing choices (in particular, leverage) of individual firms. We structure our empirical analysis around a framework developed by Manski (1993) that distinguishes the nature of interaction effects into three competing hypotheses: endogenous effects, contextual exogenous effects, and correlated effects.

4.1 Empirical framework for leverage in competition networks

We first introduce some notation and denote the leverage choices of the firms by variable L. Suppose at time t there are N firms in the economy indexed by $i = 1, \ldots, N$. Each firm competes in product markets and firm i makes strategic leverage choices L_i. Firms are described by a set of characteristic variables $\mathbf{X}$ and their position in the competition network. We denote the competition community classification to which firm i belongs as $\mathcal{C}_i$ for $i = 1, \ldots, N$. If firm j belongs to the same community as i, then $\mathcal{C}_i = \mathcal{C}_j$. The leverage choice vector in firm community $\mathcal{C}_i$ is given by $\{\mathrm{L}_j \mid j \in \mathcal{C}_i\}$. The leverage of every firm i is chosen strategically, interacting with all other firms in $\mathcal{C}_i$: $\mathrm{L}_i = \mathcal{L}(\{\mathrm{L}_j \mid j \in \mathcal{C}_i\}, \mathbf{X_i})$, where $\mathcal{L}(\cdot)$ captures the firm's equilibrium best response.

In our setting, the endogenous effect of Manski (1993) represents the propensity of a firm to decide on leverage along with the leverage choices of the competition community.[7] This is the main effect we are after, and it is similar to a situation where an individual youth's achievement in school tends to vary with the average achievement of schoolmates. The contextual effect represents the propensity of a firm to decide on leverage according to the exogenous characteristics of the competition community. This is similar to a situation where classmates' personalities and friendliness lead to improvement in an individual youth's achievement. The correlated effect, like our fixed effects, indicates a pure similarity of firms within the same community, which gives rise to similar leverage choices, much like how similar kids with similar backgrounds and abilities tend to attend the same school.

Our empirical model to capture the effect of competition community $\mathcal{C}$, as opposed to firm characteristics $\mathbf{X}$, affect firm i's leverage, we are interested in identifying parameters of the following model for leverage:

$$\mathbb{E}(\mathrm{L}_i \mid \mathcal{C}_i, \mathbf{X}_i) = \alpha + \beta \times \mathbb{E}(\mathrm{L}_i \mid \mathcal{C}_i) + \mathbb{E}(\mathbf{X}_i \mid \mathcal{C}_i)'\gamma + \delta_{\mathcal{C}_i} + \mathbf{X}_i'\eta. \tag{1}$$

A non-zero β in expression (1) indicates an endogenous effect in the competition community: a firm's leverage L_i varies with $\mathbb{E}(\mathrm{L}_i \mid \mathcal{C}_i)$, the average leverage of firms within the same community $\mathcal{C}_i$. A non-zero γ identifies a contextual effect: corporate leverage varies with $\mathbb{E}(\mathbf{X}_i \mid \mathcal{C}_i)$, the mean of the exogenous characteristic variables $\mathbf{X}_i$ among firms in the same community. When $\delta \neq 0$, the model captures correlated effects, meaning firms in the same community tend to behave similarly due to unobserved similar characteristics. The parameter η controls the direct effect of a firm's own characteristics $\mathbf{X}_i$ on its leverage choice.

The well-known reflection problem raised by Manski (1993) highlights the difficulty of distinguishing and identifying the endogenous effect and the contextual effect. We address this identification issue in Section 5. In this section, as a first step, we demonstrate the existence of at least one of the endogenous or exogenous effects within a competition community.

[7] Appendix B provides a detailed motivation for our empirical model.

4.2 Existence of community effect in leverage

The empirical tests must account for the dynamic nature of the leverage data. First, the competitor network is not fixed over time. In the data, competitors enter and exit. To capture the competition network, we introduce a time-dependent adjacency matrix, G_t, with elements $g_{i,j,t}$. Firms i and j are direct competitors in period t if $g_{i,j,t} > 0$ and are not directly competing if $g_{i,j,t} = 0$, with $\sum_j g_{i,j,t} = 1$. We define the dynamic communities through a matrix C_t at time t, with elements $c_{i,j,t}$. Firms i and j are members of the same community, involving direct and indirect competitors, if $c_{i,j,t} > 0$ in period t. Furthermore, as is standard in the literature, we lag all right-hand side variables to diminish the endogeneity of firm characteristics. Last, let $X^k_{j,t-1}$ be characteristic $k = 1, ..., K$ of firm j at time $t-1$.

Community characteristics. Motivated by expression (1), we can write the following panel model for firm i's leverage at time t, $\mathrm{L}_{i,t}$, with firm fixed effects α_i and time-industry fixed effects $\alpha_{t\times\mathrm{SIC}}$:

$$\mathrm{L}_{i,t} = \alpha_i + \alpha_{t\times\mathrm{SIC}} + \sum_{k=1}^{K} \beta^{1k} \times \underbrace{\left(\sum_{j=1}^{N} c_{i,j,t-2} X^k_{j,t-1}\right)}_{\text{Community characteristics}_{i,t-1}} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where $\varepsilon_{i,t}$ is an unobserved mean-zero error term. In expression (2) the β^{1k}, $k = 1, ..., K$, coefficients measure the impact of the community on the firm's leverage after controlling for the firm's own characteristics. Since in all specifications we control for both firm and time fixed effects, any common confounding effect must be present at the firm-quarter level.

Table 4 presents the results for these characteristics-based regressions. Panel A focuses on the impact of community characteristics on firm leverage. It shows that the average characteristics of the firms in the community significantly impact the firm's leverage after controlling for the Rajan-Zingales variables and various fixed effects. Across specifications, $\mathrm{ROA}_{\mathrm{Community},t-1}$ and $\mathrm{MB}_{\mathrm{Community},t-1}$ in specifications (1) and (2), while $\mathrm{Size}_{\mathrm{Community},t-1}$

and $\text{Tang}_{\text{Community},t-1}$ are significant in all four specifications.

The non-zero significant coefficients β^{1k} in (2), according to Proposition 1 of Manski (1993), indicates that either β, η or γ in (1) must be non-zero. This implies that at least one of the exogenous or endogenous effects is significant, i.e., a peer effect by the competition community is indeed present. Our network setting also satisfies the restrictions in the Corollary of Manski (1993) regarding the manner in which characteristics vary with community classification: $\mathbb{E}(\mathbf{X} \mid \mathcal{C}_i)$ varies non-linearly with $\mathcal{C}_i$, and $Var(\mathbf{X} \mid \mathcal{C}_i) > 0$. Note that our $\mathcal{C}_i$ is a classification of firms, which is dynamically assigned to each individual firm based on all firms' topological positions in the complex network of each period.[8] Also, as pointed out by Manski (1993), we assume that firms are aware of the competition community (i.e., specification of the reference group) or that they perceive these groups. This is a reasonable assumption, as the link data source is based on self-declared public information. Firms know this information since they report it themselves.

Direct vs. indirect competitors. We now focus on the distinction between direct and indirect competitors which is one of the main goals of our analysis. While a large literature has documented peer effects from direct competitors on firms' financial leverage (Frank and Goyal 2009, Leary and Roberts 2010, 2014, Hoberg and Phillips 2016), little is known about the financial choices of indirect competitors.

Building on specification (2) for firm i's leverage at time t with firm fixed effects α_i and time-industry fixed effects $\alpha_{t\times\text{SIC}}$, we estimate the model with direct and indirect competi-

[8]The scalar value of our $\mathbb{E}(\mathbf{X} \mid \mathcal{C}_i)$ is not a linear function of $\mathcal{C}_i$ when $\mathcal{C}_i$ is just a group label and it varies with $\mathcal{C}_i$. Additionally, none of the firm characteristics is a straightforward function of the community classification label. Therefore, we satisfy the composite parameter identification requirement of Manski (1993).

tors' characteristics in the same specification using panel regressions:

$$\mathrm{L}_{i,t} = \alpha_i + \alpha_{t\times \mathrm{SIC}} + \sum_{k=1}^{K} \beta^{1k} \times \underbrace{\left(\sum_{j=1}^{N} g_{i,j,t-2} X^k_{j,t-1}\right)}_{\text{Direct competitors' characteristics}_{i,t-1}} + \\ + \sum_{k=1}^{K} \beta^{2k} \times \underbrace{\left(\sum_{j=1}^{N} \mathbb{1}_{i\neq j} g^2_{i,j,t-2} X^k_{j,t-1}\right)}_{\text{Indirect competitors' characteristics}_{i,t-1}} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}. \quad (3)$$

Table 5 shows the results. Throughout all specifications, the firms' own lagged characteristics ROA_{t-1}, MB_{t-1}, and Tang_{t-1} matter while firm size is insignificant. For the direct and indirect competitors, ROA and MB are economically and statistically significant determinants of firm leverage with the same sign as the firm's own characteristics. A firm thus has lower leverage the larger its own profitability, or the profitability of its competitors, or the profitability of its competitors' competitors. Comparing the magnitude of the coefficients, the firm's own profitability matters the most, followed by the indirect competitors, and only last the direct competitors' profitability. The same ordering holds true for the market-to-book ratio.

