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Reshaping the supply chain network: The role of vertical common shareholders

by FERNANDEZ, Daniel*

The paper exploits additions and deletions from the S&P 500 index to investigate the association between the ownership and supply chain network in the US, revealing a one-standard-deviation increase in the cosine similarity of the ownership structure of companies increases the likelihood of an active trading partnership by 16%. Furthermore, I show overlapping owners play a role in alleviating contractual and information frictions; however, increasing the relative concentration of shareholders from the bottom to the top decile boosts the effect from 5% to 101%, suggesting that non-overlapping shareholders could also subsidize overlapping owners' private benefits.
JEL: D22,L14,L21,G32

In the past, some have mistakenly assumed that our predominantly passive management style suggests a passive attitude with respect to corporate governance. Nothing could be further from the truth

William McNabb III
Vanguard's CEO, 2008-2018

Much of the literature on industrial organization and corporate finance assumes that managers make decisions to increase the value of companies; however, shareholders do not care about maximizing the value of each individual firm they own. Rather than that, they benefit from the joint maximization of the portfolio's total worth. Therefore, the ownership structure of a company should affect its objectives, behavior, and business relationships, either by the direct influence of investors or because managers internalize other benefits from pleasing pivotal shareholders. To that end, this paper aims to study whether shareholders can influence managerial decisions regarding trading partnerships and what are the implications.

How the ownership structure of strategically interacting firms affects market outcomes has been the subject of theoretical and empirical studies for decades. For example, several studies in the industrial organization literature introduced the ownership structure in conduct models to explore its effects on market outcomes (Nevo, 2001; Thomadsen, 2005; Backus, Conlon and Sinkinson, 2021*a*).

However, the recent proliferation of large asset management institutions has raised the question of whether diversified minority shareholders, such as Vanguard, BlackRock, or State Street, can also influence the corporate strategy of firms (Schmalz, 2018). The fast expansion of institutional financial intermediaries and a renewed preference for passive indexing strategies achieved that a short list of institutional investors usually appears among the top shareholders of any publicly-listed company in the US. For instance, Figure 1 depicts the similarity of the ownership structure among the 500 most influential companies in the American economy, as well as their competitors and

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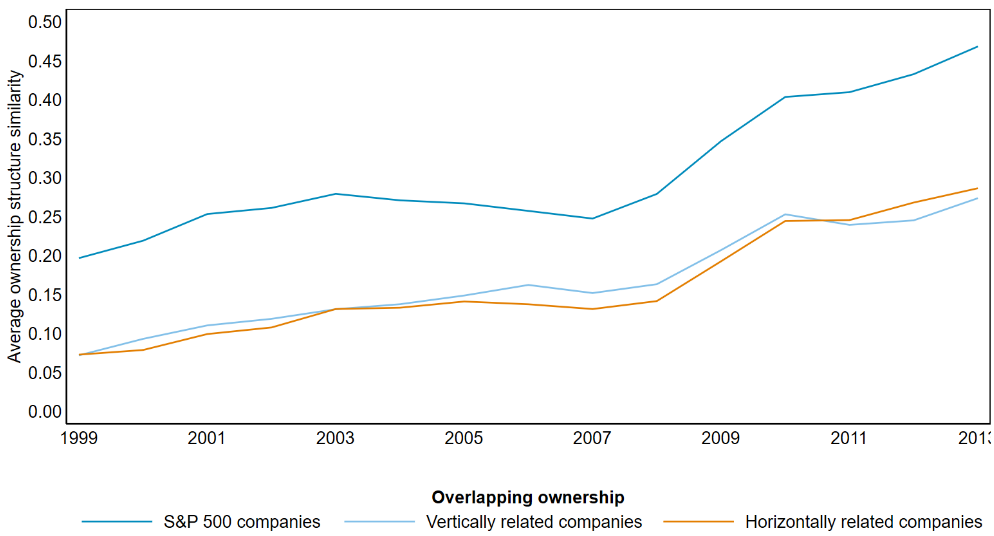
Figure 1 — Average ownership structure similarity in the US (1999-2013)



Notes: The figure depicts the average similarity in the ownership structure of companies by year between 1999 and 2013. I assemble all the permutations of publicly-listed companies in the US and compute the cosine similarity of the ownership structure. The blue line represents the average cosine similarity by year for combinations of S&P 500 constituents that same year. Then, the light blue line illustrates the average cosine similarity by year among competitors, according to the text-based network industry classification, where at least one of the firms belongs to the S&P 500 index that year. Finally, the orange line displays the average cosine similarity by year among customer-supplier dyads in which at least one company belongs to the list of S&P 500 constituents.

trading partners, representing in all cases an upward trend since the *subprime crisis* of 2007-2008. While the literature on *common ownership* explores the effects of overlapping shareholders among competitors, its role in vertical relations remains somewhat unexplored despite both phenomena exhibiting a similar growth pattern.

The common-ownership concept dates back to Rotemberg (1984), a theoretical framework in which companies tend to act collusively in favor of shareholders with diversified portfolios. However, the topic seized the attention of economists and the public when several empirical studies started showcasing its effects across multiple industries and outcomes, such as higher degrees of market concentration (He and Huang, 2017), product variety (Aslan, 2019), and prices (Azar, Schmalz and Tecu, 2018; Park and Seo, 2019; Torshizi and Clapp, 2021). Additionally, researchers indicate that overlapping owners can lead to positive spillovers on research and development (R&D) activities (Anton et al., 2021; López and Vives, 2019) and the diffusion of innovation (Kostovetsky and Manconi, 2020), although it negatively affects employment, wages (Azar, Qiu and Sojourner, 2021), and market entry (Newham, Seldeslachts and Banal-Estañol, 2019; Xie and Gerakos, 2020).

Instead, I turn my attention to the effects on the supply chain network and find that the ownership structure of companies affects the identity of customers and suppliers with whom they engage in business relationships, which, in turn, has implications in the upstream and downstream market structure. The reasoning for focusing on vertical relations seems straightforward: if diversified overlapping shareholders influence companies to assess the externalities they impose on horizontally associated firms, managers should also consider how corporate decisions would affect vertically related companies. Surprisingly, the literature on the topic features a limited number of studies. For instance, researchers suggest that companies having overlapping owners with a bank obtain larger loans with lower interest rates (Ojeda, 2018) and have higher chances of striking a deal from syndicated loans (Cici, Gibson and Rosenfeld, 2015). Similarly, the presence of vertical overlapping shareholders increases the likelihood of companies joining strategic alliances (Lindsey, 2008), discourages suppliers from engaging in upward earnings management (Gao et al., 2022), and boost upstream partner-specific investments (Deng and Li, 2022).

My research consists of a panel data analysis using a two-way fixed-effects linear probability model on whether the likelihood of trading partnerships among companies depends on their degree of overlapping ownership, forcing me to restrict my attention to companies I can identify in both networks. I begin my analysis by establishing the ownership network from 13D, 13F, and 13G filings with the Securities and Exchange Commission (SEC), covering large institutional investors and blockholders from 1999 to 2013, which I use to construct overlapping ownership measures for all combinations of pubicly-listed companies in the US according to the framework of Rotemberg (1984). Next, I retrieve the supply chain network from 10K filings, where companies disclose the identity of all customers that comprise at least 10% of their total annual sales. Freeman (2021) follows a similar approach to investigate the intensive margin of trading partnerships and provides evidence of overlapping shareholders extending their duration. Instead, I add to the literature by factoring in the extensive margin of the relationship and exploring the role of overlapping shareholders in establishing new supply chain relationships, which requires identifying all feasible but inactive supply chain links among customer-supplier dyads I do not observe in the data. To overcome the challenge, I employ the *vertical upstream relatedness* dataset from Frésard, Hoberg and Phillips (2020), which consists of directed measures on how the products of one firm relate as inputs of the other company.

Presumably, the main challenge in assessing the causality between the degree of overlapping ownership and the likelihood of trading partnerships is the absence of valid identification strategies at the dyad level. According to the literature, the sources of exogenous variation used by other papers exploring the role of vertical common shareholders do not meet the exclusion restriction. Furthermore, the strategy from Boller and Morton (2020), using S&P 500 additions as exogenous changes in the ownership structure of competitors, does not work in vertical settings.

I contribute to the literature with an identification strategy that takes the original idea one step further by focusing on customer-supplier dyads involving companies unrelated to the changes of constituents. I exploit differences in the market value of annual additions and deletions from the S&P 500 index to purge the endogenous ingredients of the portfolio composition of investors and construct new measures of overlapping ownership from these predictions to use as instruments. Intuitively, institutional asset managers often hold passive indexing funds replicating the holdings and weightings of the indexes they track. Then, when asset managers react to changes in the index constituents, they affect the ownership structure of companies not involved in the additions and deletions, which is the source of exogenous variation I exploit in the paper.

My findings suggest that a one-standard-deviation increase in the similarity between the ownership structure of companies among feasible supply chain links raises the unconditional probability of an active trading partnership between 18% and 23%. Moreover, the results are robust to alternative methodological definitions, such as different overlapping ownership measures, functional forms for constructing the instrument, and sample definitions. In this way, my paper also contributes to the literature on network structures of production by providing evidence of an underlying factor in the creation of new trading partnerships, which complements other studies analyzing aspects regarding the shape of the American supply chain network, such as the average rates of link formation, destruction, and rewiring (Atalay et al., 2011).

The role that vertical overlapping shareholders play in corporate decisions compares to the consequences of vertical integration and vertical control, so it is not surprising the underlying mechanisms behind my findings are closely related to those of partial vertical integration. Despite being well-documented that companies can boost their profits through coordination or long-term contracting, the prevalence of incomplete contracts or injunctions from competition policy authorities can pose an obstacle for some trading partnerships, and vertical common shareholders could help alleviate the contractual frictions and asymmetric information issues those companies face. Alternatively, overlapping shareholders could benefit from corporate decisions at the expense of one of the firms by exploiting asymmetric incentives among managers. Either by transferring resources out of a company or by pursuing other goals, such as foreclosing markets (Levy, Spiegel and Gilo, 2018; Boehm and Sonntag, 2022) or deterring entry (Newham, Seldeslachts and Banal-Estañol, 2019).

The role of overlapping shareholders in corporate decisions regarding trading partnerships compares to the consequences of vertical integration and vertical control; thus, it is not surprising the underlying mechanisms behind my findings are closely related to the ambiguous empirical results of partial vertical integrations. Despite being well-documented that companies can boost their profits through coordination or long-term contracting, the prevalence of contractual frictions and asymmetric information problems can pose an obstacle for some trading partnerships that vertical common shareholders could help alleviate. Alternatively, overlapping shareholders could benefit from corporate decisions at the expense of one of the firms by exploiting asymmetric incentives among managers, either by transferring resources out of a company or by pursuing other goals, such as foreclosure or entry deterrence.

The results of my paper indicate that overlapping shareholders play a significant role not only in situations of double marginalization and holdup but also in inducing asymmetric incentives among managers that result in trading partnerships primarily benefitting one side of the relationship. I analyze whether the effects among feasible supply chain links that face holdup and double marginalization strengthen and find that an increase of one standard deviation in the similarity of the ownership structure of companies raises the unconditional probability of an active trading partnership between 32% and 51% when both companies have an above-average innovation input, and between 40% to 43% when upstream and downstream markets portray lower degrees of competition. Similarly, I investigate the interaction between similarity and distribution of shareholders across ownership structures and find that increasing the relative concentration of shareholders within a firm from the bottom to the top decile boosts the effect of one-standard-deviation increase in the degree of overlapping ownership from 81% to 168%.

The remainder of the paper proceeds as follows. Section I details the data and describes the sample and the overlapping ownership measures. Section II discusses the empirical strategy and presents the baseline results while section III addresses the usual concerns about endogeneity. Next, Section IV delves deeper into the potential mechanisms behind the results. Section V deals with robustness considerations, limitations of the analysis, and a brief discussion of subjects beyond the empirical analysis. Finally, Section VI concludes.

I. Data

Throughout the manuscript, I explore the relationship between common shareholders and trading partnerships among firms in their portfolios, which requires restricting my attention to companies I can identify in both networks. The data about ownership ties are available for public-listed companies in the United States and Canada starting from 1999, while the data about supply chain relationships is available until 2013. Following the literature, I exclude companies in the financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) sectors; therefore, my sample of firms consists solely of active American companies in the remaining industries within those years.

I use *Compustat North America – Fundamentals* to obtain quarterly information about outstanding shares, market value, closing price, net sales, total assets, and levels of research and development (R&D) for all publicly-listed companies in the US. In addition, I compute the age of each company by the first time they report book assets on Compustat since 1976 and include the Herfindahl-Hirschman Index (HHI) from the text-based network industry classification (TNIC) published by Hoberg and Phillips (2016). I winsorize all continuous variables at the 1^{st} and 99^{th} percentiles of their distributions except for net sales, market value, and the HHI. Furthermore, I adjust nominal values by inflation to 2012 US dollars using the GDP deflator of the Bureau of Economic Analysis.

In this way, I retrieve 112,382 annual observations of 15,433 unique companies between 1999 and 2013. Panel A in Table 1 displays the cross-year average characteristics for active publicly-listed companies in industries other than the financial and the utility sector, which on average is less than half (6,319) for any given year.

Table 1 — Average characteristics for companies in Compustat

	N	3-digit SIC industries	Age	Market value	Annual sales	Total assets	R&D intensity	HHI	MB ratio
Panel A - Compustat									
All companies	6,319	220	8.91	2,553.72	1,970.66	1,663.01	22.43%	3,306	5.23
Panel B - Feasible supply chain links									
Customers	3,690	129	15.06	4,362.03	3,762.88	2,732.82	12.11%	3,212	2.77
Suppliers	3,715	129	14.63	3,388.52	2,609.09	2,076.42	12.90%	3,208	2.83
Panel C - Active trading partnerships									
Customers	670	29	19.80	23,544.81	20,626.25	12,576.12	5.52%	2,757	3.39
Suppliers	1,949	64	14.59	3,642.25	2,340.77	2,082.19	13.78%	3,082	2.73
Panel D - Disclosing suppliers									
Customers	527	21	19.65	23,171.19	20,116.17	12,768.06	5.99%	2,737	3.60
Suppliers	1,420	44	15.41	3,757.86	2,450.71	2,095.14	13.34%	2,992	2.46
Panel E - Non-disclosing suppliers									
Customers	219	10	19.43	21,886.88	17,663.34	10,908.73	5.54%	2,675	3.81
Suppliers	530	20	12.54	3,327.43	2,097.54	2,037.07	15.22%	3,353	3.32

Notes: The table reports the cross-year average characteristics of publicly-listed companies in the *Compustat North America – Fundamentals* dataset. Panel A describes all active companies in industries other than the financial and utility sector between 1999 and 2013. Panel B focuses on customers and suppliers belonging to the sample of feasible supply chain links according to their vertical upstream relatedness. Panel C reports the same information for customers and suppliers in active trading partnerships according to the *Compustat – Customer Segment.* Finally, Panels D and E report separate cross-year averages for disclosing and non-disclosing suppliers and their respective customers.

A. *Vertical relatedness and the supply chain network*

In the following subsection, I focus my attention on two aspects related to the supply chain network in the US. On the one hand, since I only observe active trading partnerships, I cannot distinguish from the data whether a non-observed supply chain link depicts a potential trading relationship that remains inactive or whether it is actually unfeasible due to the nature of the firms under consideration. Therefore, I propose a method to identify all feasible customer-supplier dyads among publicly-listed companies in the US. On the other hand, recognizing active trading partnerships among potential supply chain links still poses some challenges.