In summary, the leverage regressions show throughout that the leverage in a firm's competition network matters beyond the impact of the firm's direct competitors. As illustrated in these empirical findings, the spillover on a firm's leverage from its indirect competitors and the rest community members are positive. The impact of the firm's community is at least as large as the direct effect of competition.

The magnitude of these indirect effects is bigger than one would expect with an exponential decay with distance in the competitor network. In a standard network model featuring linear interactions between firms' leverage, for example, based on the Leontief Inverse matrix, the higher-order neighbours would have exponentially diminishing influence on the firm's leverage (Grieser et al. 2022). Thus, only a model with non-linear interaction pattern among community members can possibly match our empirical findings.

5 Strategic Financing and Competition Communities

Up until now, we have shown that the characteristics of the firm in competition networks matters beyond the impact of the firm's direct competitors. We now explore whether peer effects in competition communities extend beyond a firm's direct competitors and depend on community leverage. In the empirical framework (1) this means there exist endogenous network effects in firms' financing decisions resulting from strategic interactions.

5.1 Community leverage

We start by estimating the relation between firm leverage and community leverage. To operationalize Hypothesis 1, we introduce a new variable Community leverage$_{i,t}$, defined as the average leverage in the firm's community:

$$\text{Community leverage}_{i,t} = \sum_{j=1}^{N} c_{i,j,t-1} \mathrm{L}_{j,t}. \tag{4}$$

The following empirical specification with firm and time-industry fixed effects and the set of control variables $\mathbf{X}$ captures the strategic leverage choice of firm i:

$$\mathrm{L}_{i,t} = \alpha_i + \alpha_{t\times\mathrm{SIC}} + \beta \times \text{Community leverage}_{i,t-1} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where $\varepsilon_{i,t}$ is an unobserved mean-zero error term. We again include among the controls $\mathbf{X}$ the standard Rajan and Zingales (1995) variables, including profitability, market-to-book ratio, firm size, and tangibility. All control variable definitions can be found in Table 1.

We first implement (5) by panel data methods. The results of the regressions are presented in Table 6. Panel A shows that leverage in a firm's community is a significant determinant of firm leverage in the next period. Based on the specification a 100bps increase in community leverage increases firm leverage by between 17.5bps and 55.3bps. Across specifications, we control for the firms' own leverage determinants, including profitability, market-to-book, size, and tangibility. All of these firm characteristics have been shown to determine leverage. Across specifications, we also vary the fixed effects between firm fixed effects (column (1)), firm and time fixed effects (column (2) and (3)), and firm and industry x time fixed effects and the coefficients on $\mathrm{L}_{\text{Community},t-1}$ are robustly positive.

Relating these results back to the Manski (1993)-type framework (1), the positive statistically significant β means there exist positive endogenous network effects in firms' financing decisions. The positive coefficient is consistent with theoretical models of product market competition where financing decisions are strategic complements.

5.2 Evidence from granular IV

While the reduced-form analysis of firms' financial decisions in Section 4 is largely immune to confounding factors and simultaneity problems, the analysis of peer effects in competition communities requires distinguishing between direct and indirect effects of financial leverage. We attempt to do so by constructing a granular instrumental variables approach in the spirit of Bartik (1991) and Gabaix and Koijen (2024).

To explain firms' leverage decisions through (4), we must address the issue of joint endogeneity that arises from unobserved common shocks affecting both firm and community leverage. These shocks can lead to simultaneous determination via the aggregate behavior across all firms. To mitigate this endogeneity issue, we build on Welch (2004) by using firm-level stock returns as shocks to community leverage. Welch (2004) computes the implied leverage ratio that comes about if the corporation neither issues debt nor equity such that all market leverage changes are mechanically due to stock price movements $R_{i,t}$: $\text{Imputed leverage}_{i,t} = \text{Book debt}_{i,t-1}/(\text{Book debt}_{i,t-1} + \text{Market value}_{i,t-1} \times (1 + R_{i,t}))$. From this, we can construct a shock by taking the difference between the imputed leverage and actual lagged leverage: $Z_{i,t} = \text{Imputed leverage}_{i,t} - \mathrm{L}_{i,t-1}$. Changes in this variable are not due to equity or debt issuances in the current period. As a robustness and for comparison, we define an alternative shock that is based on the change in leverage, that is $Z_{i,t} = \mathrm{L}_{i,t} - \mathrm{L}_{i,t-1}$.

To leverage the cross-section of firms, we denote by $x_{j,t}$ the eigenvector centrality of firm j belonging to community c shared with firm i at time t. For each period t and firm i, the centrality-weights of firm j in i's community are defined as $S^c_{i,j,t} = \frac{x_{j,t}}{\sum_{k \in c} x_{k,t}}$. Eigenvector centrality measures a firm's influence within a network by considering not only its direct connections but also the centrality of its neighbors. A firm has high eigenvector centrality if it is connected to other highly central firms, emphasizing the quality of connections rather than just the quantity.[9] This approach effectively assesses a firm's importance within its community by leveraging the interconnected structure of the network.

We then incorporate in our GIV the lagged relative weights $w_{i,j,t-l} = S^c_{i,j,t-1} - \frac{1}{N}$, reflecting the network centrality of each firm in the competition community compared to equal weighting, as these weights indicate the relative importance of each firm in its respective community (Goldsmith-Pinkham et al. 2020). This method follows the frameworks of Gabaix and Koijen (2024) and Borusyak et al. (2022, 2024), by constructing a granular instrument similar to shift-share instruments (Bartik 1991), defined as weighted averages of market-wide shocks to imputed leverage ('shift') with weights based on past network centrality ('shares') netting out the equal-weighted market-wide shock as suggested by Gabaix and Koijen (2024). This approach measures the firm-specific effect of community leverage without relying on contemporaneous firm-quarter accounting information, thus diminishing simultaneity concerns. The GIV is defined as

$$z^{\text{Community}}_{i,t} \quad = \quad \sum_{j=1}^{N} (S^c_{i,j,t-1} - \tfrac{1}{N}) Z_{j,t}, \tag{6}$$

where $\sum_{j=1}^{N} S^c_{i,j,t-1} = 1$ and non-zero if j is in i's community. $Z_{j,t}$ is based on the stock return from quarter $t-1$ to t.

[9] The centrality values are derived from the equation: $Gx = \lambda x$, where G is the adjacency matrix of an undirected graph, x is the eigenvector of centrality values, and λ is the corresponding eigenvalue. While the naïve row sum of G provides the node degrees, the eigenvector corresponding to the largest eigenvalue (by modulus) offers a more insightful measure of centrality that accounts for the influence of connected firms. Normalizing G by the largest eigenvalue, we get: $Ax = Ix \implies (I - A)x = 0$, where I is the identity matrix. The existence of the Leontief inverse matrix $(I - A)^{-1}$, which captures the cumulative effect of direct and indirect connections, guarantees non-trivial solutions.

The idea is that the instrument value is zero when the network is completely connected. In this case, the connection density/sparsity is the same among any sub-group of the network and thus, there is only one community which is the whole network. Also, there is no difference among the centralities of nodes and therefore, any centrality-alike weighting scheme would give equal weights among members. Consequently, the any centrality-weighting scheme within the community is the same as equal-weighting on all nodes of the whole network. Only when the network structure deviates from a same-centrality structure, such as a star network, will the instrument value be non-zero.