Exploring the extensive margin of the supply chain network requires identifying which supply chain relationships among the ones I do not observe were feasible but not active between 1999 and 2013. For example, in 2011, Nokia Oyj announced it would ditch its flagship operating system, Symbian, and license Windows 7 and Bing from Microsoft Corporation. Therefore, I am interested in capturing in my sample that Microsoft was a potential supplier of Nokia before 2011. Or, in other words, that the relationship was feasible but just inactive until then. In the same way, I want to capture supply chain links I do not observe on the network until 2013 that might have been equally feasible. On the other hand, let us consider the case of Activision Blizzard Inc., a video game holding company, and Alexion Pharmaceuticals Inc., a subsidiary of the pharmaceutical and biotechnology company AstraZeneca PLC. Despite being publicly traded since 2006, it would be unreasonable to expect a supply chain relationship between them, independently of the degree of overlapping ownership they might entail, given the commodities they produce.

Unfeasible supply chain links, such as Activision Blizzard and Alexion Pharmaceuticals, can bias my results. However, it is not straightforward to judge in which direction. If unfeasible links were likely to exhibit a high degree of overlapping ownership, it would bias my results downwards, given that any specification would capture that these dyads remain inactive even if it is impossible for them to engage in the relationship. On the other hand, if unfeasible links exhibit lower levels of overlapping ownership than average, results would be biased upwards for the opposite reason.

To overcome the challenge, I rely on the *vertical upstream relatedness* measure from Frésard, Hoberg and Phillips (2020). The authors map the product description of 10K filings for all publicly-listed companies in the US to a large set of commodities. By combining this information with input-output intensities between these commodities, the authors construct a squared matrix with directed measures of how the products of one firm relate as inputs of the other company.

Then, I start from the following conditional probability I am interested in

$$\mathbb{P}(Link_{sct}|OvrOwn_{sct}, F_{sct})$$

where $Link_{sct}$ denotes whether supplier s engages in a trading partnership with customer c at period t, $OvrOwn_{sct}$ states the degree of overlapping ownership between the two companies, and F_{sct} indicates the supply chain relationships is feasible, something I cannot directly observe.

However, as long as the measures of overlapping ownership and vertical upstream relatedness are independent, I can perform the following decomposition

$$\begin{aligned}\mathbb{P}(Link_{sct}|OvrOwn_{sct}, VertRel_{sct}) = {} & \mathbb{P}(Link_{sct}|OvrOwn_{sct}, F_{sct})\mathbb{P}(F_{sct}|VertRel_{sct}) \\ & + \mathbb{P}(Link_{sct}|OvrOwn_{sct}, \neg F_{sct})\mathbb{P}(\neg F_{sct}|VertRel_{sct})\end{aligned}$$

where $VertRel_{sct}$ denotes the degree of vertical upstream relatedness of firm s with respect to firm c at time t and $\neg F_{sct}$ indicates the supply chain relationships is unfeasible. The presumption that unfeasible supply chain relationship cannot engage in active trading partnerships eliminates the second term, so I can condition on dyads with a positive vertical upstream relatedness and focus on

$$\mathbb{P}(Link_{sct}|OvrOwn_{sct})\mathbb{P}(F_{sct}|VertRel_{sct}) \tag{1}$$

where I can assume that $\mathbb{P}(F_{sct}|VertRel_{sct})$ is proportional to $VertRel_{sct}$ to use this variable as weights on my estimations.

Something to keep in mind is the authors lose dyads during the mapping process from CUSIP to GVKEY identifiers, which might lead to supposedly unfeasible supply chain links engaging in trading activities. To account for that, I assign the yearly average vertical upstream relatedness to all trading partnerships not in Frésard, Hoberg and Phillips (2020). In Section V, I discuss how the results change upon a different assumption and if, instead, I draw on ad-hoc criteria to identify feasible trading partnerships from the original supply chain network.

Therefore, my main sample consists of 193,795,735 observations of 43,212,666 unique dyads among 7,798 customers and 8,014 suppliers operating in industries other than the financial and utility sector between 1999 and 2013. Panel B in Table 1 displays the cross-year average characteristics of these potential customers and suppliers, showing that only half of them stay in business as potential trading partners in a given year. Furthermore, these companies boast longer lifespans and higher sales, assets, and market value, though they have a lower R&D intensity and market-to-book ratio.

Next, I turn my attention to active trading partnerships in the US between 1999 and 2013. Data about these ties come from the *Compustat North America – Customer Segment*, which collects public 10K filings of companies with the SEC that disclose the identity of all customers that comprise at least 10% of their total annual sales. This requirement originates in the Statement of Financial Accounting Standard (SFAS) N°131, which supersedes SFAS N°14.

The Customer Segment does not provide identifiers for the customers, so recovering the network requires matching them by name. Previous studies have resorted to manually identifying these companies, often with the help of phonetic string-matching algorithms (Fee, Hadlock and Thomas, 2006; Wu and Birge, 2014; Cheung et al., 2020). Instead, I took advantage of a clean dataset published by Barrot and Sauvagnat (2016)[1] that contains supply chain ties among publicly-listed companies in the United States and Canada between 1976 and 2013. Following the authors, I consider a trading partnership active in all periods ranging from the first to the last year a company reports the other one as a major customer.

Notice there are some limitations associated with the data. First, it only comprises filings from publicly-listed companies in North America for non-retail sales. Unlike other studies that use the same data, omitting privately held firms, governmental entities, and household consumption does not pose a problem in my work. Second, matching customers from names disclosed by companies can introduce noise into the data since firms with similar names could refer to unrelated organizations despite their shared historical roots[2]. Third, the wording of SFAS N°131 could introduce sample selection since it is more likely for small suppliers and large customers to exceed the 10% threshold.

Nonetheless, the SEC requires all suppliers to disclose their customers when they proceed with their 10K filings, so there is no underrepresentation of large suppliers in the data[3]. For instance, after excluding companies in the financial and utility sector, the Customer Segment identifies 29,413 observations among 1,499 customers and 3,119 suppliers engaging in 8,081 unique trading partnerships between 1999 and 2013. Panel C in Table 1 shows that in a given year, around 1,949 suppliers are operational with average characteristics that do not differ significantly from those of Panel B.

On the contrary, the concerns revolve around relatively small companies relying on a few key suppliers, which are significant supply chain relationships I am missing due to

[1] Data can be retrieved from `https://sites.google.com/hec.fr/jnbarrot/data`.

[2] For instance, in 2000, A.T. Massey Coal Company spun off Massey Energy Co. and changed its name to Fluor Corp. Therefore, the string "Massey Coal Company" should be matched to "Fluor Corp." rather than "Massey Energy Co.," which most phonetic string-matching algorithms would miss.

[3] For further discussion, see Barrot and Sauvagnat (2016) and Wu and Birge (2014). Both papers compare the Compustat – Customer Segment with alternative data sources, such as Capital IQ and Bloomberg SPLC.

the wording of SFAS N°131. These companies, due to their lower levels of purchases, would rarely reach the 10% threshold to be considered substantial enough to show up in the supplier's 10K filings. Indeed, Panel C shows that, in a given year, approximately only 670 companies constitute the list of major customers in the US economy. Moreover, these companies report, on average, significantly higher levels of sales, market value, assets, and market-to-book ratio compared to customers in Panel B. In addition, these companies exhibit a lifespan of nearly five additional years and a lesser engagement in R&D activities.

At the same time, several companies voluntarily include customers below the prescribed threshold despite not being required by the Statement, which could potentially introduce an additional source of bias. To assess whether differences between disclosing and non-disclosing suppliers might be an issue, I exploit the fact that I observe the sales to customers of 20,613 (70%) trading partnerships. Next, I identify dyads involving suppliers who have listed customers below the threshold at least once since 1976 (Panel D), representing approximately three-quarters of the suppliers and covering almost 80% of the customers in a given year. Panel E displays the same information for the remaining dyads in the Customer Segment.

Notice there are no significant differences across Panel C, D, and E, suggesting that suppliers do not have preferences on when to report the name of a company when it falls below the 10% threshold. However, it is also consistent with suppliers having incentives to claim to their shareholders that they trade with the most important companies in the US economy, even if these are not among the main customers of the suppliers themselves. In any case, Section V discusses whether all these limitations can affect the results I obtain in the following sections.

B. Overlapping ownership

Constructing the overlapping ownership measures I use throughout the paper requires collecting data about the owner-firm ties between 1999 and 2013. Thus, I establish the ownership network from two publicly available datasets of previous studies, which enables me to consider both large institutional investors and blockholders. Then, I follow Rotemberg (1984), or more recently Backus, Conlon and Sinkinson (2021*b*), to compute the *profit weight values* of companies across all feasible supply chain links.

First, I collect 13F filings with the SEC between 1999 and 2017 from Backus, Conlon and Sinkinson (2021*b*). The SEC requires all investment managers with over USD 100 million in holdings among North American securities to disclose this information quarterly, allowing me to retrieve ownership ties of large institutional investors independently of the fraction of shares they own on those companies. The authors use Thomson Reuters S34, a commercial database broadly used by common ownership researchers. However, they augment the information by web-scraping 13F filings from the SEC website and fetching prices and outstanding shares from the Center for Research in Security Prices (CRSP). Therefore, their dataset provides a broader coverage of companies and ownership ties, entailing an improvement over the original data source.

Second, I retrieve 13D and 13G filings with the SEC between 1998 and 2016 from Schwartz-Ziv and Volkova (2021)[4]. Shareholders must file 13D filings with the SEC within ten days they reach at least 5% of the outstanding shares of a company and annually after that. Instead, 13G filings are a shorter version reserved only for shareholders that do not pursue to control, influence, or engage in active trading with those securities, such as passive investors or other stakeholders. In this way, the dataset allows me to identify ownership ties of active and passive blockholders independently of

[4]Data can be retrieved from `https://www.dropbox.com/s/yp2r7graixxus7r/Blocks.csv`.

the value of the assets they manage.

I combine both sources in a unique dataset with 10,781,778 annual observations of 3,316,767 unique ownership ties between 33,861 investors and 15,459 firms, indicating the fraction of outstanding shares owned by each shareholder in each one of the companies.

With this information, I compute the profit weight values of every company in my sample with their potential customers and suppliers. In Section A.A1 in the Appendix, I provide a thorough derivation of the measure from a micro-fundamented model. There, the manager does not maximize the profits of the firm that appointed her. Instead, she opts for maximizing a weighted average of the market value of the portfolios held by all the shareholders in the company. As a result, the interpretation of the profit weight value κ_{abt} would be the weight the manager at a would impose on the profits of firm b in period t when making a decision that has externalities on that company.

$$\kappa_{abt} = \overbrace{cos(\beta_{at}, \beta_{bt})}^{\substack{\text{Overlapping} \\ \text{ownership}}} \cdot \underbrace{\sqrt{\frac{IHHI_{bt}}{IHHI_{at}}}}_{\substack{\text{Relative} \\ \text{concentration}}} \tag{2}$$

Furthermore, Equation 2 shows how to decompose each weight into the product of the cosine similarity[5] of the ownership structure vectors, β_{at} and β_{bt}, and the relative concentration of investors in the weighted firm with respect to the company of the manager. The first measure describes the similitude in the ownership structure of both companies. Despite being a widespread concept in text analysis, the *cosine similarity* has been recently introduced into Economics, in this case, to depict the incentives managers have to internalize the profits of other companies (Antón et al., 2023). The additional term contains the ratio between the HHI of all investors at the firms, which measures how concentrated is the ownership structure in the companies. The term proves compelling because it incorporates into the analysis the trade-off between incentives and influence within companies' boards. The intuition is that the more concentrated the ownership structure in company b or the more diluted on company a, the more inclined the manager at company a to internalize the externalities they may impose on company b. Interestingly, this interpretation directly connects with the idea that investors can passively influence managers' decisions.

However, notice that every dyad in my sample has two profit weight values: One for the supplier with respect to the customer and one for the customer with respect to the supplier. Therefore, I focus my analysis on the role of overlapping ownership across firms, measured by the cosine similarity of the ownership structures, which can take values that range from 0 to 1. Intuitively, a higher cosine similarity value indicates an increased presence of common vertical shareholders and a strengthened alignment of their interests.For instance, consider the scenario where two shareholders, each holding stock exclusively in one of the companies, were to sell their shares to a single investor who previously had no holdings, the degree of overlapping ownership would rise due to the increased presence of overlapping shareholders. Similarly, when two vertical common shareholders possess stock in both firms but with a higher fraction in one than the other, exchanging shares would result in a growth in the degree of overlapping

[5]Cosine similarity is the complement of the angular distance between two vectors in an inner product space, and it characterizes whether they point in roughly the same direction. Furthermore, the formula $cos(A, B) = \frac{A \cdot B}{\|A\|\|B\|}$ comes from the polar notation of the cross product of the vectors.

ownership because their interests would become more aligned.

Nonetheless, if anything characterizes the literature on common ownership since the subject awakened the interest of researchers, it is the ongoing debate on how to measure it. Thus, I devote Section V to discuss the implications of using alternative measures in the literature. Understandably, differences across alternative measures are unavoidable, and I may find myself dealing with measurement error. Though I have no reason to believe this limitation should lead to biases other than attenuation bias, it should be kept in mind when interpreting the results since every measure captures different dynamics.

II. Empirical strategy

My work aims to empirically assess whether a higher degree of overlapping owners among feasible customer-supplier dyads increases the likelihood they would engage in a trading partnership. Consequently, I dedicate this section of the manuscript to describe the empirical model used for my research and to illustrate the baseline results of the analysis.

A. Methodology

My research consists of a panel data analysis using a linear probability model, focusing on whether the likelihood of trading partnerships among companies depends on their degree of overlapping ownership. The following paragraphs detail the empirical strategy used to test for this particular hypothesis, though I use similar versions to explore the potential mechanisms in Section IV. Furthermore, I present a normalization I perform on the overlapping ownership measures, which facilitates the interpretation of the results.

A linear probability model combines the effects on both margins of the supply chain relationship. On the one hand, it captures whether companies with a high degree of overlapping ownership engage in a new trading partnership. On the other hand, it captures whether companies selling one to the other choose to maintain the relationship for an additional year. Indeed, a previous study by Freeman (2021) shows that companies with a higher degree of overlapping ownership prolong the duration of their supply chain relationships; though, her analysis pays no attention to whether companies could anticipate this to prefer certain trading partnerships over others.

A recurring aspect of my analysis is the need to control for unobserved characteristics of firms that could potentially influence their likelihood of engaging in trading partnerships with other companies. As a result, this section describes results for two baseline specifications that account for unobserved characteristics of companies within the dyad.

First, the following two-way fixed-effect linear probability model

$$Link_{cst} = \delta_t + \delta_c + \delta_s + \tau\, cos_{cst} + \varepsilon_{cst} \tag{3}$$

where $Link_{cst}$ identifies whether customer c and supplier s engage in a trading partnership at time t. The model includes two sets of fixed effects to control for time-invariant unobservable characteristics of companies, a customer fixed effects δ_c and a supplier fixed effects δ_s. I also include time fixed-effects δ_t to control for time trends in the average likelihood of supply chain relationships.

Second, I present an alternative specification

$$Link_{cst} = \delta_{ct} + \delta_{st} + \tau\, cos_{cst} + \varepsilon_{cst} \tag{4}$$

that controls for time-varying unobservable characteristics of companies by including fixed effects δ_{ct} and δ_{st}, which I can estimate since all companies have multiple feasible trading partners in my sample. These allow me to control for idiosyncratic trends across firms and account for usual controls in the literature, such as age, size (log of total assets), annual sales, market share, market-to-book ratio, or industry concentration measures, many of which could be endogenous and act as *bad controls* if I add them directly to the empirical model.

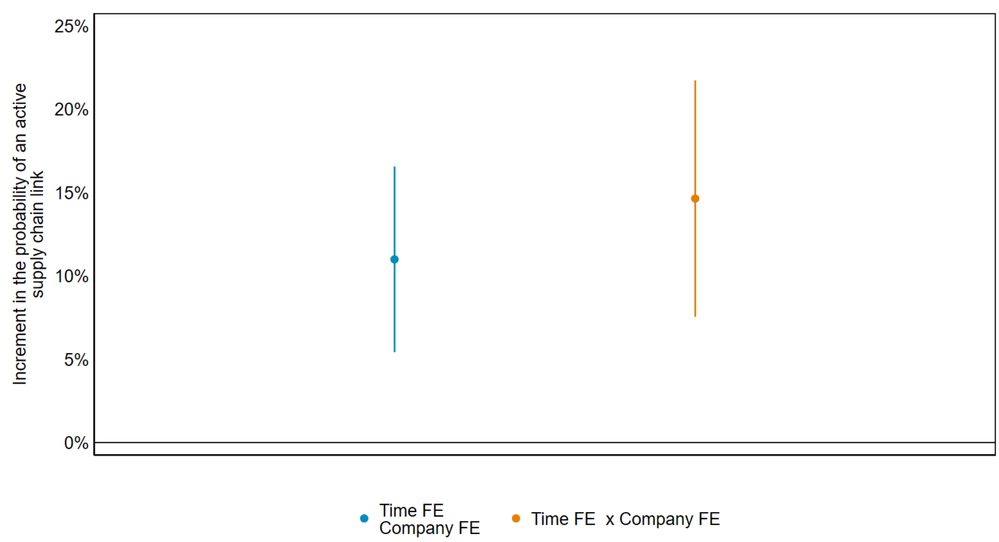
To facilitate the interpretation of the estimated coefficients, I normalize the cosine similarity of the ownership structures of companies as standard deviations (0.1360) with respect to the average cosine similarity among feasible supply chain links (0.0905). Moreover, I divide the variable by the mean of the outcome in the sample (0.02%). Therefore, the coefficient report relative changes with respect to the unconditional probability of an active trading partnership given a one-standard-deviation increase in the degree of overlapping ownership. In this way, I avoid having to interpret small-scale percentage point changes due to the large number of feasible but inactive supply chain links in the sample.

B. Baseline results

Figure 2 displays the association between a higher degree of overlapping ownership among potential customer-supplier dyads and a higher likelihood that they would actively engage in a trading partnership. These estimates might not necessarily entail a causal relationship; however, Section III addresses these concerns by employing an instrumental variable approach.

The coefficient associated with the degree of overlapping ownership among potential trading partners is positive and significant in both specifications, suggesting that a one-standard-deviation increase in the cosine similarity of the ownership structure

Figure 2 — Baseline results



Notes: The figure depicts the coefficients and confidence intervals associated with OLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 1999 and 2013 using different fixed-effect specifications. I report the effect of one standard deviation (0.1319) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0842). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. For further information, refer to Table A1 in the Appendix.

of feasible supply chain links exhibits, on average, an unconditional probability for an active trading partnership 10.99% to 14.64% higher. Table A1 in the Appendix reports the same results, while Columns (1) and (4) of Table A2 in the Appendix report the results between 2000 and 2013 for comparability with the instrumental variable approach.

III. Addressing endogeneity

The previous section suggests a strong connection between the ownership and supply chain network; however, the fact that investors endogenously choose their portfolios and might be paying attention to the evolution of trading partnerships would cast doubt on whether it is reasonable to accept this relationship as causal. The following section delves deeper into the issue, proposes an empirical strategy to work around it, and shows results supporting the idea this entails a causal relationship.

Although the literature has focused on the endogeneity problems related to horizontal settings, several examples support similar concerns for vertical settings. For instance, active investors are known for gathering thousands of data points before committing to a decision. Thus, it is not far-fetched to assume that several institutional investors follow rumors of changes in the trading partners of companies, so my estimates would suffer from reverse causality. Similarly, unobservable shocks might simultaneously affect the overlapping ownership and the trading partnerships, leading to omitted variable bias. For example, let us consider a substantial technological innovation from a company. On the one hand, the company could potentially engage in new trading partnerships due to the technological advancement, either to supply the inputs required to manufacture or to distribute the new product. On the other hand, the new patent might attract the attention of informed investors, increasing their holdings not only in the innovator but in other companies they believe might benefit from the novelty along the supply chain network.

The main setback to addressing the endogeneity concerns and assessing whether the degree of overlapping ownership affects the likelihood of trading partnerships is the absence of valid identification strategies at the dyad level. Though Boller and Morton (2020) and Antón et al. (2023) find an exogenous variation of the overlapping ownership at the market and firm level, it does not work on vertical settings since it relies on the addition of competitors in the S&P 500 index. At the same time, other papers exploring the role of vertical common shareholders in the supply chain network depend on sources of exogenous variation that, according to the literature, do not meet the exclusion restriction. For example, Berger (2023) highlights the challenges associated with using fire sales resulting from mutual fund scandals, and Lewellen and Lowry (2021) discuss issues related to mergers of financial institutions and analyzing companies added to indexes.

Instead, I exploit differences in the market value of annual additions and deletions from the S&P 500 index to isolate the exogenous component of shareholding positions of investors across US companies. Then, I construct new measures of overlapping ownership from these predicted shareholdings to use as instruments. The following subsections provide more details on the construction of this instrument and display the corresponding results.

A. *Additions and deletions from S&P 500*

Several studies have used changes in indices components as exogenous shocks in the ownership structure of companies. The idea revolves around the premise that index funds offer value to their investors by tracking a diversified index of assets, such as the S&P 500. Therefore, changes in the constituents of the index should push these funds, and other investors who replicate their strategy, to acquire equity of companies entering the index and to sell shares of companies leaving it[6]. However, Lewellen and Lowry (2021) suggest that using S&P 500 additions as an instrument can be inappropriate for addressing endogeneity. First, the responsibility of choosing which companies make the cut into the index is held by a committee[7], whose decisions might be affected by a company's most recent performance. In particular, the committee's members might be awaiting improved supply chain relationships for the company entering the index and the opposite for companies leaving it. Second, upon being added to the index, companies receive more attention from media and analysts, suggesting the company's ownership structure could be affected through hard-to-isolate channels. For example, the authors show that companies recently added to the index increase their levels of institutional ownership while crowding out blockholders.

However, Boller and Morton (2020) and Antón et al. (2023) take a different approach when using S&P 500 additions. Instead of focusing on the added company, they consider the effects on its competitors, for whom the addition and the consequent increase in overlapping ownership prove to be completely exogenous. The proposal stands out in horizontal settings, where managers perform unilateral decisions. In these contexts, changes in index constituents would affect firms' choices only through changes in the degree of overlapping ownership because the ownership structure of the competitor remains unaltered, supporting the exclusion restriction.

The same approach does not hold for vertical settings, where both companies must be willing to engage in a trading partnership. Since the addition to the index affects the ownership structure of one of the firms in the dyad, the exclusion restriction no longer holds.

As a workaround for the issue, my identification strategy takes the original idea one step further by focusing on customer-supplier dyads involving companies unrelated to the changes of constituents. The connection between index changes and managerial decisions becomes less straightforward in this context, so the method requires modeling how additions and deletions affect the portfolio composition of asset managers. Consequently, I take advantage of the fact that most institutional investors typically employ a diversified strategy that combines active and passive funds. In particular, indexing has become a widely extended form of passive investing whereby investors seek to replicate the performance of a specific market index, such as the S&P 500, by closely matching the holdings and weighting of the index it tracks.

The missing piece that bridges S&P 500 additions and deletions with managerial decisions lies in the index-weight changes taking place due to differences in the market value of companies entering and exiting the index. Because the index lists the 500 most influential companies in the US according to S&P Indices, a typical change of its constituents would associate the addition of a firm with the removal of a different one. However, publicly-listed companies in the US continuously confront mergers, acquisitions, and spin-offs, so the S&P Indices Committee must react to many of these operations involving index constituents and not always substitute low-market capitalization companies with high-market capitalization ones, making it challenging to anticipate the

[6]For further reference, some examples of studies that have used Russel Index reconstitutions as an instrument are Boone and White (2015), Kennedy et al. (2017), Brooks, Chen and Zeng (2018), and Kostovetsky and Manconi (2020). On the other hand, Aghion, Van Reenen and Zingales (2013) and Kwon (2016) have opted for S&P 500 additions.

[7]According to the S&P 500 US Indices Methodology documentation: "Constituent selection is at the discretion of the Index Committee and is based on the eligibility criteria. [...] Sector balance, [...] in the relevant market capitalization range, is also considered in the selection of companies for the indices". It later adds, "S&P Dow Jones Indices Index Committees reserve the right to make exceptions when applying the methodology if the need arises. In any scenario where the treatment differs from the general rules stated in this document or supplemental documents, clients will receive sufficient notice, whenever possible".

net market value of the constituent's change[8]. Furthermore, the weighting of each company within the index depends on the market capitalization of the firms, so they should shift according to the differences in the market value of additions and deletions. For instance, faced with a positive difference, the index weights of the remaining companies would adjust proportionally downwards to make room for the higher index weights of the entrants. The opposite holds as well.

The identification strategy requires eliminating other potential sources of endogeneity affecting the chain of effects that links additions and deletions with the ownership structures of companies. Therefore, the first step isolates the computation of index weights from variable components, such as the firm's market capitalization, thereby minimizing the influence of other factors related to outstanding shares and share prices.

S&P 500 belongs to the *float-adjusted market capitalization weighted indices* segment of S&P Dow Jones, so higher market capitalization stocks have a more extensive impact on the index's performance compared to those with a lower market capitalization. The adjustment entails the exclusion of shares held by long-term strategic shareholders, such as insiders, private equity, or the government[9]; however, I start from a simple definition of index weights $\omega_{f,t}$

$$\omega_{f,t} = \frac{MktVal_{f,t}}{\sum_{\forall g} MktVal_{g,t}} = \frac{MktVal_{f,t}}{IdxVal_t}$$

where $MktVal_{f,t}$ is the market capitalization of company f at time t and $IdxVal_t$ is the aggregate market value of all 500 companies in the index during period t[10]. Then, I manipulate the expression to circumvent the said issue. By assuming away changes in the market capitalization of company f, I can state an expression for the relative change of index weights as a function of the index aggregate value and the differences in the market capitalization of additions and deletions. More specifically, I compute the quarterly aggregate value of the index during the previous year and use the cross-year average to obtain

$$\begin{aligned} \frac{\omega_{f,t} - \omega_{f,t-1}}{\omega_{f,t-1}} &= \frac{IdxVal_{t-1}}{IdxVal_t} - 1 \\ &= \frac{IdxVal_{t-1}}{IdxVal_{t-1} + \sum_g MktVal_{g,t}(\mathbb{1}_{g \in Add} - \mathbb{1}_{g \in Del})} - 1 \end{aligned}$$

The second step requires predicting how shareholders react to shifts in the index weights. Since asset managers hold index funds tracking the index weighting, I expect

[8] For example, on December 14, 2011, S&P Indices announced that by December 20, TripAdvisor Inc. would replace Tellabs Inc. in the S&P 500 index. According to the press release, the announced day corresponds to the expected date on which the S&P 500 constituent Expedia Inc. was to complete the proceedings to spin off TripAdvisor. Assuming a fixed number of outstanding shares and their prices, the market capitalization of Expedia before the spin-off should amount to the sum of Trip Advisor and Expedia during the first quarter of 2012. Therefore, this particular change of constituents only portrays deleted market value from the exit of Tellabs. Similarly, on March 27, 2000, Standard & Poor's announced that Linear Technology Corp. and Pharmacia Corp. would replace Monsanto Company and Pharmacia & Upjohn in the S&P 500 index. The press release explains that Pharmacia is the merger of Monsanto and Pharmacia & Upjohn, meaning the change of constituents solely depicts added market value from the entry of Linear Technology. There are many other examples, with 51 spin-offs, 158 merges and acquisitions, and several changes of names and tickers between 1999 and 2013.

[9] For more information about the float adjustment methodology and investable weight factors, check `https://www.spglobal.com/spdji/en/documents/index-policies/methodology-sp-float-adjustment.pdf`.

[10] Notice the summation of the market value of all companies in the S&P 500 index does not coincide with the index's market capitalization, even by including investable weight factors. The difference comes forth since S&P Dow Jones Indices scales the aggregate index value to avoid abrupt changes in its price.

investors to purchase additional shares when weights increase and to sell when they fall. Therefore, I employ the following Markovin process to predict the shareholders' reaction

$$\beta_{if,t} = \alpha + \rho\, \beta_{if,t-1} + \tau\, W_{f,t} + u_{if,t} \tag{5}$$

where $\beta_{if,t}$ represents the fraction of shares investor i owns on company f at time t and W_{ft} depicts the corresponding index weight shift for company f during period t,

$$W_{ft} = \begin{cases} \dfrac{\omega_{f,t} - \omega_{f,t-1}}{\omega_{f,t-1}} & \text{if } \; f \in \text{S\&P 500} - \{Add_t, Del_t, Rel_t\} \\ 0 & \text{if } \qquad f \notin \text{S\&P 500} \end{cases}$$

Out of the 10,238,314 ownership ties between 2000 and 2013, I eliminate 300,514 observations regarding 610 companies participating in the index additions and deletions. Furthermore, I drop 3,248,053 ties involving asset managers with improper behavior for passive indexing investors since they do not hold outstanding shares in the company the previous year. With the remaining 6,648,273 ownership ties, I estimate (5) and obtain $(\alpha, \rho, \tau) = (0.9074, 0.0193, 0.0007)$. All coefficients are statistically significant with a 99% confidence level, and the R^2 amounts to 0.815, indicating the model can predict the behavior of passive indexing investors in companies unrelated to changes in the S&P 500 constituents.

The third and final step employs the predicted shares owned by shareholders, $\hat{\beta}_{if,t}$, to compute the same overlapping ownership measures and use them as instrumental variables. The identification assumption for the instrument is that $u_{if,t}$ collects all variation coming from endogenous investment decisions, i.e., that differences in the market capitalization of companies entering and exiting the S&P 500 index and the ownership structure of firms in the previous period do not affect the likelihood of active trading partnerships through a channel other than the degree of overlapping ownership.

A natural concern of the assumption is that active trading partnerships might be persistent, so higher degrees of past overlapping ownership could affect the likelihood of present active trading partnerships by having established the relationship at first. An argument against it would be that after controlling for potential sources of persistence in the supply chain network, if past degrees of overlapping ownership played a decisive role in creating the trading partnership, the current degree would be pivotal for the decision of continuing the relationship for an additional year. Therefore, if the persistence would stem from the intrinsic characteristics of customers and suppliers, I could employ time-invariant and time-varying firm fixed-effects to account for its sources; however, if it is rooted in idiosyncratic conditions of the trading partnership itself, the instrument would invalid, as my identification strategy cannot account for that.