We proceed in two stages. We first regress Community leverage$_{i,t}$ defined in (4) on $z_{i,t}^{\text{Community}}$ as an instrument. We have the first-stage panel regression

$$\text{Community leverage}_{i,t} = \alpha_i + \alpha_{t\times\text{SIC}} + \delta \times z_{i,t}^{\text{Community}} + \gamma' \mathbf{X_{i,t}} + u_{i,t}. \tag{7}$$

Based on the coefficient estimates in (7), we define the prediction used in place of Community leverage$_{i,t-1}$ in the second-stage panel regression (5) as $\widehat{\text{Community leverage}}_{i,t-1} = \widehat{\alpha}_i + \widehat{\alpha}_{t-1\times\text{SIC}} + \widehat{\delta} \times z_{i,t-1}^{\text{Community}} + \widehat{\gamma}' \mathbf{X}_{i,t-1}$, with firm leverage $\mathrm{L}_{i,t}$ as the dependent variable. This 2SLS approach results in a consistent estimator of β in specification (5) under the GIV validity condition: $\mathbb{E}[\varepsilon_{i,t} \cdot z_{i,t-1}^{\text{Community}}] = 0 \Leftrightarrow \sum_{j=1}^{N} \mathbb{E}[\varepsilon_{i,t} \cdot w_{i,j,t-1} \cdot R_{j,t-1}] = 0$. This exclusion restriction is valid so long as the historical community weights $w_{i,j,t-1}$ can be taken as exogenous or predetermined from the perspective of the model of competition underlying the firms' leverage decisions.[10]

Table 6, Panel B reports the main results. The results correspond to columns (3) and (4) in Panel A and reinforce the significant impact of community leverage on a firm's leverage within the granular IV framework. The coefficients on the community leverage variable, which are instrumented using a weighted sum of stock return shocks from the firm's com-

[10] The exclusion restriction can be interpreted as that the return $R_{j,t-1}$ at time $t-1$ is uncorrelated with the compound error $\varepsilon_{j,t} \equiv \frac{1}{\sum_i w_{i,j,t-1}} \sum_i w_{i,j,t-1} \varepsilon_{i,t}$, which is the share-weighted average across firms in the unexplained component of firm-level leverage at time t and, in particular, the error term of the firm most exposed to that shock. By construction, endogenous changes of the centralities and endogenous firm-specific trends do not cause a variation in the instrument across firms and over time.

munity members (specifications (1) and (2)) or a weighted sum of leverage changes from the firm's community members (specifications (3) and (4)) are positive and statistically significant. This suggests that as the leverage of a firm's community members increases, the firm's own leverage tends to rise as well. Specifically, the coefficients range from 0.532 to 0.752, indicating that a one standard deviation increase in community leverage is associated with an increase in firm leverage by 4.5 (=0.532*0.084) to 6.3 (=0.752*0.084) percentage points. The statistical significance of the coefficients (at the 1% or 5% levels) suggests the relationship is statistically and economically significant. It is interesting to compare the magnitude of the coefficients to the ones in columns (3) and (4) of Panel A which contains the results for the same specifications without GIV. In Panel B, the β coefficients are three times larger than in Panel A.

These findings suggest that firms are influenced by the financial behaviors of their community. The presence of fixed effects controls for unobserved heterogeneity at the firm, quarter, and industry×quarter levels. The pass-through rate of financial shocks ranges between about 0.5 and 0.8 in Table 6. Overall, the results suggest that a firm's leverage decisions are not made in isolation but are significantly affected by the leverage dynamics within its community.

5.3 Falsification tests and robustness

Two types of falsification tests support the validity of the granular IV design. First, in a pre-trend test, we replace the dependent variable at time t by its value in a prior period and we rerun the IV. For the lag we use one year. Second, in placebo tests, we replace the dependent variable at time t by a contemporaneous placebo outcome that we do not expect to be causally affected by the treatment, for example firm investment.

Table 7 reports the results. The results show that community leverage is, as expected, economically immaterial in explaining lagged leverage. For the false discovery test, the results reveal that community leverage is economically immaterial in explaining firm investment. In unreported results for brevity, we show that these results hold true if we replace the dependent variable with the market-to-boot ratio or return on equity. Overall, these falsification tests lend support for the validity of our empirical design.

5.4 Community vs. competitors

To rule out that the effects are driven solely by the firm's direct competitors (Hypothesis 2), we next augment the model by competitor leverage, defined as the average leverage of the firm's direct competitors:

$$\text{Competitor leverage}_{i,t} = \sum_{j=1}^{N} g_{i,j,t-1} \mathrm{L}_{j,t}. \tag{8}$$

With the additional determinant Competitor leverage$_{i,t-1}$, we run the following regression:

$$\mathrm{L}_{i,t} = \alpha_i + \alpha_{t\times\mathrm{SIC}} + \beta^1 \times \text{Community leverage}_{i,t-1} + \beta^2 \times \text{Competitor leverage}_{i,t-1} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \tag{9}$$

where $\mathbf{X}$ is the same set of controls as in (5).

Table 8 shows that leverage in a firm's community is as important as the leverage of the firm's direct competitors. Across specifications, the coefficient on $\mathrm{L}_{\text{Community},t-1}$ is about two to three times larger than the coefficient on $\mathrm{L}_{\text{Direct competitors},t-1}$ and statistically significant throughout. Though, there can be correlation between the direct competitor average variable and the community variable, the average number of direct competitors to a firm is below 7 while the average number of firms in the same community to a firm is above 200. While we are using equal-weighting, it is impossible that the dynamics of community average to a specific firm is only driven by the its direct competitors by over-weighting. Similarly, the average number of second-order neighbours who are indirectly linked to a firm via one intermediate, is above 60. In economic terms, based on the GIV estimates in column (2), a one standard deviation increase in community leverage is associated with an increase in firm leverage by 3.3 (=0.387*0.084) percentage points, while a one standard deviation increase in competitor leverage is associated with a 2.3 (=0.145*0.160) percentage points increase.

5.5 Direct vs. indirect competitors

Now we decompose the total effect of the firm's community into the effects originating at the firm's direct competitors, the competitors of the competitors, and so forth (Hypothesis 3). A comparison between the coefficients on the direct and indirect competitors allows to assess the extent of propagation of leverage shocks and the magnitude of the spillovers. In models with linear interactions, the effect of indirect connections dies out exponentially, suggesting that direct have bigger impact than indirect neighbors.

To check the magnitude of direct compared to indirect competitors, we estimate the model with direct and indirect competitors' leverage in the same specification while eliminating feedback loops. The coefficients $g^1_{i,j,t-1}$ are the (i,j)-elements of the matrix G_{t-1} that captures the competitor network at time $t-1$. The coefficients $g^2_{i,j,t-1}$ are the (i,j)-elements of the matrix $G^2_{t-1} = G_{t-1} \cdot G_{t-1}$ that captures the competitors' competitors. In principle, we can estimate $\beta^l, l = 1, 2, ...$, for higher-order expansions of the competitor network, but higher powers of G become increasingly singular and the estimates become therefore less reliable. Another complication arises from the fact that a competitor of a firm's competitor is the firm itself. Competition loops of this sort are captured by the diagonal elements of G_{t-1}.

To distinguish between the effect of competition loops and competition chains, we further split the matrix capturing competitors' competitors, $G^2_{t-1} = G_{t-1} \cdot G_{t-1}$, into the effects coming from the off-diagonal elements, $g^2_{i,j,t-1}$ with $i \neq j$ and the diagonal elements, $g^2_{i,j,t-1}$ with $i = j$. Accordingly, we define the indirect competitors' leverage by

$$\begin{aligned}
\text{Direct competitors' leverage}_{i,t-1} &= \textstyle\sum_{j=1}^{N} g^1_{i,j,t-1} \mathrm{L}_{j,t-1}, \\
\text{Indirect competitors' leverage}_{i,t-1} &= \textstyle\sum_{j=1}^{N} \mathbb{1}_{i \neq j} g^2_{i,j,t-1} \mathrm{L}_{j,t-1}, \\
\mathrm{L}^{\text{Diagonal}}_{\text{Indirect competitors},t-1} &= \textstyle\sum_{j=1}^{N} \mathbb{1}_{i=j} g^2_{i,j,t-1} \mathrm{L}_{j,t-1}.
\end{aligned} \tag{10}$$

We can now estimate the model by including the direct and indirect competitors' leverage in the same specification and eliminate feedback loops by dropping $\mathrm{L}^{\text{Diagonal}}_{\text{Indirect competitors},t-1}$ from the panel regression specification:

$$\mathrm{L}_{i,t} = \alpha_i + \alpha_{t\times\mathrm{SIC}} + \beta^1 \times \text{Direct competitors' leverage}_{i,t-1} + \\ + \beta^2 \times \text{Indirect competitors' leverage}_{i,t-1} + \gamma'\mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \quad (11)$$

where $\mathbf{X}$ is the same set of control variables as in (5). The results are presented in Table 9.

Table 9, Panel A shows the estimates for β^1 which vary between 0.092 and 0.224 and are all statistically significant. Panel B shows the estimates for β^2 which vary between 0.120 and 0.429 and are all statistically significant. Panel C shows the estimates for β^1 and β^2 jointly. Both coefficients remain statistically significant but the coefficient β^2 tends to be up to more than twice as large as β^1. In economic terms, based on the OLS estimates, a one standard deviation increase in indirect competitor leverage is associated with an increase in firm leverage by 1.1 (=0.087*0.119) percentage points while a one standard deviation increase in direct competitor leverage is associated with a 1.3 (=0.082*0.160) percentage points increase. It thus is the case that the indirect competitors have about as large an impact on the firm's leverage as the direct competitors.