Another potential threat to identification comes from the non-linearities of the overlapping ownership measures since they might capture unintended interactions between the shifts of index weights. To account for this, I linearize the cosine similarity function by implementing a first-order Taylor expansion. Nevertheless, Section V displays and discusses results using a second-order Taylor expansion and the whole functional form.

From the 167,902,174 feasible supply chain links between 2000 and 2013, I drop 3,291,935 observations involving 381 customers and 374 suppliers participating in the index additions and deletions. Among the remaining observations, the index's change of constituents affects the ownership structure of at least one of the trading partners in

30,044,876 (18.25% of the sample) feasible supply chain links. Therefore, the estimates of the 2SLS regression should report the effect that increasing the degree of overlapping ownership would have on the likelihood of active trading partnership among the compliers of these supply chain links. In particular, dyads that would not have engaged in one if it had not been for the similarity in the ownership structure of the companies involved.

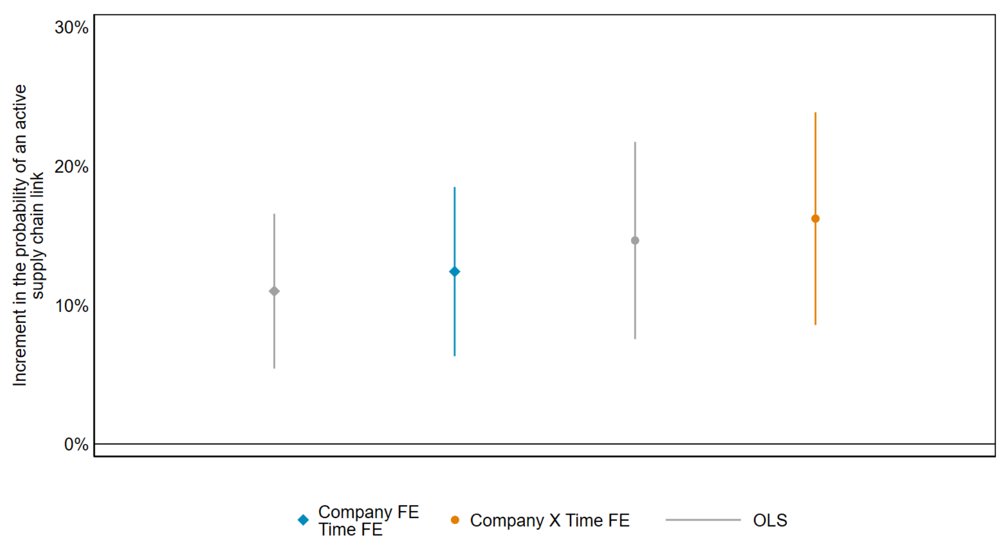
B. Overlapping ownership and the supply chain network

I estimate the OLS and 2SLS models for the sample of feasible supply chain links between 2000 and 2013 to assess whether a higher degree of overlapping ownership between two companies affects the likelihood they would engage in a trading partnership. The coefficients associated with the variable of interest are positive and significant for all specifications and almost double for the 2SLS model, suggesting that a one-standard-deviation increase in the cosine similarity of the ownership structure of feasible supply chain links raises the unconditional probability of an active trading partnership between 14.93% to 16.21%. For more details, see Table A2 in the Appendix, which reports OLS and 2SLS estimates, including the corresponding first-stages.

Figure 3 displays the coefficients for all the regression models, showing in gray the estimates corresponding to the OLS model for both time-invariant and time-varying company fixed effects. Notice that by restricting the sample to a comparable period, the OLS coefficients exhibit a slight increase (11,02% and 14,93%, respectively) with respect to the reported ones in the baseline results, although there is no statistically significant difference.

Although the 2SLS estimation finds higher coefficients, the figure shows that, with a 95% confidence level, they do not statistically differ from OLS estimates. Since any mea-

Figure 3 — OLS and 2SLS results



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 1999 and 2013 using different fixed-effect specifications. I report the effect of one standard deviation (0.1361) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0905). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. For further information, refer to Table A2 in the Appendix.

sure of overlapping ownership has to deal with measurement error, the instrumental-variable regressions have probably addressed the concerns about attenuation bias, which is why the coefficients are slightly higher. However, observing no statistically significant difference between the OLS and the 2SLS estimates makes one wonder about endogeneity concerns. In contrast to the literature on common ownership, where there is a close connection between investment decisions and market capitalization, market shares, or managerial decisions about prices, R&D investment, quality, and so on, my findings suggest that passive indexing strategies are less interested about the supply chain network. In fact, the result does not imply endogeneity concerns could have been unsubstantiated, nor that active investment funds do not care about the identity of customers and suppliers when choosing a firm for their portfolio. On the contrary, these are local results that apply to the compliers of my instrument, i.e., passive indexing investors, who track and replicate known indices and do not consider trading partners when choosing a portfolio; they focus solely on which specific indexes to track.

Nevertheless, my findings suggest that passive funds still affect the supply chain network when they invest in an indexed company by influencing managerial decisions about trading partners. Not necessarily because they directly persuade executives to do so, something beyond the scope of my work, but because managers tend to please pivotal shareholders and factor in how their decisions affect other companies in the shareholders' portfolios.

IV. Economic mechanisms

The findings described in the previous section raise immediate questions about the economic mechanisms and channels through which a higher degree of overlapping ownership across companies increases the likelihood they would engage in a trading partnership. Fortunately, Rotemberg (1984) offers a helpful framework to analyze potential mechanisms involved, though it does not provide an immediate answer.

Within the model, the company faces a maximization program that exhibits two different ingredients that draw the attention and interest of particular fields in the economic literature. On the one hand, the corporate governance literature emphasizes the role of γ_{fit}, the Pareto-weight the firm imposes on each shareholder, and how managers become aware of how their decisions affect investors' returns. On the other hand, the industrial organization literature highlights how profit weight values κ_{fgt} can affect market outcomes by making the manager internalize the effects of their decisions on other firms, namely, $\pi(x_{ft}, x_{-ft})$.

My paper focuses on the second feature, on how firms can affect upstream and downstream market outcomes by incorporating the externalities of engaging in particular trading partnerships. By the very nature of vertical relationships, these mechanisms should be closely related to the tropes of partial vertical integration, so the following subsection presents a comprehensive description of the insights known about the topic and discusses whether this could be beneficial or detrimental for other investors or firms.

A. The tropes of partial vertical integration

Several studies in the industrial organization literature show that vertical integration strategies can affect upstream and downstream market outcomes (Bolton and Whinston, 1993; Lee, 2013; Boehm and Sonntag, 2022). However, partial integration and vertical overlapping shareholders can attain similar results without companies engaging in mergers and acquisitions. For example, Fee, Hadlock and Thomas (2006) explore the role of partial vertical integration on the stability of customer-supplier relationships, while Freeman (2021) extrapolates similar results to third-party overlapping shareholders. Therefore, it seems reasonable to consider that overlapping shareholders affect the supply chain network through typical features of vertical integration and vertical control[11].

To begin with, overlapping owners could enable valuable trading partnerships that otherwise would not exist due to contractual frictions, such as incomplete contracts or injunctions from competition policy authorities[12]. For example, by easing access to data, overlapping shareholders could help to reduce the cost of getting information about prospective trading partners and alleviate conflicting interests. Since the screening process and transaction costs occur on both sides of the supply chain relationship, they could make it more likely for companies with similar ownership structures to pick each other. Moreover, competition policy authorities often overlook ownership ties across companies, so overlapping shareholders could act as substitutes for the contracts, mergers, and acquisitions that authorities would deem anti-competitive behavior. Similarly, they could help work around the discouraging costs associated with such financial transactions.

Additionally, managers could internalize the benefits of engaging and keeping redundant trading partnerships to reduce the systemic risk in the supply chain network, thereby reducing the impact of natural disasters (Carvalho et al., 2021; Barrot and Sauvagnat, 2016), bullwhip effects (Croson and Donohue, 2005) or alternative external shocks. Moreover, they could increase supply reliability for customers (Bolton and Whinston, 1993; Wu and Birge, 2014), alleviate supplier's cash constraints (Fee, Hadlock and Thomas, 2006), smooth sales dependence on inherently uncertain markets (Pfeffer, 1987), or provide companies that hold or require essential facilities with a competitive advantage.

Ultimately, overlapping shareholders could employ trading partnerships for ripping private benefits at the expense of one of the companies. For example, upstream or downstream markets could exhibit the foreclosure of companies not belonging to the portfolio of shareholders (Levy, Spiegel and Gilo, 2018; Boehm and Sonntag, 2022), tighter market-entry barriers (Newham, Seldeslachts and Banal-Estañol, 2019), or incentives among managers to tunnel value from one company to another, similar to the case where firms set different *transfer prices* to carry profits from one division into another.

Establishing the contribution of each potential mechanism poses a challenge for identification, and therefore, in the following subsections, I offer only suggestive evidence regarding some underlying factors. For instance, my findings support the belief that overlapping shareholders could help alleviate information asymmetry problems in the presence of holdup and double marginalization since effects become more pronounced when the supplier exhibits a higher R&D intensity or when companies face a lower degree of competition. Interestingly, the degree of overlapping ownership also exerts a more substantial impact on the likelihood of trading partnerships when the ownership structure is relatively more concentrated within a firm, suggesting that overlapping shareholders might exploit supply chain relationships to obtain private benefits.

[11] Vertical integration is a way of organizing a trading relationship in which a company aims to gain control of multiple steps along the supply chain. Instead, vertical control implies transferring decision-making rights of some but not all aspects of the trading partnership.

[12] As an illustration, revenue-sharing contracts have been under scrutiny by competition policy authorities in both the US and Europe. In 2018, the Directorate-General for Competition of the European Commission accused Google of using these contracts to bundle Google Chrome and the PlayStore to the Android Operative System.

B. Holdup and double marginalization

A number of contexts provide trading partners with the opportunity to boost their profits through coordination or long-term contracting. In the face of significant gains, firms may even consider merging or acquiring each other; however, due to the associated costs, firms would engage in these strategies only when signing a contract is out of the picture. The issue is that contracting becomes unfeasible under certain circumstances, e.g., due to competition policy constraints or when information asymmetries prevent them from agreeing on the contract content or choosing who should keep residual control over it. Here, the presumption is that overlapping shareholders could help alleviate the information asymmetry problems by disclosing sensitive information or serving as enforcers of unhewn agreements, only to avoid more complicated arrangements.

Holdup is a typical example of contractual frictions between trading partners. The problem arises when parties disagree on splitting the profits from partnership-specific investments. In particular, due to the temporal inconsistency of agents who cannot truthfully commit without a binding document. Nevertheless, Freeman (2021) shows that overlapping shareholders extend the length of trading partnerships and improve several innovation outcomes. Similarly, Deng and Li (2022) find evidence that suppliers invest more in partnership-specific assets when customers share common institutional shareholders.

My take on the issue is that overlapping shareholders are pivotal agents in reducing the costs of holdup, not only by extending the trading partnerships over time but also by helping work around the obstacles to create one in the first place. To account for this possibility, I explore the heterogeneous effects of the degree of overlapping ownership and check whether the impact on the supply chain network strengthens when holdup becomes prevalent.

The literature considers three dimensions to identify innovation activities related to holdup. The innovation input reflects resources and efforts invested by firms; the innovation output represents the outcomes of the innovation process; and the innovation specificity relates to the degree of customization concerning the needs of a particular trading partner. I measure the prevalence of holdup by classifying companies across their level of R&D intensity, i.e., the ratio between annual R&D expenses over total book assets, which is a standard proxy for innovation input in the literature. The caveat of only using innovation input is that it only captures the average likelihood that companies could face holdup problems with any given trading partner, unlike input specificity, which provides a pairwise measure that would allow the classification of dyads instead of individual companies. In any case, using input innovation still offers a way to identify the prevalence of holdup and extend suggestive evidence about the role overlapping shareholders might play in alleviating it.

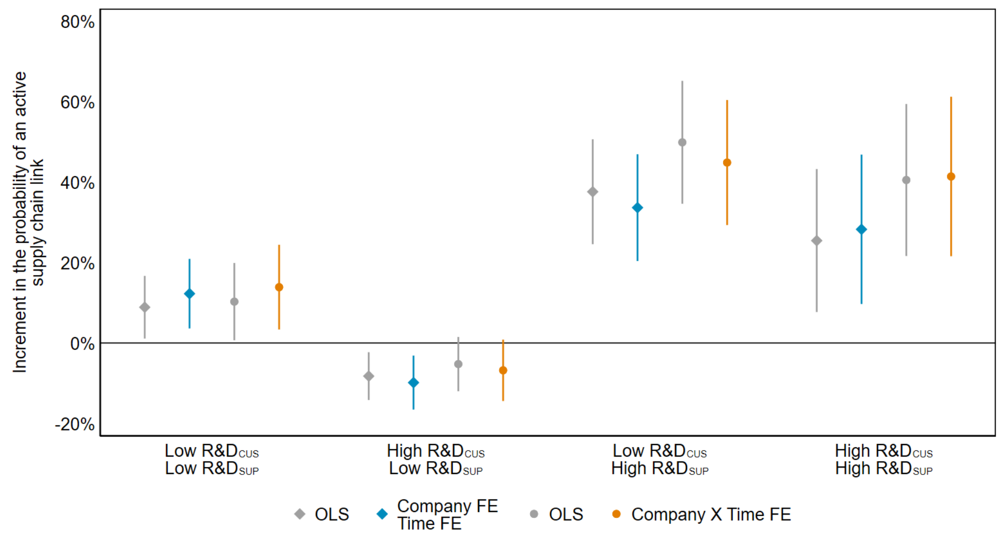
I classify customers and suppliers by whether they are above or below the average R&D intensity (6.89%) for publicly-listed companies in the US between 1999 and 2013 in industries other than the financial and utility sector. Then, I rewrite Equations (3) and (4) to estimate a two-way fixed-effects linear probability model like the following

$$Link_{cst} = \delta_t + \delta_c + \delta_s + \sum_{i \in L,H} \sum_{j \in L,H} \tau_{i,j} \, \mathbb{1}_{\{R\&D_c = i\}} \mathbb{1}_{\{R\&D_s = j\}} \, cos_{cst} + \varepsilon_{cst} \tag{6}$$

and compare the values of coefficients across the different combinations of R&D intensities.

Figure 4 shows the coefficients associated with the degree of overlapping ownership are of a higher magnitude when suppliers have an R&D investment above the average, consistent with the results of Freeman (2021) and Deng and Li (2022), who find that

Figure 4 — Holdup



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I classify dyads into four bins depending on whether customers and suppliers exhibit an R&D intensity above or below the average (6.89%) observed between 1999 and 2013 and drop observations with missing information on R&D intensity. Each coefficient portrays the effect of one standard deviation (0.1319) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0842). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. For further information, refer to Table A3 in the Appendix.

overlapping shareholders only facilitate the innovation process on the supplier side. When the supplier is the only company in the trading partnership engaging intensively in R&D activities, an increase of one-standard-deviation in the cosine similarity of the ownership structure of potential trading partners raises the unconditional probability of an active trade between 33.67% to 44.88%; however, effects are comparatively smaller, ranging from 28.27% to 41.41%, when both companies have an above-average innovation input. Interestingly, when both the customer and the supplier have a below-average R&D intensity, coefficients become slightly below the observed in the 2SLS, 12.27% to 13.89%. For further details of these results, see Table A3 in the Appendix.

Next, I turn my attention to double marginalization, where companies operating in less competitive markets apply successive markups to their marginal costs. Despite not being a general rule, double marginalization tends to decrease profits for all companies along the supply chain (Hamilton and Mqasqas, 1996), so firms often avoid this by employing downstream-profit revenue-sharing contracts and non-linear pricing. While these contracts might also cover goals like product quality or retail services, they would require parties to be fully informed about each other's actions, something that is increasingly demanding the more steps in the supply chain. Therefore, double marginalization represents another example of contractual frictions between trading partners where overlapping shareholders might play a decisive role.

To empirically test for this, first, I obtain a particular version of HHI from Hoberg and Phillips (2016). The authors offer a text-based network industry classification (TNIC) of all publicly-listed companies in the US and compute a market concentration measure that relies on product differentiation distances between firms. The most noteworthy feature of the TNIC version of the HHI is that it allows identifying competitors of multi-product firms and companies without close substitutes within other market classifications, such as SIC or NAICS.

Next, I classify customers and suppliers by whether they are above or below the median TNIC-HHI (2,040 out of 10,000) for all publicly-listed companies in the US between 1999 and 2013 in industries other than the financial and utility sector, and I estimate a similar empirical model as before

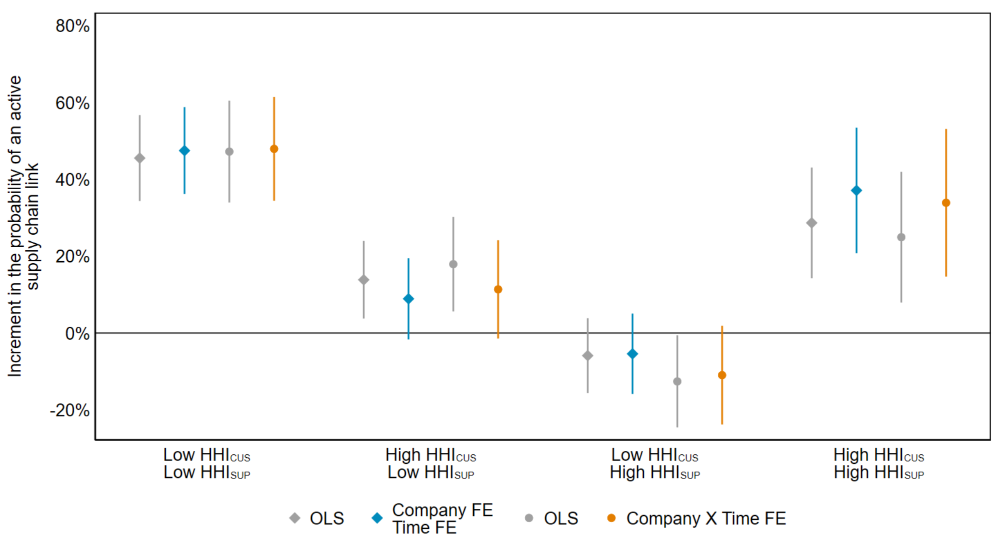
$$Link_{cst} = \delta_t + \delta_c + \delta_s + \sum_{i \in L,H} \sum_{j \in L,H} \tau_{i,j} \, \mathbb{1}_{\{HHI_c = i\}} \mathbb{1}_{\{HHI_s = j\}} \, cos_{cst} + \varepsilon_{cst} \tag{7}$$

to compare the values of coefficients across combinations of concentration degrees.

Figure 5 illustrates several insightful results. First, overlapping shareholders seem to play an extensive role in double marginalization settings since the coefficients associated with the degree of overlapping ownership range from 33.87% to 37.08%. However, when upstream and downstream markets portray low concentration, effects display a higher magnitude, approximately 47.43% to 47.88%, suggesting that other mechanisms play a significant role when market competition becomes more intense. For further details on the estimations, refer to Table A4 in the Appendix.

All in all, it seems that overlapping shareholders help to work around information asymmetry problems among potential customers and suppliers, offering a simple solution to efficiency problems that often require more cumbersome arrangements. In particular, my findings suggest that overlapping owners increase the likelihood of active trading partnerships, albeit with more important repercussions when holdup and double marginalization problems are prevalent. However, these findings do not rule out that something similar may happen upon other contractual or informational frictions

Figure 5 — Double marginalization



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I classify dyads into four bins depending on whether customers and suppliers exhibit a TNIC-HHI above or below the median (2,040 out of 10,000) for publicly-listed companies in the US between 1999 and 2013 in industries other than the financial and utility sector, and I drop observations with missing information on TNIC-HHI. Each coefficient portrays the effect of one standard deviation (0.1326) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0856). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. For further information, refer to Table A4 in the Appendix.

and systemic risks such as the ones described above, which could explain the magnitude of the coefficients when trading partners face more intense competition with their rivals.

These results add to the literature stating the benefits of overlapping ownership and describing its potential to create value for the trading partners, their shareholders, and the economy (Freeman, 2021; Deng and Li, 2022; Gao et al., 2022; Riva, 2022). In particular, my findings suggest that overlapping owners, beyond extending the duration of trading partnerships facing information asymmetries, also facilitate the creation of supply chain relationships that might not have occurred otherwise.

C. Relative concentration of shareholders

In the following subsection, I shift my focus to mechanisms in which overlapping shareholders benefit from managerial decisions at the expense of one of the companies. The idea reminisces the concept of *tunneling* (Johnson et al., 2000; Atanasov et al., 2007), where a company has the ability to transfer assets or cash flows from another firm. For example, imagine a group of overlapping owners holding 60% of the equity of customer c and 20% of the equity of supplier s. If these shareholders could set a lower input price than usual, then for every USD 100 million the customer saves on input costs, overlapping shareholders would pocket USD 40 million. Similarly, non-overlapping shareholders in the downstream firm would benefit as well, obtaining another USD 40 million, while non-overlapping shareholders in the upstream firm would lose USD 80 million.

However, Ehrhardt and Nowak (2015) highlight that tunneling can take many forms and does not necessarily convey money transfers if shareholders can also pursue amenities to assert a higher degree of control in the future or -I should add- if they can affect the supply chain network or the degree of competition among companies. For instance, Levy, Spiegel and Gilo (2018) proposes a model where companies acquire partial stakes in vertically related companies to foreclose rivals and finds that the profitability of these partial acquisitions depends on the ownership structure and corporate governance of firms. Similarly, Boehm and Sonntag (2022) shows that vertical merges and acquisitions increase the likelihood that integrated firms would foreclose rival companies. In my setting, overlapping shareholders could play a similar role by affecting managerial decisions to prefer certain trading partners over others. Additionally, they could serve as a deterrent to potential entrants who might anticipate the likelihood of foreclosure.

To test for this particular mechanism, I need to take one step back to the expression of profit weight values since the cosine similarity of the ownership structure of companies fails to capture the asymmetric incentives among managers. According to Backus, Conlon and Sinkinson (2021*b*), a profit weight value $\kappa_{ab} > 1$ becomes a clear indicator of tunneling incentives for the manager in company a since she cares more about the profits of company b than those of the firm that appointed her.

Unfortunately, Amel-Zadeh, Kasperk and Schmalz (2022) draw attention to the substantial presence of insiders as the largest stockholders in a significant fraction of the largest firms in the American economy. The SEC considers officers, directors, and blockholders with more than 10% of any class of securities in a company as insiders and requires them to file forms 3, 4, and 5. According to the authors, blockholders and insiders hold less diversified portfolios and constitute a considerable component of the ownership structures of companies, affecting the reliability of the relative concentration measures when using solely filings 13F, 13D, and 13G, albeit it does not significantly impact the cosine similarity.

Consequently, I forgo specifying dyads with κ_{abt} above one and instead focus on a different approach that leverages the asymmetry of profit weight values, given the two relative concentration components of the expression are inversely related for any pair of companies

$$\kappa_{cst} = cos(\beta_{ct}, \beta_{st}) \cdot \sqrt{\frac{IHHI_{st}}{IHHI_{ct}}} \qquad \kappa_{sct} = cos(\beta_{ct}, \beta_{st}) \cdot \sqrt{\frac{IHHI_{ct}}{IHHI_{st}}}$$

meaning that an increase in the cosine similarity between firms' ownership structures would affect profit weight values disproportionately unless the relative concentration is exactly 1.

I propose the following two-way fixed-effect linear probability model

$$(8) \quad Link_{cst} = \delta_t + \delta_c + \delta_s + \tau_0\ cos_{cst} + \tau_1\ maxRelCon_{cst} + \tau_2\ maxKappa_{cst} + \varepsilon_{cst}$$

where $maxRelCon_{cst}$ and $maxKappa_{cst}$ represent the highest relative concentration and the highest profit weight value among customer c and supplier s at time t, respectively. Before proceeding, notice that using the highest or lowest values would yield comparable results due to the inverse relationship between the two; however, my choice benefits in interpreting the coefficients. Moreover, the highest profit weight value is the product of the other two terms by construction, allowing me to study the interaction between similarity and relative concentration of ownership structures.

However, using the relative concentration as a covariate presents two challenges to overcome. On the one hand, due to the lack of ownership ties from Forms 3 to 5 filings, I underestimate the concentration of shareholders among firms with a significant representation of insiders[13]. For that reason, I drop all observations where the highest relative concentration lies above the 90^{th} percentile (5.8918). On the other hand, the metric suffers from identical endogeneity concerns as the cosine similarity of the ownership structures. Therefore, I instrument the variable by constructing a similar version using the predicted shareholders as discussed in Section III.

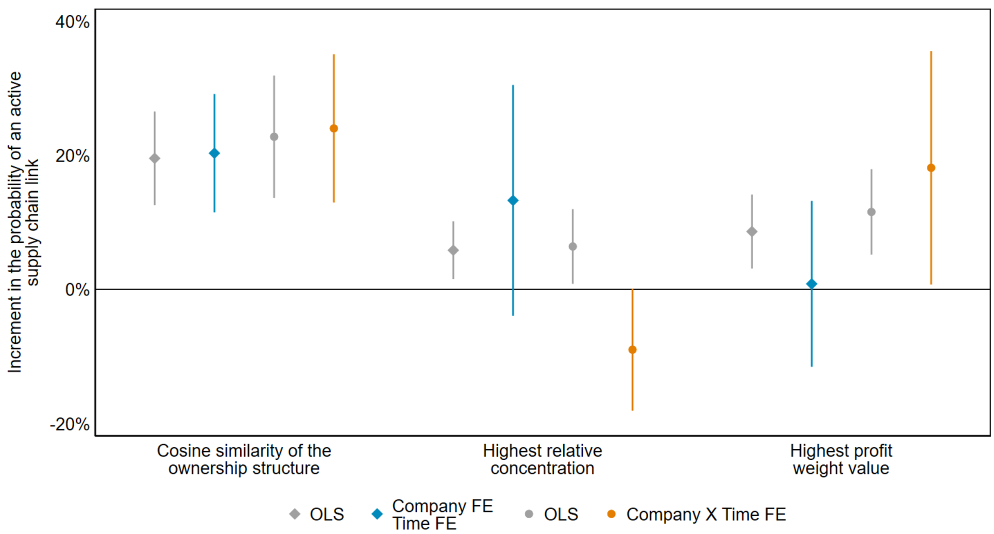
With Equation (8) and the corresponding version using time-varying company fixed-effects, I test whether trading partnerships become more likely when a manager unilaterally has incentives to take actions that benefit a potential trading partner. Intuitively, if the effect of increasing the degree of overlapping ownership does not exhibit statistically significant differences across different degrees of relative concentration, it would mean that disparities in managerial incentives play no role in the likelihood of engaging in a trading partnership. Otherwise, it would constitute suggestive evidence that overlapping owners can employ trading partnerships to transfer value from one company to another, presumably pursuing private benefits.

Figure 6 compares the effects of all three components, showing the cosine similarity of the ownership structure of companies plays a role independently of the introduction of the additional variables, with coefficients ranging from 20.33% to 24.02%. The difference with the estimations in the previous Section arises because, for this empirical exercise, I exclude observations with low degrees of overlapping ownership due to the significant prevalence of insiders in the ownership structure of their companies. Incidentally, these observations contain one-third of the active trading partnerships in the sample, thereby mechanically increasing the coefficients.

In contrast, the estimates for the highest relative concentration of shareholders support the intuition that ownership distribution across firms lacks a significant influence on the likelihood of active trading partnerships in the absence of overlapping sharehold-

[13]For example, among the 167,902,174 feasible customer-supplier dyads between 2000 and 2013, no large institutional fund nor block-holder reported ownership on 8,460,557 customers and 8,471,013 suppliers, amounting to 16,931,570 potential supply chain links with an infinite profit weight value.

Figure 6 — Cosine similarity, relative concentration, and profit weight values



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure, the highest relative concentration, and the highest profit weight value for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I drop observations with the highest relative concentration above the 90^{th} percentile (5.8918) because of the missing information for insiders. The first coefficient portrays the effect of one standard deviation (0.1427) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.1056). The second coefficient reports the effect of one standard deviation (1.0218) with respect to the average highest relative concentration in the sample (1.9725). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). The third coefficient reports the interaction of the first two. I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity, the highest relative concentration, and the highest profit weight value computed by using predicted shareholdings. For further information, refer to Table A5 in the Appendix.

ers, despite the non-negligible coefficient under the specification with time-invariant company fixed-effects.

However, the estimate for the highest profit weight value amounts to 18.14% when employing time-varying company fixed-effects, which is statistically significant at a 90% confidence level, suggesting that an increase in the relative concentration from the bottom (1.0838) to the top (3.4820) decile amplifies the effect of one-standard-deviation increase in the degree of overlapping ownership from 5.68% to 101.44%. Similarly, by increasing the cosine similarity in the ownership structure of companies from the bottom (0.0035) to the top (0.3188) decile, the impact of a one-standard-deviation increase in the highest relative concentration rises from a negative 29.19% to a positive effect of 294.07%. For a more comprehensive description of results, please refer to Table A5 in the Appendix.

The magnitude of the interaction between the degree of overlapping ownership and the relative concentration of shareholders implies that trading partnerships become more likely when one manager weighs heavily on the externalities she imposes on the other company despite her peer paying little attention to her actions. The tunneling conjecture fits these results appropriately because they offer suggestive evidence of managers making decisions that may go against the firm that appointed them. However, the presence of asymmetric incentives among corporate executives does not imply that transfers of assets and cashflows are taking place, as there are other admissible alternative explanations.

For instance, managers with asymmetric incentives could create new supply chain links in the network that would alter the competition structure in the upstream and downstream markets by affecting the likelihood of other trading partnerships breaking up. While one might expect that recently created trading partnerships would substitute less efficient ones, overlapping shareholders could influence the market structure by affecting corporate decisions to prefer some trading partners over others. However, directly testing for the hypothesis imposes many requirements on the data for a correct identification strategy, and thus, it is beyond the scope of my work.

V. Discussion

The results of the paper show the ownership structure of companies affects the identity of customers and suppliers with whom they engage in business relationships, which, in turn, might have implications in the upstream and downstream market structure. An interesting aspect of studying the role of overlapping shareholders in vertical relationships is the complexity of the mechanisms involved, which relates to the ambiguous empirical evidence about the effects of partial vertical integrations. Indeed, my findings suggest the ownership structure of firms can be beneficial or detrimental to other firms or shareholders, depending on the case. In terms of policy, this would imply the need to assess whether, in the face of drastic changes in the ownership structure of firms, the outcome alleviates informational frictions the companies face or, instead, affects managerial decisions in such a way that it hinders competition in upstream or downstream markets.