6 Composition of Competition Communities

We now explore the composition and evolution of competition communities in the U.S. economy, and we compare the Revere data to competition communities built upon the methodology developed by Hoberg and Phillips (2010, 2016).

6.1 Characteristics and evolution of competition communities

To give a better interpretation to the identified firm groups, we document the properties of the eleven competition communities, focusing on their characteristics, evolution over time, and their size as captured by their degree distributions.

Description of communities. Exploring the composition of each community, we find that each community exhibits distinct industrial compositions and financial characteristics, reflecting how different sectors influence the financial behavior of firms within these competition communities. The last column in Table 3 reports the three most prominent SIC codes in each community. Community 1 ("Innovative Chemical and Medical Services") is predominantly composed of firms in the chemicals and allied products industry, with a significant presence in medical and optical goods. These industries typically have high R&D costs, reflected in the relatively lower average leverage (0.195) and negative ROA (-0.056), suggesting potential challenges in profitability or heavy investment phases. The high market-to-book ratio (3.411) indicates that these firms are likely valued for future growth potential despite current earnings challenges.

Community 2 ("High-Tech Manufacturing and Services") is dominated by firms in the electronics and machinery sectors. These industries typically require significant capital investment, which is reflected in their relatively high average firm size (6.029) and moderate leverage (0.223). The close to zero ROA (-0.001) suggests these firms are operating at break-even levels, potentially due to high competition or ongoing capital expenditures. The market-to-book ratio (2.308) is moderate, indicating balanced growth expectations.

Community 3 ("Diversified Tech and Equipment") is diverse, with significant representation from medical goods, machinery, and electronics. These sectors are often characterized by a mix of stable cash flows and innovation-driven growth, reflected in their moderate leverage (0.265) and positive ROA (0.008). The size of firms (6.119) and tangibility (0.164) are moderate, supporting a balanced financial profile with moderate market-to-book ratio

(1.974).

Community 4 ("Service-Oriented Business Solutions") is heavily skewed toward business services, with some presence in communications and machinery. These industries tend to have lower asset tangibility (0.122) and are service-oriented, leading to higher leverage (0.286) as these firms may rely more on financing. The positive ROA (0.008) suggests operational profitability, and the moderate market-to-book ratio (2.459) reflects reasonable growth expectations.

Community 5 ("Consumer Retail and Apparel") focuses on retail and apparel, sectors that are generally consumer-driven. These industries exhibit higher leverage (0.334), possibly due to the need for inventory financing and capital investment in retail operations. The positive ROA (0.023) suggests profitability, supported by a larger average firm size (6.956) and relatively high tangibility (0.265). The market-to-book ratio (2.047) indicates moderate growth expectations.

Community 6 ("Consumer Products and Food Services") is characterized by firms in the food, chemicals, and food services industries. These sectors tend to have stable cash flows and higher asset tangibility (0.326), leading to higher leverage (0.343) as firms can secure debt against tangible assets. The positive ROA (0.018) indicates modest profitability, while the market-to-book ratio (2.133) reflects balanced market expectations.

Community 7 ("Health and Professional Services") includes firms primarily from health and business services, with some representation in professional services. These industries typically have lower asset tangibility (0.179) and operate with higher leverage (0.345) due to the service-oriented nature of their business. The slightly positive ROA (0.015) reflects modest profitability, while the market-to-book ratio (2.070) suggests moderate growth potential.

Community 8 ("Capital-Intensive Energy and Chemicals") is focused on capital-intensive industries like oil and gas extraction, chemicals, and electronics. These sectors exhibit high asset tangibility (0.421) and correspondingly high leverage (0.365), supported by tangible assets. The low ROA (0.005) suggests that these firms may face profitability challenges, perhaps due to high capital expenditures. The market-to-book ratio (1.768) is relatively low, indicating limited growth expectations.

Community 9 ("Electronics and Durable Goods Trade") is characterized by a mix of electronics, durable goods wholesale, and business services. These industries show moderate asset tangibility (0.218) and leverage (0.388). The positive ROA (0.014) indicates operational profitability, while the low market-to-book ratio (1.672) suggests limited growth potential compared to other communities.

Community 10 ("Industrial and Professional Services") includes firms from transportation equipment, professional services, and oil and gas. These industries have a balanced financial profile with relatively high leverage (0.400) and tangibility (0.298), supported by capital-intensive operations. The positive ROA (0.013) suggests profitability, albeit with a lower market-to-book ratio (1.603), indicating cautious market expectations.

Community 11 ("Heavy Manufacturing and Industrial Goods") is focused on transportation equipment, industrial machinery, and paper products. These capital-intensive industries have the highest leverage (0.428) among the communities, supported by significant tangible assets (Tang: 0.280). The slightly positive ROA (0.014) indicates profitability, while the low market-to-book ratio (1.611) suggests conservative growth expectations.

Evolution in competition communities. We now explore the evolution of the competition communities. Dynamically, there are 150 competition communities that have ever appeared over the entire sample period. However, when considering communities with a minimum of 10 firms, their numbers show remarkable stability, consistently fluctuating within a narrow range between 12 and 16 in every quarter. Importantly, eleven major communities persist throughout our entire sample period. Despite this apparent stability, the evolution and composition of these communities remain susceptible to various factors, including technological innovations, globalization, and the growing world of e-commerce.

One noteworthy example of the advent of disruptive technologies is the introduction of the iPhone. Steve Jobs, co-founder of Apple, unveiled the first iPhone on January 9, 2007, and it reached the market on June 29, 2007. This momentum continued with the announcement of the highly successful iPhone 3G on June 9, 2008, followed by its release on July 11, 2008. Interestingly, Apple resided in one of the eleven major competition communities.

When we examine the percentage changes in the membership of Apple's community, we observe significant changes during 2007Q2 and 2007Q3, with the composition of firms changing as much as 11.99% and 7.02%, respectively. This pattern continues into 2008 with changes of 11.15% and 15.11% during 2008Q2 and 2008Q3. However, prior to and after these significant quarters, the composition fluctuations of this community were more muted, staying within a 2% to 5% range. Also, we can observe the impact of technological innovation on network structure. Not surprisingly, the second biggest change (17.39%) in Apple's competitor connection degree occurred in 2008Q2 as well. The largest alteration (17.64%) in Apple's connection degree was in 2006Q2, coinciding with the announcements of the first two MacBook Pro models in January and April 2006.

Heavy-tailed degree distribution. We further explore the property of the competition networks' node degree distribution. This is important as the number of direct and indirect competitors, respectively, and the broader network structure of peers and peers of peers can affect the nature of strategic interactions. For instance, two large firms competing directly may make different product market and financial choices as one large firm competing with many small firms, even if the total size of the small firms is the same as the large.

The degree of a node represents the number of connections it has with other nodes within the network. A node degree distribution measures how these degrees are spread across the nodes, reflecting the connectivity within the network. A heavy-tailed degree distribution highlights the prevalence of nodes with significantly higher degrees than the average. This characteristic often appears in networks where a few firms have an unusually large number of

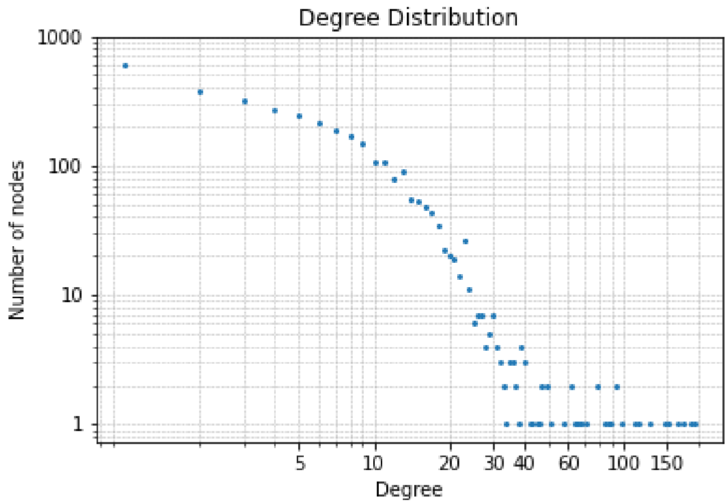

Figure 3: Log-log plot of the node degree distribution for the network of the quarter 2018Q1. The x-axis reports node degrees. The y-axis reports the frequency of nodes having a specific degree. The overall trend suggests a heavy-tailed distribution where a few nodes have very high degrees (hubs) and majority nodes have low degrees.

connections compared to the majority of firms. In fact, it is a common feature, also known as a *scale-free network*, in many real-world complex networks, such as movie-actor networks and protein interaction networks.