These results are robust to alternative methodological definitions, such as different overlapping ownership measures, functional forms of the instrument construction, and sample definitions.

There are several candidate metrics to assess the degree of overlapping ownership across firms. While I favor the use of cosine similarity and profit weight values for their microfundamented interpretation, I test the consistency of the findings by using two standard measures in the literature and proposing a third metric that combines the profit weight values at the dyad level. The first metric is the *overlapping market value* among companies (Antón and Polk, 2014; Freeman, 2021)

$$ovrMktVal_{cst} = \frac{\sum_i V_{cit} + V_{sit}}{V_{ct} + V_{st}}$$

which is the fraction of the sum of the market value of both supplier V_{st} and customer V_{ct} owned by the set of overlapping shareholders i at time t. The second alternative is the *overlapping-shares product* (Hansen and Lott, 1996; Freeman, 2021)

$$ovrShrProd_{cst} = \sum_i \beta_{cit} \times \sum_i \beta_{sit}$$

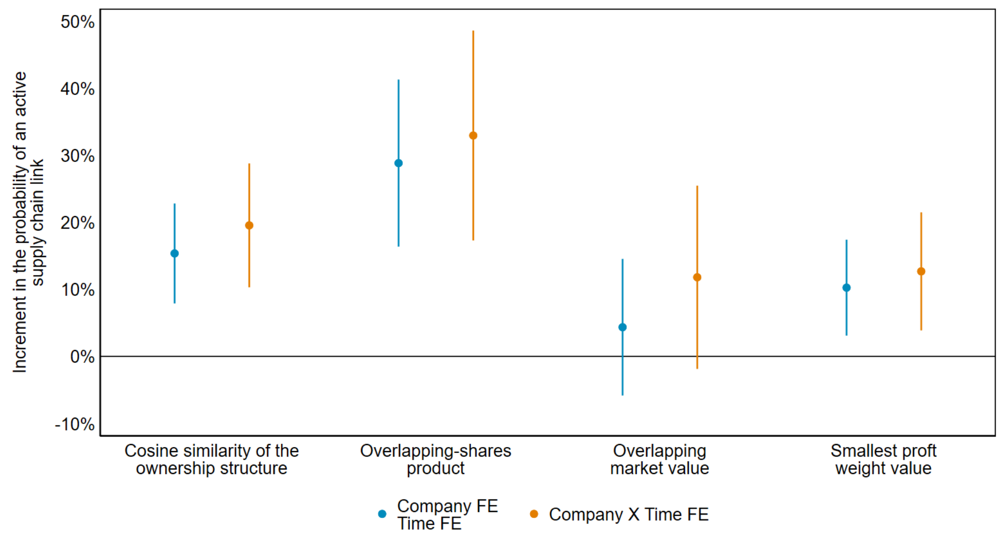
which multiplies the fraction of shares owned by overlapping shareholders i in the two firms. Finally, I propose to use the smallest of the two profit weight values as a third option,

$$minKappa_{cst} = min(\kappa_{cst}, \kappa_{cst})$$

given that it should capture when both managers in a feasible supply chain link internalize the benefits of engaging in a trading partnership.

Figure 7 shows that coefficients are positive and statistically significant for all alternative metrics except for the overlapping market value. However, there are two reasons why the disparity should not be a concern. First, the magnitude of the coefficients appears consistent with Freeman (2021) findings, where she reports effects up to a half than other metrics when using the overlapping market value. Second, this is the only

Figure 7 — Alternative overlapping ownership measures



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on different metrics for the degree of overlapping ownership among publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. Each coefficient displays the effect of one standard deviation increase with respect to the average value of the metric in the sample. Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. I employ the complete functional form of the overlapping ownership measures as instruments by using the predicted shareholdings to construct them. For further information, refer to Table A6 in the Appendix.

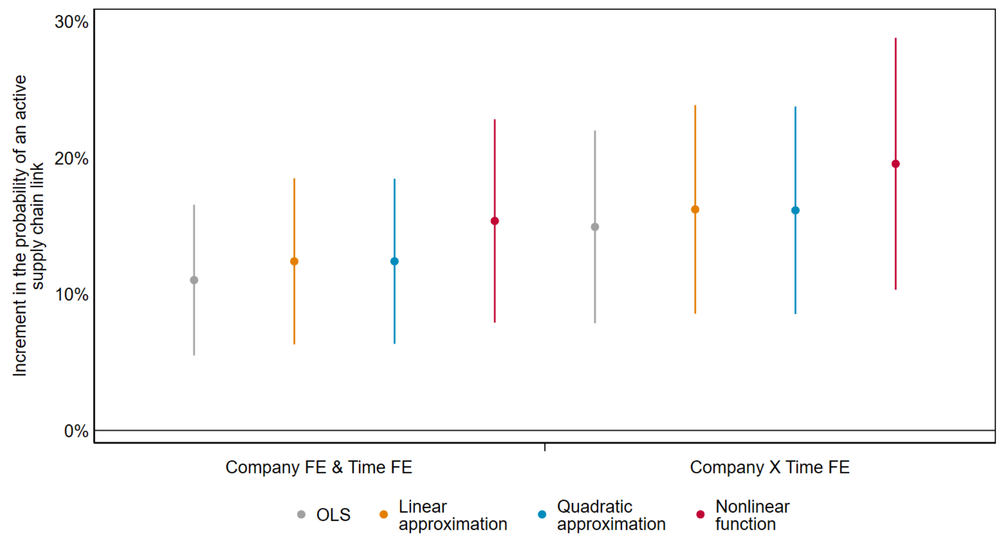
overlapping ownership measure that uses data on market capitalization in addition to the ownership structure, incorporating a further source of endogeneity to the analysis that I am not addressing with my identification strategy. Therefore, it would not be surprising if it suffered from a downward bias. For further details on the estimations, see Table A6 in the Appendix.

Continuing with the instrument, a potential threat to identification could originate in the non-linearities of the overlapping ownership measures, which could capture unintended interactions. To address these concerns, I perform a robustness check by implementing a first-order Taylor expansion, as shown in Section III, and a second-order one. Furthermore, I include an estimation using the whole expression to construct the instrument. Opportunely, Figure 8 confirms that using any functional form conveys almost identical quantitative results, so the methodological choices regarding the instrument construction are not driving the results. In any case, A7 in the Appendix offers more details about the estimations.

On a different note, the sample and outcome definitions pose two challenges for identification. The first issue is that I do not observe all active trading partnerships due to the wording of SFAS N°131. The Statement obliges companies to disclose customers representing at least 10% of their annual sales, although several firms include companies below the suggested threshold. Because of this, the concerns in my analysis involve trading partnerships of relatively small companies buying inputs from a few key suppliers. Unfortunately, anticipating whether the degree of overlapping ownership in these dyads would be above or below the sample average is not straightforward to acknowledge the direction of the bias in the OLS.

However, the 2SLS regressions estimate local effects, which allows me to focus on the relevant customers and suppliers to identify a reasonable direction for the potential bias. Notice the compliers of my instrument concern feasible supply chain links with at

Figure 8 — Alternative instrument functional forms



Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. Each coefficient corresponds to a different functional form of the cosine similarity to construct the instrument from predicted shareholdings. I report the effect of one standard deviation (0.1361) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0905). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. For further information, refer to Table A7 in the Appendix.

least one trading partner non-related to the additions and deletions from the S&P 500 index, so the set of potentially missing compliers would involve small companies not in the index trading with a supplier among the S&P 500 constituents. One insight I could draw from this characterization is that results would not change qualitatively since the compliers consist of firms that would not have engaged in a trading partnership if not were due to the increase in the degree of overlapping ownership or, conversely, companies that would have done it if not were due to its decrease. Quantitatively, on the other hand, one might fear the coefficients could be upward biased. But then, it would be necessary for the missing trading partnerships to consistently face significant shifts in the ownership structure, whereas most of the variation coming from changes of constituents in the index appears to be limited in magnitude.

If anything, the SFAS N°131 wording could have introduced a downward bias, which could be especially relevant in the empirical exercises for double marginalization and holdup because the concerning missing trading partnerships would often be those in which the customer requires a higher level of customization for its inputs or faces a monopolist supplier, implying the correspondings effects should be higher than reported.

A second challenge involves the contradiction between the data sources I use to identify feasible and active supply chain relationships. On the one hand, Frésard, Hoberg and Phillips (2020) mention they lose dyads when mapping from CUSIP to GVKEY identifiers. On the other hand, Barrot and Sauvagnat (2016) explain they use phonetic string-matching algorithms and a posterior manual check to map customers' names in the Customer Segment to GVKEY identifiers. Then, the discrepancies should indicate errors in one or both sources.

So far, I have proposed a compromise solution by assigning the yearly average vertical upstream relatedness to all trading partnerships in the Customer Segment that have a null value and leaving the observed number to the remaining dyads in the Customer Segment. To assess the importance of the assumption in my findings, I explore alternative identification strategies for feasible and active supply chain relationships.

For example, I consider two distinct scenarios in which the source of the error comes solely from one of the datasets. Should inconsistencies arise from improper mapping between companies' names and GVKEY identifiers, I exclude all dyads without a vertical upstream relatedness, even if they appear in the Customer Segment. Instead, if discrepancies originate when mapping vertical upstream relatedness from CUSIP to GVKEY identifiers, I include all supply chain relationships in the Customer Segment and assign them a weight of 1.

In addition, I identify a different set of feasible trading partnerships from patterns in the original supply chain network and the text-based network industry classification. First, using the Customer Segment, I blend all observations between 1976 and 2013 into a unique supply chain network, a common practice in the literature of *link analysis*. After that, I proceeded as follows. To begin with, for any arbitrary customer C_0, I identify all its suppliers in the network and label the set as S_0. Next, I retrieve all customers trading with S_0 companies and tag them as C_1, which offers a set of closely related firms to C_0 that might operate in different industries. Therefore, I define all the suppliers trading with C_1 companies as feasible suppliers of C_0. After repeating this procedure for each customer, I keep only dyads with firms simultaneously reporting book assets to the SEC between 1999 and 2013 in industries other than the financial and utility sector.

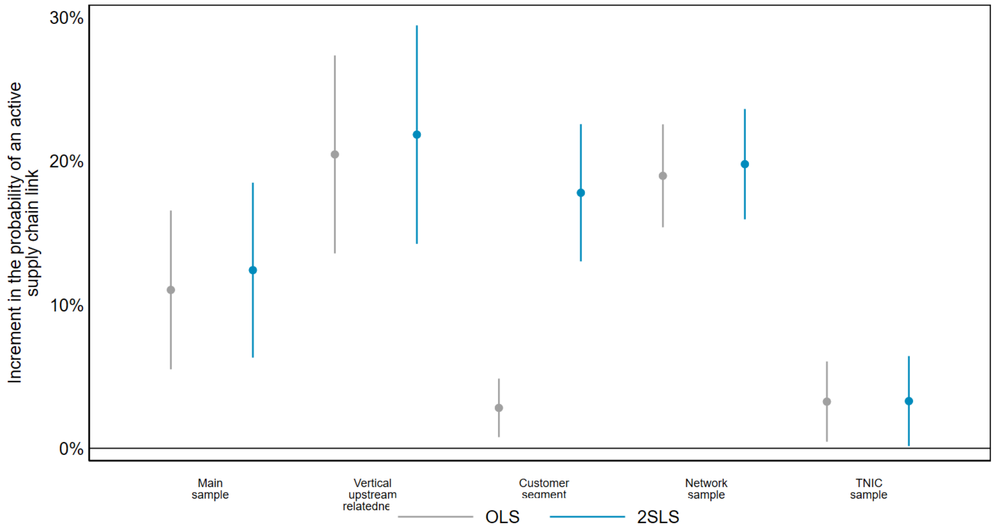
Second, by using the text-based network industry classification from Hoberg and Phillips (2016), I identify all competitors of customers and suppliers in the Customer Segment operating in industries other than the financial and utility sector. Then, for any given year and customer C_0, I define all of its competitors as feasible customers for all the suppliers of C_0. Then, I proceed likewise for all suppliers in the Customer Segment.

Figure 9 shows that results are qualitatively and quantitatively similar throughout the alternative samples, except for the version constructed from the text-based network industry classification since the differences between coefficients in both fixed-effect specifications are statistically significant. Nevertheless, regardless of any disparities in magnitudes, all the specifications point to the same conclusion concerning the causal relationship between the degree of overlapping ownership between firms and the likelihood they would engage in trading partnerships.

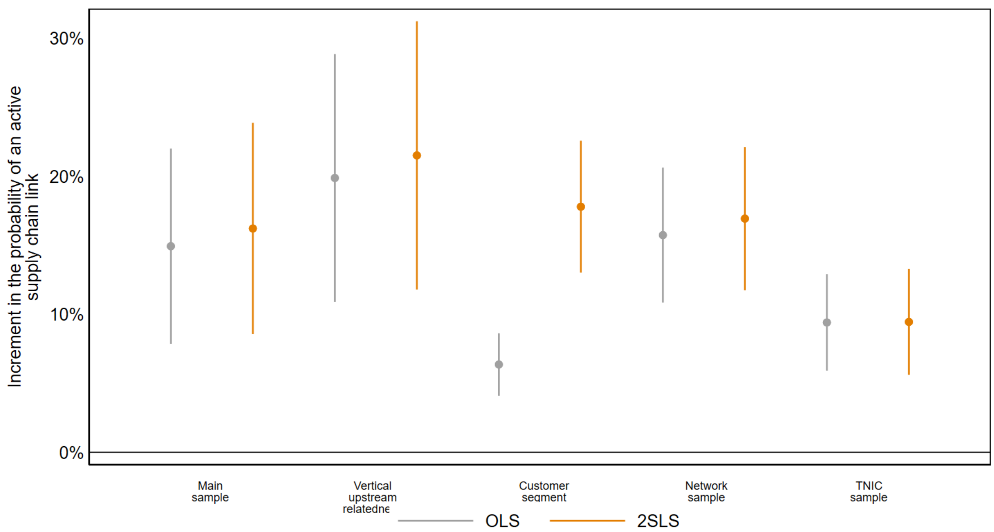
Regarding the association between ownership structures and managerial decisions, the literature on common ownership studies two classes of activities through which managers gain awareness of how their choices affect investor portfolios. The first class revolves around board members and executives learning by themselves. For example, by having a seat in multiple firms where the same institutional investors hold stock, i.e., *interlocking board members* (Azar, 2022), by accessing otherwise private information that overlapping shareholders willingly disclose (Pawliczek, Skinner and Zechman, 2022; Boone and White, 2015), or by being on the payroll of institutional funds (Freeman, 2021). The second class claims that asset managers find a way to meddle in managerial decisions, including what the literature defines as *selective omission*, where shareholders encourage actions that simultaneously benefit the firm's profits and investors' portfolios. For instance, Wells (2016) describes how institutional investment funds tipped the scales and amplified their voice in corporate decision-making since the late 90s, enumerating several means at their disposal, e.g., jawboning, shareholders' proposals, proxy voting, among others.

The empirical evidence of the second class of mechanism has remained elusive to the

Figure 9 — Alternative sample definitions



(a) Time-invariant FE



(b) Time-varying FE

Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications and sample definitions. The upper and lower subfigures display results using time-invariant and time-varying firm fixed-effects, respectively. From left to right, the coefficients reported correspond to the following samples: the one I use throughout the paper, a subsample using only observations with a positive vertical upstream relatedness, a version imposing a weight equal to 1 on all dyads in the Customer Segment, a different sample using the original supply chain network between 1976 and 2013 to identify trading partners of closely related firms in the network as feasible supply chain links, and a version using a text-based network industry classification to identify competitors of trading partners as feasible supply chain relationships. I report the effect of one standard deviation increase with respect to the sample average cosine similarity of the ownership structure. Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample. I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The 2SLS estimations employ as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. For further information, refer to Tables A8 and A9 in the Appendix.

literature; however, a few studies suggest that even passive indexing funds can use their voting rights to push particular agendas (Fichtner, Heemskerk and Garcia-Bernardo, 2017; Bubb and Catan, 2022). For instance, Antón et al. (2023) show that overlapping shareholders can exert their right to say-on-pay and alter managers' incentives by modifying their contracts. Although it seems implausible that shareholders use relative components in managers' contracts to guide corporate decisions towards particular trading partners, ESG-based or similar compensation schemes could play a role by restricting options (Bebchuk and Tallarita, 2022). For instance, by imposing conditions on the characteristics that customers and suppliers should meet.

Even though my findings do not rule out theories involving agency from institutional investors, all results would go through if board members and executives learned by themselves or shareholders passively influenced corporate decisions, with one exception. The results suggesting asymmetric managerial incentives play a role in the likelihood of active trading partnerships contradict the hypothesis of selective omission because investors cannot make a proposal that benefits the firm and themselves. Nevertheless, managers could still incorporate into the decision-making process the externalities they impose on other companies.

The compelling aspect of the passive influence hypothesis, including corporate officers learning by themselves, is that firms would engage in trading partnerships because overlapping shareholders align incentives at the dyad level and not because they collude and influence executives or board members. A potential explanation could be that managers keep career concerns and tend to please large institutional shareholders to gain their favor. For example, they might see it as an implicit requirement to retain their seats on the executive board or board of directors, or moreover, they might expect diversified institutional shareholders to have a say in the appointments at top positions in other companies they plan to apply in the future.

VI. Conclusions

In this paper, I explore whether diversified overlapping shareholders can shape the supply chain network in the US by creating incentives for managers to internalize how their decisions affect potential trading partners and what mechanism could be behind the results.

To explore the relationship between ownership structure and trading partnerships, I retrieve information about the supply chain and the ownership network from public filings that companies must disclose periodically to the Securities and Exchange Commission of the United States. More specifically, I take advantage of publicly available datasets from previous research papers that collect, on the one hand, information about 13D, 13F, and 13G filings and, on the other hand, the Customer Segment of Compustat from 10K filings. I combine this information with the universe of publicly-listed companies from Compustat and measures of vertical relatedness from Frésard, Hoberg and Phillips (2020) to identify all feasible trading partnerships among publicly-listed companies in industries other than the financial and utility sector between 1999 and 2013. Then, I estimate two-way fixed-effects linear probability models and exploit an exogenous source of variation in the ownership structure of companies that take advantage of the additions and deletions from the S&P 500 index.

My findings suggest the degree of overlapping ownership between a potential customer and supplier affects the likelihood they would engage in a trading partnership. In addition, the relationship has implications in the upstream and downstream market structure, which can benefit or harm other firms and shareholders, depending on the case. For example, overlapping owners play a significant role in alleviating contractual frictions and information asymmetries related to the usual consequences of vertical integration, such as holdup and double marginalization. Nevertheless, the relation can also entail opportunities for overlapping shareholders to create value for a company at the expense of other firms and shareholders. In terms of policy, this would reflect the lack of general rules and the need to study the implications of mergers and buyouts case by case.

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Appendix

A1. Derivation of profit weight values

I dedicate the following section of the Appendix to briefly describe the derivation of profit weights values from an objective function for managerial decisions first introduced by Rotemberg (1984). For a more comprehensive description of the assumptions and properties of the model, see Backus, Conlon and Sinkinson (2021*b*).

The first assumption of the model is that shareholders aim to maximize the cash flow rights in all the companies they own shares, representing the overall market value of their portfolios.

$$V_{it} = \sum_{\forall g} \beta^i_{gt} \pi_{gt} \tag{A1}$$

where β^i_{gt} represents the fraction of shares an investor i holds in firm g at time t, and π_{gt} amounts to the profits of said company. Thus, i becomes an overlapping shareholder of companies a and b whenever $\beta^i_a, \beta^i_b > 0$.

The second assumption of the model is that managers do not aim to maximize the profits of the companies that appointed them but a weighted average of the overall market value of portfolios in hands of shareholders that own stocks in the company.

$$Q_{ft}\left(x_{ft}, x_{-ft}\right) = \sum_{\forall i} \gamma^i_{ft} \;\; V_{it}(x_{ft}, x_{-ft}) \tag{A2}$$

where γ^i_{ft} represents the control or influence investor i holds on company f at time t, which is what the manager uses to weigh the externalities of their decisions x_{ft} on the profits of other companies.

The framework follows the claim that a firm should always answer to its investors (Jensen and Meckling, 1976), though it might as well reflect a shift in the power dynamics between shareholders and managers since the late 1990s. For example, Wells (2016) lists a series of events that contributed to the rise of shareholder power and the crystallization of two critical instruments for shareholder activism[14]: jawboning and shareholder proposals. The first one started in 1992 when the SEC, by revising the proxy solicitation rules that aimed to ease communication between large shareholders, unintendedly increased the frequency of meetings and other less formal and visible interactions between shareholders and corporate management. The second one became widely used in the mid-90s and led to the creation of shareholder coalitions that discuss and design these proposals on a daily basis[15].

By combining assumptions A1 and A2, profit weight values arise from the following

[14]For example, the author mentions the creation of the Institutional Shareholder Services (ISS) in 1985, the issuance of the "Avon Letter" by the US Department of Labor in 1988, the increasing focus of unions on their pension funds since the mid-90s that fostered closer ties with institutional shareholders, or the enactment of the Dodd-Frank Act by the US Congress in 2010. For a more in-depth explanation on how these changes affected the corporate power dynamics, see Wells (2016)

[15]For example, James McRitchie, founder of the blog Corporate Governance acted as the plaintiff in a lawsuit against Meta Platforms Inc. executive officers, including Mark Zuckerberg. The accusation is that board members own an excessive fraction of shares in the company, thereby making decisions that, though beneficial for Meta, ignore the effect these have on stockholders' portfolios. The full document can be found on `https://www.documentcloud.org/documents/23117937-james-mcritchie-v-board-of-directors-meta`.

derivation

$$\begin{aligned}
Q_{ft}\left(x_{ft}, x_{-ft}\right) &= \sum_{\forall i} \gamma_{ft}^{i}\ \ V_{it}(x_{ft}, x_{-ft}) \\
&= \sum_{\forall i} \gamma_{ft}^{i} \sum_{\forall g} \beta_{gt}^{i} \pi_{gt}(x_{ft}, x_{-ft}) \\
&= \sum_{\forall g} \sum_{\forall i} \gamma_{ft}^{i}\ \ \beta_{gt}^{i}\ \ \pi_{gt}(x_{ft}, x_{-ft}) \\
&\propto \pi_{ft} + \sum_{g \neq f} \left(\frac{\sum_{\forall i} \gamma_{ft}^{i}\ \ \beta_{gt}^{i}}{\sum_{\forall i} \gamma_{ft}^{i}\ \ \beta_{ft}^{i}} \right) \pi_{gt}(x_{ft}, x_{-ft}) \\
&\propto \pi_{ft} + \sum_{g \neq f} \kappa_{fgt}\ \ \pi_{gt}(x_{ft}, x_{-ft})
\end{aligned}$$

Thus, the profit weight value κ_{fgt} measures how the manager appointed by firm f would weigh the profits of company g in period t when making a decision x_{ft} that has externalities on that company. In addition, one can use vectorial notation to rewrite profit weight values as a ratio of cross products, which leads to the following decomposition

$$\begin{aligned}
\kappa_{fgt} &= \frac{\sum_{\forall i} \gamma_{ft}^{i}\ \ \beta_{gt}^{i}}{\sum_{\forall i} \gamma_{ft}^{i}\ \ \beta_{ft}^{i}} \\
&= \frac{\langle \gamma_{ft}, \beta_{gt} \rangle}{\langle \gamma_{ft}, \beta_{ft} \rangle} \\
&= \frac{cos(\gamma_{ft}, \beta_{gt})}{cos(\gamma_{ft}, \beta_{ft})} \frac{||\gamma_{ft}||}{||\gamma_{ft}||} \frac{||\beta_{gt}||}{||\beta_{ft}||}
\end{aligned}$$

Changing to polar notation allows us to separate the measure into two components. On the one hand, the degree of cashflow rights concentration across firms, given that the degree of control rights concentration cancels out. On the other hand, the relationship between the influence of each shareholder in company f with the cashflow rights they hold on each company. Therefore, discussing overlapping ownership at the dyad level requires establishing a clear relationship between ownership and control, even if we opt for a systemic rather than an agency interpretation of the channels and mechanisms.

Throughout the manuscript, I presume proportional control, $\gamma_{ft} = \beta_{ft}$. Although the premise is not harmless[16], assuming otherwise would require modeling how managerial incentives react to different ownership structures, something that remains elusive in the literature on Corporate Governance. Then, notice the expression for profit weight values reduces to the following

$$\kappa_{fgt} = cos(\beta_{ft}, \beta_{gt}) \sqrt{\frac{IHHI_{gt}}{IHHI_{ft}}} \tag{A3}$$

[16] For example, Gilje, Gormley and Levit (2020) argue that attentiveness affects whether managers internalize the externalities they impose on competitors, while Newham, Seldeslachts and Banal-Estañol (2019) discuss the trade-off between incentives and influence.

A2. Tables and figures

Table A1 — Baseline results (1999-2013)

Dependent variable: Active trading partnership

	(1)	(2)
Overlapping ownership	0.1099***	0.1464***
	(0.028411)	(0.036190)
N	193,795,569	193,792,645
R^2	0.154	0.161
Time FE	✓	
Company FE	✓	
Time × Company FE		✓

Notes: The table documents panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 1999 and 2013 using different fixed-effect specifications. The first two columns describe OLS estimates. I report the effect of one standard deviation (0.1319) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0842). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A2 — OLS and 2SLS results (2000-2013)

Dependent variable: Active trading partnership

	OLS		FS		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Overlapping ownership	0.1102***	0.1493***			0.1240***	0.1621***
	(0.028192)	(0.036067)			(0.031058)	(0.039039)
Predicted overlapping ownership			0.8126***	0.8176***		
			(0.000130)	(0.000141)		
N	167,902,019	167,899,338	147,818,198	147,815,827	147,818,198	147,815,827
F-statistic			39,156,655	33,591,125		
Time FE	✓		✓		✓	
Company FE	✓		✓		✓	
Time × Company FE		✓		✓		✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. The first two columns describe OLS estimates. I report the effect of one standard deviation (0.1361) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0905). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The last two columns describe 2SLS estimates employing as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings, while columns (3) and (4) display first-stage estimates and report the Kleibergen-Paap Wald rk F statistic.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Table A3 — Holdup

Dependent variable: Active trading partnership

	OLS	FS				2SLS	OLS	FS				2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overlapping ownership												
$R\&D^{Low}_{CUS}$ $R\&D^{Low}_{SUP}$	0.0889*					0.1227**	0.1028*					0.1389**
	(0.039740)					(0.044128)	(0.049014)					(0.053715)
$R\&D^{High}_{CUS}$ $R\&D^{Low}_{SUP}$	-0.0824**					-0.0984**	-0.0525					-0.0679
	(0.030303)					(0.034250)	(0.034442)					(0.038965)
$R\&D^{Low}_{CUS}$ $R\&D^{High}_{SUP}$	0.3762***					0.3367***	0.4991***					0.4488***
	(0.066563)					(0.067756)	(0.077959)					(0.079340)
$R\&D^{High}_{CUS}$ $R\&D^{High}_{SUP}$	0.2547**					0.2827**	0.4053***					0.4141***
	(0.090724)					(0.094780)	(0.096413)					(0.101183)
Predicted overlapping ownership												
$R\&D^{Low}_{CUS}$ $R\&D^{Low}_{SUP}$		0.8338***	-0.0048***	-0.0046***	-0.0019***			0.8357***	-0.0039***	-0.0037***	-0.0016***	
		(0.000155)	(0.000019)	(0.000018)	(0.000007)			(0.000168)	(0.000025)	(0.000025)	(0.000007)	
$R\&D^{High}_{CUS}$ $R\&D^{Low}_{SUP}$		-0.0184***	0.8229***	-0.0042***	-0.0030***			-0.0149***	0.8242***	-0.0029***	-0.0025***	
		(0.000050)	(0.000244)	(0.000016)	(0.000024)			(0.000068)	(0.000252)	(0.000016)	(0.000041)	
$R\&D^{Low}_{CUS}$ $R\&D^{High}_{SUP}$		-0.0185***	-0.0044***	0.8241***	-0.0030***			-0.0149***	-0.0031***	0.8253***	-0.0024***	
		(0.000050)	(0.000016)	(0.000236)	(0.000024)			(0.000068)	(0.000017)	(0.000247)	(0.000041)	
$R\&D^{High}_{CUS}$ $R\&D^{High}_{SUP}$		-0.0110***	-0.0114***	-0.0111***	0.8151***			-0.0076***	-0.0092***	-0.0092***	0.8161***	
		(0.000037)	(0.000061)	(0.000059)	(0.000390)			(0.000037)	(0.000098)	(0.000095)	(0.000394)	
N	167,868,548	147,786,912	147,786,912	147,786,912	147,786,912	147,786,912	167,865,873	147,784,546	147,784,546	147,784,546	147,784,546	147,784,546
F-statistic		30,740,905	15,033,197	15,703,394	7,016,266	8,489,255		26,556,748	14,023,141	14,507,691	7,000,641	5,912,669
Time FE	✓	✓	✓	✓	✓	✓						
Company FE	✓	✓	✓	✓	✓	✓						
Time × Company FE							✓	✓	✓	✓	✓	✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I classify dyads into four bins depending on whether customers and suppliers exhibit an R&D intensity above or below the average (6.89%) observed between 1999 and 2013 and drop observations with missing information on R&D intensity. Columns (1) and (7) describe OLS estimates. Each coefficient reports the effect of one standard deviation (0.1319) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0842). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. Columns (6) and (12) describe 2SLS estimates and report the Kleibergen-Paap Wald rk F statistic. I employ the first-order Taylor expansion of the cosine similarity as an instrument constructed from the predicted shareholdings. Similarly, columns (2) to (5) and (7) to (11) display first-stage estimates and report the Sanderson-Windmeijer F Statistic for each endogenous regressor.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4 — Double marginalization