Figure 3 shows a log-log plot of the node degree distribution for the network of the quarter 2018Q1. The figure reveals that the degree distribution is heavy-tailed. Table 10 further supports this empirical evidence both for the entire network as well as within the eleven persistent major communities. The detailed breakdown allows for comparison between the overall network and its sub-communities, revealing how tail behaviors—important for describing the topology of the network structure—vary across different communities of the network. The table specifically reports on three metrics including skewness, kurtosis, and the Hill estimator, with values presented as averages across all quarters for both the entire network and each major persistent community. For the entire network, the skewness is 7.510, indicating a highly asymmetric distribution, with a longer tail on one side. The kurtosis is 89.064, suggesting a distribution with extremely heavy tails compared to a normal distribution. The Hill Estimator, which is used to estimate the tail index of the distribution, is 2.074.

On average, the competition communities exhibit a skewness of 3.296, which is lower than the entire network, indicating less asymmetry within individual communities. The average kurtosis across communities is 18.051, still heavy-tailed but significantly lower than the overall network, implying less extreme tail behavior. The Hill Estimator average for communities is 2.597, indicating variability in the tail behavior among the communities. Additionally, the table also lists specific values for each community. For instance, Community 1 has a skewness of 2.347, kurtosis of 9.378, and a Hill Estimator of 3.355, indicating moderate asymmetry and heavy tails. On the other hand, Community 5 has a skewness of 7.197 and kurtosis of 63.518, which are closer to the overall network's values, reflecting more extreme distribution characteristics.

6.2 Comparison with TNIC

When studying the competitive dynamics within competition communities, knowledge about the network of relationships between firms is crucial. Both the Factset Revere data and the TNIC measure of Hoberg and Phillips (2016) provide insights into these competitive networks but employ different methodologies and data granularity. By comparing these two datasets, we aim to assess the consistency and validity of the community structures that we have revealed. This comparison is important for validating the robustness of our network-based analysis and for ensuring that our findings are not artifacts of specific data sources or methodologies. Our goal in this section is to understand how variations in data granularity and coverage impact the detected competitive communities and to align our findings with established metrics.

Standard data cleaning and differences. To compare the Factset Revere data with the TNIC measure, we start with the TNIC-3 similarity scores which provide networks matching the granularity of SIC-3 levels. We restrict the data to our Revere sample period and conduct the same cleaning on the pool of firms. These include similarly excluding utilities firms, financial firms, and international affairs non-operating establishments and removing the firms with missing information required to calculate the characteristics used in main empirical analysis.

At this step, TNIC-3 data includes 6,291 firms throughout the sample which is larger than our REVERE dataset. This wider range of firms is facilitated by merging via GVKEY in TNIC, whereas the Revere dataset is limited by the use of CUSIP and the WRDS merge table. However, looking into each quarter, the coverage of the REVERE data is richer. For example, in the third quarter of 2018, the cleaned TNIC-3 covers 2,518 firms, while the cleaned Revere covers 3,351 firms.[11]

Moreover, the TNIC-3 contains 5 stable communities, significantly fewer than the 11 persistent communities identified in the Factset Revere dataset. This discrepancy can be attributed to the broader classification used in SIC-3, which groups firms more generally compared to the more stringent direct competition criteria applied in the Revere data by their analysts. This more flexible classification in TNIC results in denser networks, as evidenced by higher average degrees, which contrasts with the sparser networks in Revere data. For example, throughout the sample periods, on average the average node degree in Revere is 8, whereas the TNIC-3 has 88. These differences illustrate the impact of data granularity and coverage on community detection, highlighting the need to align the datasets more closely for meaningful comparisons.

Extra cleaning. To have a more comparable network structure and to make sure we treat each firm and relation link homogeneously, we further clean the TNIC-3 data by leveling up the similarity score threshold. Simply assigning a threshold of value between 0.1 and 0.2 can lead to an increase in classified communities, as individual firm's identified linked competitors are fewer and the network is sparser. For example, setting a threshold of 0.15 leads to 11 persistent major communities (that are present in all quarters), exactly the same

[11] If we do not clean TNIC-3 at all, the raw one covers 3,917 firms in 2018Q3.

number of persistent communities as in the dynamic network of Revere data. In the later comparison analysis, we set a threshold of 0.1 similarity scores in TNIC-3 data for all firm pairs, trying to keep as much data as possible. This step leads to 13 persistent communities, reduces the total coverage of TNIC to 4,002 firms and reduces the average node degrees to 49.

As the TNIC similarity scores enable the ranking of closest firms, Grieser et al. (2022) introduce a restriction—for every firm they limit the direct competitors top 10 firms according to the scores. However, this impacts the structure of the competition network, resulting in an asymmetric adjacency matrix. If Firm A considers Firm B as a competitor due to high similarity score, it does not necessarily imply that Firm B views Firm A as a competitor as there could be other firms than A having higher similarity scores with B. This asymmetry arises because their analysis focuses on direct competitors—firms that compete with each other in a straightforward manner—without considering the network of second-order neighbors (i.e., competitors of competitors). This methodological choice has implications for how competitive relationships are represented and analyzed. By focusing on direct neighbors, Grieser et al. (2022) effectively construct a network that reflects immediate competitive interactions but excludes the broader context of indirect competitive relationships. Consequently, their approach can lead to an adjacency matrix where connections are not reciprocated, potentially affecting the detected community structures and network properties. For our analysis, we do not need to follow the asymmetric framework. Instead, we adopt the approach that considers mutual competition relationship and adapt both direct and higher-order competitive relationships, allowing us to consider the impact of indirectly linked neighbors.

TNIC comparison. Given the same pair of firms, we investigate the pairwise difference between TNIC and Factset Revere. To enable comparison, we limit ourselves to firms that exist in both datasets. For example, in 2018Q3, Factset Revere after filtering provides 3,351 firms while TNIC is available for 1,190 firms, for an overlapping total of 897. We then check how many competitive links overlap between the two datasets at the firm-firm level. From this, we construct a contingency table illustrating the overlap between the two.

After populating the contingency table with the values for (Revere, TNIC)=(Yes,Yes), (Yes,No), (No,No), and (No,Yes) from the two datasets, we compute both an overlap ratio and the F-score oftenly used in prediction analysis. These metrics provide a comprehensive view of the overlap and divergence. In our analysis, it is in spirit similar to either treating Revere as the true labels of classification and TNIC as the predicted labels or the other way around in order to check the difference between the actual and the predicted.

The overlap ratio measures the overall percentage of same classified pairs (both linked and not linked) in both Revere and TNIC out of the total number of links evaluated:

$$\text{Overlap} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{12}$$

where TP is the number of links that exist in both datasets, TN is the number of non-links in both datasets, FP is the number of non-links identified in Revere whereby TNIC identifies links, and FN is the number of links that exist in Revere but not in TNIC. The F-score considers both precision (the number of true positive results divided by the number of all predicted positive results) and recall (the number of true positives divided by the total number of actual positives.). The F-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns:

$$\text{Precision} = \tfrac{TP}{TP+FP}, \quad \text{Recall} = \tfrac{TP}{TP+FN}, \quad F\text{-score} = 2 \times \tfrac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}. \tag{13}$$

Table 11 reports the results. The average overlap score for Revere relative to TNIC is 0.983. The average precision rate is 0.15. The average recall is 0.34. The average F-score is 0.2. These measures send a mixed message. On the one hand, the overlap is quite large in that most non-links are the same in both dataset. Also, many links exist in both datasets. However, TNIC identifies many links that Revere does not recognize. Interestingly, though, there also exist many connections in Revere that TNIC does not consider. Overall, the link information extracted from the two data sources seems to be complementary with Revere focusing on larger, more significant links while TNIC is more comprehensive. When we increase the similarity score threshold to 0.15, the two networks become directly comparable with one another since many of the (No,Yes) links get eliminated, and we identify eleven stable communities in both datasets.

7 Conclusion

We document novel facts about financial leverage among U.S. corporations. First, using data on firms' self-declared competitors, we identify that firms operate within *competition communities* that span both within and across traditional industries. A competition community is defined as a group of firms that compete in product markets directly or indirectly through their connections with other firms within the same group, while being relatively sparsely connected with firms outside the group. By employing a machine-learning approach, we detect eleven stable competition communities in the U.S. economy.

Second, we investigate the propagation of financial shocks across these competition communities. Our findings reveal that a firm's leverage decisions are influenced not only by its own characteristics but also by the characteristics and leverage choices of its direct competitors, indirect competitors, and the broader community. Notably, the impact of the community on a firm's leverage is strongly positive and economically significant, with a magnitude comparable to that of direct competitors. These findings are consistent with models of product market competition where financing decisions act as strategic complements. This highlights a potential channel for the amplification of financial shocks and, more generally, the importance of indirect competitors and the overall network structure of the competitive environment for the transmission of financial shocks.

APPENDIX

A Louvain Method

This section provides a summary of the Louvain method proposed by Blondel et al. (2008) and the modification by Aynaud and Guillaume (2010) for network evolution.

The static Louvain method achieves optimization via multiple big iterations. Every big iteration corresponds to one hierarchy of analysis and consists of two stages. Within the first stage, there is another set of loops going through all nodes of the network of this hierarchy.

Imagine a (weighted) network consisting of N nodes to begin. In the first stage, the algorithm initially assigns each node to one uniquely labeled community, resulting in N communities. For each neighbor j of node i, the modularity gain is evaluated when moving i to the community of j. Node i is then moved to the community that provides the highest positive modularity gain. If no positive gain is possible, node i remains in its original community. A node can be reconsidered multiple times. This iterative process is repeated for all nodes until no further modularity improvement can be made, thus concluding the first phase with a local modularity maximum. Then, no single node move can further enhance modularity. Removing a node from a community to isolate it, and then adding the isolated node to another community, both cause changes in modularity. To speed up the process, the first phase can be stopped as soon as the relative gain in modularity does not exceed a default threshold. The outcome of the algorithm can vary slightly based on the order in which nodes are processed, though this primarily affects optimization speed rather than the final modularity value.

The change in modularity ΔQ obtained by moving an isolated node i into a community C can be computed explicitly by

$$\Delta Q = \left[\frac{\sum_{\text{in}} + 2k_{i,\text{in}}}{2m} - \left(\frac{\sum_{\text{tot}} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{\text{in}}}{2m} - \left(\frac{\sum_{\text{tot}}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right], \tag{14}$$

where the latter large square bracket represents the sum of the modularity of the community without node i and the modularity of the isolated cluster of node i, while the first large square bracket represents the modularity of the community after adding node i. $\sum_{\text{in}}$ represents the sum of the weights of the links within C, $\sum_{\text{tot}}$ is the sum of the weights of the links incident to nodes in C, k_i denotes the sum of the weights of the links incident to node i, $k_{i,\text{in}}$ is the sum of the weights of the links from i to nodes in C, and m is the sum of the weights of all the links in the network. A similar expression is used to evaluate the change in modularity when i is removed from its community.

In the second stage, each of the classified communities at the current hierarchy is re-represented as a node to form a new network at a higher hierarchy. Edges connecting nodes from C to other communities are likewise reduced to a single weighted edge. Connections among nodes within the same community result in weighted self-loop for that community in the new network. Once the new graph is created, the second stage has ended, completing the entire big iteration of the algorithm. Then, the steps in the two stages are repeated on the new-hierarchy network.

The iterations continue until no further changes are observed and total modularity is maximized. The classified communities at this highest hierarchy are then considered the final result of community detection for the original graph.

Below we provide a pseudo code summary of the algorithm.

What Aynaud and Guillaume (2010) improved on the static algorithm to stabilize it for evolving dynamic graphs is the change in the initialization of the network. At time t, the algorithm initializes G with the optimized partitioned network from $t-1$, instead of restarting the entire computation with every node in its own unique community and regrouping them from the lowest hierarchy. Then, the same algorithm for moving nodes continues with iterations until no further gain in modularity is possible. Each community, once classified in the final optimization of a time period, is uniquely labeled for tracking.

However, the network topology could change dramatically over some periods, making

Algorithm 1 Pseudo-code of Louvain Method

```
G = the initial network; Repeat = True
while Repeat do
    Let each node of G be a unique community; MoveNode = True
    while MoveNode do
        for every node n of G do
            Move n to one of the neighboring communities that has the highest positive
            gain in modularity. If no positive gain is possible, leave it unmoved.
        end for
        if No move happened then MoveNode = False
        end if
    end while
    if the new modularity is higher than the previous hierarchy then
        G = the new network among communities of G
    else
        Repeat = False
    end if
end while
```

the optimal partition from the previous period suboptimal for initialization in terms of final modularity maximization, although it is good for stabilization. Thus, instead of strictly initializing with the exact same previously optimal partition, Aynaud and Guillaume (2010) place $x\%$ of randomly selected nodes in their own unique communities during the initial iteration. The higher the value of x, the more the algorithm can modify the communities, as the nodes placed alone in their communities during the initial iteration are highly likely to be moved. If $x = 100\%$, the modified algorithm functions exactly the same as the static Louvain method. A low level of 2% provides a good compromise between stability and improved modularity maximization.

B Motivation for Empirical Model

Consider the following regression model for financial leverage y:

$$\mathbb{E}(y \mid x, z) = \alpha + \beta\mathbb{E}(y \mid x) + \mathbb{E}(z \mid x)'\gamma + x'\delta + z'\eta. \tag{15}$$

The reflection problem arises out of the presence of $\mathbb{E}(y \mid x)$ as a regressor in (15). Integrating both sides of (15) with respect to z reveals that $\mathbb{E}(y \mid x)$ solves the "social equilibrium" equation

$$\mathbb{E}(y \mid x) = \alpha + \beta\mathbb{E}(y \mid x) + \mathbb{E}(z \mid x)'\gamma + x'\delta + \mathbb{E}(z \mid x)'\eta. \tag{16}$$

Provided that $\beta \neq 1$, equation (16) has a unique solution, namely

$$\mathbb{E}(y \mid x) = \alpha/(1-\beta) + \mathbb{E}(z \mid x)'(\gamma + \eta)/(1-\beta) + x'\delta/(1-\beta). \tag{17}$$

Thus, $\mathbb{E}(y \mid x)$ is a linear function of $[1, \mathbb{E}(z \mid x), x]$, where "1" denotes the constant. It follows that the parameters $(\alpha, \beta, \gamma, \delta)$ are all unidentified. Endogenous effects cannot be distinguished from exogenous effects or from correlated effects.

What is identified? Inserting (17) into (15) we obtain the reduced form model

$$\mathbb{E}(y \mid x, z) = \alpha/(1-\beta) + \mathbb{E}(z \mid x)'[(\gamma + \beta\eta)/(1-\beta)] + x'\delta/(1-\beta) + z'\eta. \tag{18}$$

As pointed out by Manski (1993), we assume that individuals are aware of the specification of the reference group (competition community) or that they perceive these groups. This is a reasonable assumption in our application, as the link data source is based on firms' self-declared public information. Hence firms have all the necessary information to deduce the community domain.

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Table 1: Variables definitions

Table 1 presents definitions and sources of data used.

Variable	Description
Financial indicators (Source: Compustat North America Quarterly)	
Book debt BD	Liabilities total (LTQ) + Preferred stock (PSTKQ) – Deferred taxes (TXDITCQ)
Book equity BE	Assets total (ATQ) – Book debt
Book leverage BL	Book debt/Assets total (AT)
Market value MV	Common Shares Outstanding (CSHOQ) × (Price Close (PRCCQ))
Market leverage L	Book debt/(Book debt + Market value)
Imputed leverage	Lagged book debt/(Lagged book debt + Lagged market value$\times(1 + R)$)
Stock return R	(Price Close (PRCCQ) - lagged Price Close (PRCCQ))/(lagged Price Close (PRCCQ)
Return on assets ROA	(Income before extraordinary items (IBQ) + Depreciation (DPQ))/Assets total
Market-to-book MB	(Market value + Book debt)/Assets total
Log(total assets) (Size)	Natural logarithm of Assets total)
Tangibility Tang	Property, plant, and equipment total net (PPENTQ)/Assets total
Investment	Capital Expenditures (CAPX) - Sale of Property (SPPE) /Property Plant and Equipment - Total (Gross) (PPEGT)

Table 2: Summary statistics

Panel A provides summary statistics of the main variables used in the empirical analysis. The firm-level variables are winsorized for each quarter at 1% and 99% levels. The community variables are averages of the firm-level variables of the firms in each community. The competitors variables are weighted averages (according to the adjacency matrices) of the firm-level variables of the competitor firms. Panel B provides features of the network used in the empirical analysis. 'Number of communities' excludes the communities of less than four firms. 'Nodes in community' measures the average number of firms (over time) in each community. Panel C reports the number of firms and links in Revere data for the final dataset merged with Compustat.