Dependent variable: Active trading partnership

	OLS	FS				2SLS	OLS	FS				2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overlapping ownership												
$HHI_{CUS}^{Low}\ HHI_{SUP}^{Low}$	0.4548***					0.4743***	0.4717***					0.4788***
	(0.056967)					(0.057677)	(0.067517)					(0.068798)
$HHI_{CUS}^{High}\ HHI_{SUP}^{Low}$	0.1384**					0.0890	0.1790**					0.1135
	(0.051474)					(0.053876)	(0.062796)					(0.065265)
$HHI_{CUS}^{Low}\ HHI_{SUP}^{High}$	-0.0588					-0.0540	-0.1258*					-0.1096
	(0.049675)					(0.053287)	(0.061063)					(0.065409)
$HHI_{CUS}^{High}\ HHI_{SUP}^{High}$	0.2864***					0.3708***	0.2491**					0.3387***
	(0.073376)					(0.083199)	(0.086770)					(0.097887)
Predicted overlapping ownership												
$HHI_{CUS}^{Low}\ HHI_{SUP}^{Low}$		0.8411***	-0.0070***	-0.0071***	-0.0087***			0.8408***	-0.0052***	-0.0053***	-0.0086***	
		(0.000176)	(0.000033)	(0.000033)	(0.000027)			(0.000181)	(0.000048)	(0.000049)	(0.000022)	
$HHI_{CUS}^{High}\ HHI_{SUP}^{Low}$		-0.0070***	0.8389***	-0.0066***	-0.0113***			-0.0057***	0.8396***	-0.0045***	-0.0109***	
		(0.000028)	(0.000198)	(0.000021)	(0.000042)			(0.000043)	(0.000207)	(0.000017)	(0.000062)	
$HHI_{CUS}^{Low}\ HHI_{SUP}^{High}$		-0.0070***	-0.0065***	0.8380***	-0.0113***			-0.0058***	-0.0043***	0.8387***	-0.0108***	
		(0.000028)	(0.000021)	(0.000198)	(0.000042)			(0.000043)	(0.000017)	(0.000208)	(0.000062)	
$HHI_{CUS}^{High}\ HHI_{SUP}^{High}$		-0.0055***	-0.0082***	-0.0083***	0.8304***			-0.0026***	-0.0070***	-0.0071***	0.8319***	
		(0.000016)	(0.000031)	(0.000031)	(0.000229)			(0.000014)	(0.000047)	(0.000047)	(0.000249)	
N	160,759,796	142,314,146	142,314,146	142,314,146	142,314,146	142,314,146	160,759,592	142,313,958	142,313,958	142,313,958	142,313,958	142,313,958
F-statistic		27,075,967	21,741,691	21,379,160	15,665,887	8,157,231		25,123,720	19,779,720	19,330,307	13,330,739	6,097,008
Time FE	✓	✓	✓	✓	✓	✓						
Company FE	✓	✓	✓	✓	✓	✓						
Time × Company FE							✓	✓	✓	✓	✓	✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I classify dyads into four bins depending on whether customers and suppliers exhibit a TNIC-HHI above or below the median (2,040 out of 10,000) observed between 1999 and 2013 and drop observations with missing information on TNIC-HHI. Columns (1) and (7) describe OLS estimates. Each coefficient reports the effect of one standard deviation (0.1326) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0856). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. Columns (6) and (12) describe 2SLS estimates and report the Kleibergen-Paap Wald rk F statistic. I employ the first-order Taylor expansion of the cosine similarity as an instrument constructed from the predicted shareholdings. Similarly, columns (2) to (5) and (7) to (11) display first-stage estimates and report the Sanderson-Windmeijer F Statistic for each endogenous regressor.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5 — Cosine similarity, relative concentration, and profit weight values

Dependent variable: Active trading partnership

	OLS	FS			2SLS	OLS	FS			2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overlapping ownership	0.1956***				0.2033***	0.2278***				0.2402***
	(0.035670)				(0.045049)	(0.046593)				(0.056447)
Highest relative concentration	0.0585**				0.1328	0.0640*				-0.0900
	(0.021993)				(0.087883)	(0.028415)				(0.046486)
Highest profit weight value	0.0863**				0.0083	0.1156***				0.1814*
	(0.028164)				(0.063160)	(0.032530)				(0.088881)
Predicted overlapping ownership		0.8172***	-0.1147***	-0.2591***			0.8241***	-0.1202***	-0.2750***	
		(0.000125)	(0.000170)	(0.000353)			(0.000135)	(0.000202)	(0.000399)	
Predicted highest relative concentration		-0.0072***	0.0095***	0.0088***			-0.0052***	0.0136***	0.0109***	
		(0.000067)	(0.000090)	(0.000134)			(0.000072)	(0.000129)	(0.000203)	
Predicted highest profit weight value		-0.0107***	0.0097***	0.0169***			-0.0086***	0.0099***	0.0173***	
		(0.000101)	(0.000133)	(0.000203)			(0.000093)	(0.000159)	(0.000265)	
N	134,355,491	118,984,614	118,984,614	118,984,614	118,984,614	134,354,421	118,983,694	118,983,694	118,983,694	118,983,694
F-statistic		29,014	33,860	28,305	9,615		19,361	18,825	14,660	5,306
Time FE	✓	✓	✓	✓	✓					
Company FE	✓	✓	✓	✓	✓					
Time × Company FE						✓	✓	✓	✓	✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure, the highest relative concentration, and the highest profit weight value for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. I drop observations with the highest relative concentration above the 90^{th} percentile (5.8918) because of the missing information for insiders. Columns (1) and (6) describe OLS estimates. The first coefficient reports the effect of one standard deviation (0.1427) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.1056). The second coefficient reports the effect of one standard deviation (1.0218) with respect to the average highest relative concentration in the sample (1.9725). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). The third coefficient reports the interaction of the first two. I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. Columns (5) and (10) describe 2SLS estimates and report the Kleibergen-Paap Wald rk F statistic. I employ the first-order Taylor expansion of the cosine similarity, the highest relative concentration, and the highest profit weight value computed as instruments constructed from the predicted shareholdings. Similarly, columns (2) to (4) and (6) to (9) display first-stage estimates and report the Sanderson-Windmeijer F Statistic for each endogenous regressor.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6 — Robustness: Alternative overlapping ownership measures

Dependent variable: Active trading partnership

	Cosine similarity of ownership structures						Overlapping market value					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS
Overlapping ownership	0.1102***		0.1536***	0.1493***		0.1955***	-0.0469		0.0436	0.0491		0.1180
	(0.028192)		(0.038038)	(0.036067)		(0.047149)	(0.033840)		(0.051986)	(0.046308)		(0.069769)
Predicted overlapping ownership		0.6947***			0.6968***			0.9178***			0.9425***	
		(0.000157)			(0.000175)			(0.000132)			(0.000148)	
N	167,902,019	147,818,198	147,818,198	167,899,338	147,815,827	147,815,827	167,814,861	147,737,778	147,737,778	167,812,193	147,735,417	147,735,417
F-statistic		19,457,211			15,894,432			47,979,123			40,567,465	
Time FE	✓	✓	✓				✓	✓	✓			
Company FE	✓	✓	✓				✓	✓	✓			
Time × Company FE				✓	✓	✓				✓	✓	✓

	Overlapping-shares product						Smallest profit weight value					
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS
Overlapping ownership	0.1847***		0.2884***	0.2608***		0.3296***	0.0669*		0.1026**	0.0807*		0.1269**
	(0.039561)		(0.063580)	(0.049453)		(0.079903)	(0.026380)		(0.036507)	(0.033264)		(0.044953)
Predicted overlapping ownership		0.9982***			1.0213***			0.7202***			0.7096***	
		(0.000482)			(0.000595)			(0.000177)			(0.000197)	
N	167,902,019	147,818,198	147,818,198	167,899,338	147,815,827	147,815,827	167,902,019	154,379,966	154,379,966	167,899,338	154,377,370	154,377,370
F-statistic		4,296,984			2,948,339			16,482,435			13,009,941	
Time FE	✓	✓	✓				✓	✓	✓			
Company FE	✓	✓	✓				✓	✓	✓			
Time × Company FE				✓	✓	✓				✓	✓	✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on different metrics for the degree of overlapping ownership among publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. Each coefficient displays the effect of one standard deviation increase with respect to the average value of the metric in the sample. Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. I employ the complete functional form of the overlapping ownership measures as instruments by using the predicted shareholdings to construct them. Columns displaying first-stages also report the Kleibergen-Paap Wald rk F statistic.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7 — Robustness: Alternative functional forms of the instrument

Dependent variable: Active trading partnership

	OLS	First-order Taylor expansion		Second-order Taylor expansion		Whole function form	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FS	2SLS	FS	2SLS	FS	2SLS
Overlapping ownership	0.1102***		0.1240***		0.1240***		0.1536***
	(0.028192)		(0.031058)		(0.030907)		(0.038038)
cosSimIVLinearAR		0.8126***		0.8130***		0.6947***	
		(0.000130)		(0.000130)		(0.000157)	
N	167,902,019	147,818,198	147,818,198	147,818,198	147,818,198	147,818,198	147,818,198
F-statistic		39,156,655		39,039,206		19,457,211	
Time FE		✓	✓	✓	✓	✓	✓
Company FE		✓	✓	✓	✓	✓	✓
Time × Company FE							

	OLS	First-order Taylor expansion		Second-order Taylor expansion		Whole function form	
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	FS	2SLS	FS	2SLS	FS	2SLS
Overlapping ownership	0.1493***		0.1621***		0.1614***		0.1955***
	(0.036067)		(0.039039)		(0.038830)		(0.047149)
Predicted overlapping ownership		0.8176***		0.8182***		0.6968***	
		(0.000141)		(0.000142)		(0.000175)	
N	167,899,338	147,815,827	147,815,827	147,815,827	147,815,827	147,815,827	147,815,827
F-statistic		33,591,125		33,376,791		15,894,432	
Time FE							
Company FE							
Time × Company FE		✓	✓	✓	✓	✓	✓

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications. Columns (1) and (8) describe OLS estimates. I report the effect of one standard deviation (0.1361) increase with respect to the average cosine similarity of the ownership structure of feasible supply chain links (0.0905). Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample (0.02%). I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. Columns (3), (5), and (7) describe 2SLS estimates employing different functional forms of the cosine similarity to construct the instrument from predicted shareholdings. Columns (2), (4), and (6) display the corresponding first-stage estimates and report the Kleibergen-Paap Wald rk F statistic.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8 — Robustness: Alternative sample definitions

Dependent variable: Active trading partnership									
	Main sample			Vertical upstream relatedness			Customer segment		
	(1) OLS	(2) FS	(3) 2SLS	(4) OLS	(5) FS	(6) 2SLS	(7) OLS	(8) FS	(9) 2SLS
Overlapping ownership	0.1102***		0.1240***	0.2045***		0.2183***	0.0281**		0.0969***
	(0.028192)		(0.031058)	(0.035148)		(0.038798)	(0.010395)		(0.020626)
Predicted overlapping ownership		0.8126***			0.8126***			0.8149***	
		(0.000130)			(0.000130)			(0.000289)	
N	167,902,019	147,818,198	147,818,198	167,892,799	147,810,035	147,810,035	167,902,019	147,818,198	147,818,198
F-statistic		39,156,655			39,140,670			7,930,506	
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time × Company FE									
	Main sample			Vertical upstream relatedness			Customer Segment		
	(10) OLS	(11) FS	(12) 2SLS	(13) OLS	(14) FS	(15) 2SLS	(16) OLS	(17) FS	(18) 2SLS
Overlapping ownership	0.1493***		0.1621***	0.1987***		0.2150***	0.0636***		0.1779***
	(0.036067)		(0.039039)	(0.045782)		(0.049560)	(0.011557)		(0.024368)
Predicted overlapping ownership		0.8176***			0.8176***			0.8206***	
		(0.000141)			(0.000141)			(0.000270)	
N	167,899,338	147,815,827	147,815,827	167,892,799	147,810,035	147,810,035	167,899,338	147,815,827	147,815,827
F-statistic		33,591,125			33,584,180			9,217,730	
Time FE									
Company FE									
Time × Company FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Avg. trading partnership prob.		0.0002			0.0002			0.0272	
Avg. cosine similarity		0.0905			0.0905			0.0916	
Std. cosine similarity		0.1361			0.1361			0.1375	

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications and sample definitions. Columns (1) to (3) and (10) to (12) report estimates using the sample I use throughout the paper. Columns (4) to (6) and (13) to (15) display results using only observations with a positive vertical upstream relatedness. Columns (7) to (9) and (16) to (18) show coefficients when imposing a weight equal to 1 on all dyads in the Customer Segment. The first column of each division describes OLS estimates. I report the effect of one standard deviation increase with respect to the sample average cosine similarity of the ownership structure. Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample. I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The last column of each division describes 2SLS estimates employing as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. The second column of each division displays the corresponding first-stage estimates and reports the Kleibergen-Paap Wald rk F statistic. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9 — Robustness: Alternative sample definitions

Dependent variable: Active trading partnership

	Main sample			Network sample			TNIC sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS
Overlapping ownership	0.1102***		0.1240***	0.1896***		0.1978***	0.0325*		0.0328*
	(0.028192)		(0.031058)	(0.018287)		(0.019584)	(0.014255)		(0.015989)
Predicted overlapping ownership		0.8126***			0.8657***			0.8406***	
		(0.000130)			(0.000401)			(0.001054)	
N	167,902,019	147,818,198	147,818,198	5,991,328	5,319,061	5,319,061	850,933	729,242	729,242
F-statistic		39,156,655			4,657,702			636,216	
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Company FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time × Company FE									
	Main sample			Network sample			TNIC sample		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS
Overlapping ownership	0.1493***		0.1621***	0.1573***		0.1692***	0.0940***		0.0944***
	(0.036067)		(0.039039)	(0.024919)		(0.026461)	(0.017803)		(0.019545)
Predicted overlapping ownership		0.8176***			0.8802***			0.8570***	
		(0.000141)			(0.000416)			(0.001061)	
N	167,899,338	147,815,827	147,815,827	5,989,967	5,317,802	5,317,802	839,906	718,502	718,502
F-statistic		33,591,125			4,486,139			651,975	
Time FE									
Company FE									
Time × Company FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Avg. trading partnership prob.		0.0002			0.0046			0.0322	
Avg. cosine similarity		0.0905			0.0937			0.1071	
Std. cosine similarity		0.1361			0.1503			0.1591	

Notes: The table documents OLS and 2SLS panel regressions of the likelihood of an active trading partnership on the cosine similarity of the ownership structure for publicly-listed companies in the US in industries other than the financial and utility sector between 2000 and 2013 using different fixed-effect specifications and sample definitions. Columns (1) to (3) and (10) to (12) report estimates using the sample I use throughout the paper. Columns (4) to (6) and (13) to (15) display results using the original supply chain network between 1976 and 2013 to identify trading partners of closely related firms in the network as feasible supply chain links. Columns (7) to (9) and (16) to (18) show coefficients using a text-based network industry classification to identify competitors of trading partners as feasible supply chain relationships. The first column of each division describes OLS estimates. I report the effect of one standard deviation increase with respect to the sample average cosine similarity of the ownership structure. Furthermore, I perform a normalization so they report relative changes with respect to the unconditional probability of an active trading partnership in the sample. I drop singleton observations for the corresponding fixed-effects specification. Confidence intervals correspond to cluster robust standard errors at the dyad level with a 95% confidence level. The last column of each division describes 2SLS estimates employing as an instrument the first-order Taylor expansion of the cosine similarity computed by using predicted shareholdings. The second column of each division displays the corresponding first-stage estimates and reports the Kleibergen-Paap Wald rk F statistic. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.