	Mean	SD	Min	25%	50%	75%	Max	N
				Panel A: Fundamental variables				
Market leverage (L)	0.329	0.226	0.011	0.145	0.285	0.468	0.991	120,256
Return on asset (ROA)	0.003	0.067	-0.533	0.002	0.019	0.032	0.150	120,256
Log(total assets) (Size)	6.518	2.028	1.731	5.092	6.526	7.918	11.810	120,256
Tangibility (Tang)	0.243	0.233	0.001	0.066	0.157	0.351	0.954	120,256
Market-to-book ratio (MB)	2.125	1.594	0.403	1.164	1.596	2.460	11.979	120,256
Investment	0.066	0.0754	-0.109	0.022	0.045	0.084	0.523	120,256
$L_{\text{Community}}$	0.263	0.084	0.015	0.200	0.271	0.314	0.807	120,256
$L_{\text{Direct competitors}}$	0.302	0.160	0.004	0.186	0.277	0.388	0.991	120,256
$L_{\text{Indirect competitors}}$	0.289	0.119	0.006	0.202	0.275	0.356	0.991	120,256
				Panel B: Network measures				
No. of direct competitors	7	10	1	2	4	8	194	120,256
No. of indirect competitors	70	84	1	14	36	95	846	120,256
No. of community members	254	143	2	152	207	370	601	120,256

Panel C: Network links through time

Year	Competition links	Competitor-network firms
2003	6,241	1,765
2004	5,313	1,787
2005	7,059	1,943
2006	7,524	2,068
2007	8,712	2,421
2008	11,075	2,551
2009	8,025	2,362
2010	9,044	2,342
2011	10,520	2,572
2012	11,543	2,743
2013	12,944	2,905
2014	14,610	3,157
2015	17,716	3,331
2016	19,789	3,448
2017	21,464	3,580
2018	19,205	3,378

Table 3: Characteristics of competition communities

This table reports average firm characteristics for each community. SIC2 codes - 13: Oil and Gas Extraction, 20: Food and Kindred Products, 23: Apparel, Finished Products from Fabrics & Similar Materials, 26: Paper and Allied Products, 28: Chemicals and Allied Products, 35: Industrial and Commercial Machinery and Computer Equipment, 36: Electronic & Other Electrical Equipment & Components, 37: Transportation Equipment, 38: Measuring, Photographic, Medical, & Optical Goods, & Clocks, 48: Communications, 50: Wholesale Trade - Durable Goods, 56: Apparel and Accessory Stores, 58: Eating and Drinking Places, 59: Miscellaneous Retail, 73: Business Services, 80: Health Services, 87: Engineering, Accounting, Research, and Management Services

	L	ROA	Size	Tang	MB	SIC2
Community 1	0.195	-0.056	5.294	0.118	3.411	28 (46.86%), 38 (18.20%), 80 (1.52%)
Community 2	0.223	-0.001	6.029	0.116	2.308	36 (49.47%), 35 (13.19%), 73 (9.00%)
Community 3	0.265	0.008	6.119	0.164	1.974	38 (25.08%), 35 (17.23%), 36 (15.85%)
Community 4	0.286	0.008	6.130	0.122	2.459	73 (50.52%), 48 (9.43%), 35 (4.55%)
Community 5	0.334	0.023	6.956	0.265	2.047	56 (16.58%), 59 (10.28%), 23 (9.12%)
Community 6	0.343	0.018	6.667	0.326	2.133	20 (23.38%), 28 (15.51%), 58 (15.22%)
Community 7	0.345	0.015	6.459	0.179	2.070	80 (25.51%), 73 (16.03%), 87 (7.70%)
Community 8	0.365	0.005	6.825	0.421	1.768	13 (19.00%), 28 (14.36%), 36 (13.01%)
Community 9	0.388	0.014	6.576	0.218	1.672	36 (18.60%), 50 (18.60%), 73 (8.22%)
Community 10	0.400	0.013	6.814	0.298	1.603	37 (10.48%), 87 (10.17%), 13 (8.67%)
Community 11	0.428	0.014	6.988	0.280	1.611	37 (16.51%), 35 (11.08%), 26 (8.67%)

Table 4: Impact of community characteristics

The table documents the impact of a firm's community average characteristics on the firm's leverage. The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Industries are classified at SIC 1-digit level. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable: Firm leverage $L_{i,t}$			
	(1)	(2)	(3)	(4)
$\text{ROA}_{\text{Community},t-1}$	-1.862^{***}	-0.938^{***}	-0.353^{***}	-0.192^{*}
	(0.093)	(0.120)	(0.112)	(0.114)
$\text{MB}_{\text{Community},t-1}$	-0.102^{***}	-0.041^{***}	-0.013^{***}	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)
$\text{Size}_{\text{Community},t-1}$	0.027^{***}	0.012^{***}	0.009^{***}	0.015^{***}
	(0.003)	(0.004)	(0.003)	(0.003)
$\text{Tang}_{\text{Community},t-1}$	-0.158^{***}	-0.085^{***}	-0.073^{***}	-0.115^{***}
	(0.029)	(0.030)	(0.026)	(0.026)
ROA_{t-1}			-0.472^{***}	-0.464^{***}
			(0.019)	(0.019)
MB_{t-1}			-0.039^{***}	-0.039^{***}
			(0.001)	(0.001)
Size_{t-1}			0.002	0.002
			(0.004)	(0.004)
Tang_{t-1}			0.225^{***}	0.214^{***}
			(0.022)	(0.022)
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.064	0.043	0.191	0.183

Table 5: Impact of direct and indirect competitors' characteristics

The table documents the impact of the characteristics of a firm's direct and indirect competitors on the firm's leverage . The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable: Firm leverage $L_{i,t}$			
	(1)	(2)	(3)	(4)
$ROA^{Offdiagonal}_{Indirect\ competitors,t-1}$	-1.063^{***}	-0.615^{***}	-0.322^{***}	-0.233^{***}
	(0.073)	(0.078)	(0.072)	(0.074)
$MB^{Offdiagonal}_{Indirect\ competitors,t-1}$	-0.061^{***}	-0.029^{***}	-0.013^{***}	-0.011^{***}
	(0.003)	(0.004)	(0.003)	(0.004)
$Size^{Offdiagonal}_{Indirect\ competitors,t-1}$	0.021^{***}	0.006^{***}	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
$Tang^{Offdiagonal}_{Indirect\ competitors,t-1}$	0.026	0.088^{***}	0.062^{**}	0.021
	(0.028)	(0.029)	(0.026)	(0.026)
$ROA_{Direct\ competitors,t-1}$	-0.218^{***}	-0.190^{***}	-0.109^{***}	-0.103^{***}
	(0.031)	(0.031)	(0.028)	(0.028)
$MB_{Direct\ competitors,t-1}$	-0.018^{***}	-0.014^{***}	-0.010^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
$Size_{Direct\ competitors,t-1}$	0.002^{**}	−0.001	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$Tang_{Direct\ competitors,t-1}$	−0.008	0.016	−0.017	−0.007
	(0.017)	(0.017)	(0.015)	(0.015)
ROA_{t-1}			-0.464^{***}	-0.458^{***}
			(0.018)	(0.019)
MB_{t-1}			-0.038^{***}	-0.038^{***}
			(0.001)	(0.001)
$Size_{t-1}$			0.002	0.002
			(0.004)	(0.004)
$Tang_{t-1}$			0.212^{***}	0.203^{***}
			(0.022)	(0.022)
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.066	0.052	0.198	0.196

Table 6: Impact of community leverage

The table documents the impact of a firm's community members' leverage on the firm's leverage. Panel A provides OLS estimates. Panel B provides granular IV estimates. Community leverage is instrumented with a weighted sum of shocks. For Panel B, in specifications (1) and (2) shocks are based on stock returns of community members. In specifications (3) and (4) shocks are based on changes in leverage of community members. The weights reflect the relative importance of each firm in its community and are based on eigenvalue centrality. The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Industries are classified at SIC 1-digit level. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: OLS

	Dependent variable: Firm leverage $L_{i,t}$			
	(1)	(2)	(3)	(4)
$L_{Community,t-1}$	0.553***	0.266***	0.218***	0.175***
	(0.022)	(0.029)	(0.026)	(0.027)
$ROA_{i,t-1}$			-0.475***	-0.466***
			(0.019)	(0.019)
$MB_{i,t-1}$			-0.039***	-0.038***
			(0.001)	(0.001)
$Size_{i,t-1}$			0.002	0.003
			(0.004)	(0.004)
$Tang_{i,t-1}$			0.221***	0.208***
			(0.022)	(0.022)
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.047	0.034	0.199	0.196

Panel B: Granular IV

	Dependent variable: Firm leverage $L_{i,t}$			
	Return-based GIV		Leverage-based GIV	
	(1)	(2)	(3)	(4)
$\hat{L}_{Community,t-1}$	0.752***	0.534***	0.732***	0.532**
	(0.176)	(0.187)	(0.228)	(0.256)
$ROA_{i,t-1}$	−0.465***	−0.461***	−0.466***	−0.461***
	(0.023)	(0.023)	(0.024)	(0.023)
$MB_{i,t-1}$	−0.039***	−0.038***	−0.039***	−0.038***
	(0.001)	(0.001)	(0.001)	(0.001)
$Size_{i,t-1}$	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
$Tang_{i,t-1}$	0.208***	0.202***	0.208***	0.202***
	(0.023)	(0.022)	(0.023)	(0.022)
Fixed effects	firm, time	firm, ind×time	firm, time	firm, ind×time
Observations	117765	117765	117765	117765
R^2	0.126	0.138	0.129	0.138

Table 7: Falsification tests

The table reports falsification tests supporting the validity of the granular IV framework. In the baseline granular IV, community leverage is instrumented with a weighted sum of shocks. In specifications (1) and (2) shocks are based on stock returns of community members. In specifications (3) and (4) shocks are based on changes in leverage of community members. The weights reflect the relative importance of each firm in its community and are based on eigenvalue centrality. Specifications (1) and (3) report a pre-trend test where the dependent variable is lagged by one period. Specifications (2) and (4) report a placebo tests where the dependent variable is replaced by a contemporaneous firm policy choice that is firm' investment rate. The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Industries are classified at SIC 1-digit level. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable			
	Lagged leverage$_{i,t-4}$	Investment$_{i,t}$	Lagged leverage$_{i,t-4}$	Investment$_{i,t}$
	Return-based GIV		Leverage-based GIV	
	(1)	(2)	(3)	(4)
$\hat{\text{L}}_{\text{Community},t-1}$	−0.147	−0.069	−0.329	−0.041
	(0.244)	(0.065)	(0.329)	(0.083)
ROA$_{i,t-1}$	−0.142***	0.066***	−0.142***	0.066***
	(0.022)	(0.008)	(0.022)	(0.008)
MB$_{i,t-1}$	−0.029***	0.009***	−0.029***	0.009***
	(0.001)	(0.000)	(0.001)	(0.000)
Size$_{i,t-1}$	−0.032***	0.001	−0.032***	0.001
	(0.004)	(0.001)	(0.004)	(0.001)
Tang$_{i,t-1}$	0.133***	−0.146***	0.136***	−0.146***
	(0.024)	(0.007)	(0.024)	(0.007)
Fixed effects	firm, ind×time	firm, ind×time	firm, ind×time	firm, ind×time
Observations	107296	116791	107296	116791
R^2	0.059	0.046	0.045	0.047

Table 8: Impact of direct competitors vs. community leverage

The table documents the impact of a firm's direct competitors vs. community members' leverage on the firm's leverage. Panel A provides OLS estimates. Panel B provides granular IV estimates. Direct competitor leverage and community leverage are instrumented with a weighted sum of shocks. For Panel B, in specifications (1) and (2) shocks are based on stock returns. In specifications (3) and (4) shocks are based on changes in leverage. The weights reflect the relative importance of each firm in its community and are based on eigenvalue centrality. The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Industries are classified at SIC 1-digit level. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Panel A: OLS

	Dependent variable: Firm leverage $L_{i,t}$			
	(1)	(2)	(3)	(4)
$L_{\text{Direct competitors},t-1}$	0.157***	0.128***	0.096***	0.085***
	(0.011)	(0.011)	(0.010)	(0.010)
$L_{\text{Community},t-1}$	0.439***	0.206***	0.174***	0.140***
	(0.022)	(0.029)	(0.026)	(0.027)
$\text{ROA}_{i,t-1}$			−0.470***	−0.462***
			(0.019)	(0.019)
$\text{MB}_{i,t-1}$			−0.039***	−0.038***
			(0.001)	(0.001)
$\text{Size}_{i,t-1}$			0.003	0.003
			(0.004)	(0.004)
$\text{Tang}_{i,t-1}$			0.215***	0.204***
			(0.022)	(0.022)
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.063	0.053	0.208	0.206

Panel B: Granular IV

	Dependent variable: Firm leverage $L_{i,t}$			
	Return-based GIV		Leverage-based GIV	
	(1)	(2)	(3)	(4)
$\hat{L}_{\text{Direct competitors},t-1}$	0.174***	0.145***	0.116***	0.092***
	(0.030)	(0.029)	(0.030)	(0.029)
$\hat{L}_{\text{Community},t-1}$	0.534***	0.387***	0.583***	0.422***
	(0.117)	(0.121)	(0.144)	(0.157)
$\text{ROA}_{i,t-1}$	−0.462***	−0.459***	−0.465***	−0.462***
	(0.018)	(0.018)	(0.018)	(0.018)
$\text{MB}_{i,t-1}$	−0.038***	−0.038***	−0.038***	−0.038***
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{Size}_{i,t-1}$	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
$\text{Tang}_{i,t-1}$	0.203***	0.197***	0.205***	0.199***
	(0.022)	(0.022)	(0.022)	(0.022)
Fixed effects	firm, time	firm, ind×time	firm, time	firm, ind×time
Observations	114202	114202	114202	114202
R^2	0.1475	0.1495	0.1492	0.1511

Table 9: Impact of direct and indirect competitors' leverage

The table documents the impact of leverage of a firm's direct and indirect competitors on the firm's leverage. The specifications include fixed effects at the firm, quarter, and industry×quarter levels. Industries are classified at SIC 1-digit level. Panel-robust standard errors are clustered at the firm level. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable: Firm leverage $L_{i,t}$			
	(1)	(2)	(3)	(4)
Panel A: Impact of direct competitors' leverage				
$L_{\text{Direct competitors},t-1}$	0.224***	0.141***	0.107***	0.092***
	(0.010)	(0.011)	(0.010)	(0.010)
RZ controls	no	no	yes	yes
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.037	0.032	0.197	0.195
Panel B: Impact of indirect competitors' leverage				
$L^{\text{Offdiagonal}}_{\text{Indirect competitors},t-1}$	0.429***	0.221***	0.157***	0.120***
	(0.018)	(0.021)	(0.018)	(0.018)
RZ controls	no	no	yes	yes
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.049	0.038	0.199	0.195
Panel C: Impact of direct and indirect competitors' leverage				
$L^{\text{Offdiagonal}}_{\text{Indirect competitors},t-1}$	0.341***	0.169***	0.118***	0.087***
	(0.018)	(0.020)	(0.018)	(0.018)
$L_{\text{Direct competitors},t-1}$	0.152***	0.118***	0.091***	0.082***
	(0.011)	(0.011)	(0.010)	(0.010)
RZ controls	no	no	yes	yes
Fixed effects	firm	firm, time	firm, time	firm, ind×time
Observations	114316	114316	114316	114316
R^2 (Within)	0.064	0.054	0.208	0.204

Table 10: Degree distribution of competition network and communities

This table reports tail information for the competition network and communities. The 'Entire network' shows the average measures over all quarters. Each row of 'Community i' shows the average measures over all quarters for each of the persistent major community i. The row of 'Communities' is the further average measure of all communities. The Hill estimator takes the top 5% upper order in estimation.

	Skewness	Kurtosis	Hill
Entire network	7.510	89.064	2.074
Communities	3.296	18.051	2.597
Community 1	5.568	39.138	1.629
Community 2	3.898	21.930	2.267
Community 3	3.298	15.851	2.220
Community 4	7.197	63.518	1.603
Community 5	3.640	18.984	2.212
Community 6	2.347	9.378	3.355
Community 7	1.982	4.656	2.379
Community 8	2.909	12.349	2.634
Community 9	1.284	1.361	3.913
Community 10	2.242	6.130	2.661
Community 11	1.895	5.268	3.688

Table 11: Comparison with TNIC

The table provides a comparison between the competition links in Factset Revere and the TNIC measure by Hoberg and Phillips (2016). Panel A reports the comparison for the last quarter in our sample. Panel B reports the comparison for the average across all quarters.

Panel A: Networks for last quarter

		TNIC		
		Yes	No	Total
Revere	Yes	1,044	1,464	2,508
	No	14,344	385,004	399,348
	Total	15,388	386,468	401,856

Panel B: Networks for all quarters averaged

		TNIC		
		Yes	No	Total
Revere	Yes	521	969	1,490
	No	4,232	261,959	266,191
	Total	4,753	262,928	267,681