Overlapping ownership and vertical relations

by FERNANDEZ, Daniel*

The paper investigates the association between the ownership structures and supply chain relationships of companies in the US. Using a novel identification strategy, I find that increasing the similarity in the ownership structures -among feasible customer-supplier dyads- by one standard deviation raises the likelihood of active trading partnerships by 18% to 23%. Furthermore, my findings uncover adverse effects. Vertical overlapping owners may privately benefit from vertical relations to the detriment of shareholders at firms with more diluted ownership structures. The unconditional probability of trading partnerships amounts to 51% when a manager has incentives to transfer resources out of the company.
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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

Several theoretical and empirical studies analyze the connection between the ownership structure of strategically interacting firms and market outcomes. However, much of the literature still depends on the premise that managerial decisions seek to increase company value, overlooking that shareholders -who appointed managers in the first place- prioritize the total worth of their portfolios rather than the individual value of every firm they own. Either by the direct influence of investors or because managers internalize other benefits from pleasing pivotal shareholders, it has become undeniable how the ownership structure of a company can alter its goals, market strategies, and business relationships. In this paper, I delve deeper into the issue by studying the part played by shareholders in forming and prolonging trading partnerships in the US supply chain.

The recent proliferation of large asset management institutions has emphasized the role of diversified minority shareholders over the corporate strategy of firms (Schmalz, 2018). Besides, the fast expansion of institutional financial intermediaries and a renewed preference for passive indexing strategies have led a few institutional investors, such as Vanguard, BlackRock, or State Street, to stand among the top shareholders of most publicly listed companies in the US.

A growing body of literature on *common ownership* describes how overlapping shareholders affect competition and market outcomes, though their role in vertical relations remains somewhat underexplored. But, if overlapping shareholders drive executives into assessing the externalities they impose on competitors, what would stop them from incorporating effects across upstream and downstream markets?

* CEMFI, Calle Casado del Alisal 5, Madrid, Spain (e-mail: daniel.fernandez@cemfi.edu.es). I acknowledge financial support from Grant PRE2022-101381 funded by MCIN/AEI/ 10.13039/501100011033 and by "ESF +", Fundación Carolina, and CEMFI. This paper has benefited from helpful comments from Guillermo Caruana, Gerard Llobet, Manuel Arrellano, Dmitry Arkhangelski, Vicente Cuñat, Harald Hau, José Azar, and seminar participants at the CEMFI Workshop of Firms & Markets and the NBIM-Oxford Conference on Common Ownership, Experimental Governance, and Industrial Organization. All errors are my own.

My findings, on the one hand, support similar results in the literature. Higher degrees of overlapping ownership increases the likelihood of active trading partnerships, helping firms to circumvent contractual and informational frictions. On the other hand, they reveal a novel mechanism. Overlapping owners may thwart firms and shareholders by extracting private benefits from supply chain relationships.

The research centers on publicly listed companies in the United States and Canada between 1999 and 2013 and combines several publicly available data sources. I retrieve feasible customer-supplier dyads -among all possible combinations- by leveraging measures of vertical upstream relatedness (Frésard, Hoberg and Phillips, 2020), i.e., directed measures on how outputs from a firm serve as inputs of another. For the remaining variables, I rely on previous research papers that compiled several public filings that companies must disclose periodically to the Securities and Exchange Commission (SEC) of the United States. Ownership ties -covering large institutional investors and blockholders- come from 13D, 13F, and 13G filings, and I use this information to construct overlapping ownership measures according to the framework of Rotemberg (1984). Active trading partnerships come from 10K filings, in which firms disclose the identity of all customers that comprise at least 10% of their total annual sales.

The analysis employs two-way fixed-effects regressions to link ownership structures and trading partnerships between firms. In addition, I combine two strategies to deal with biases arising from sample selection and endogeneity. First, I bring in weights for dealing with concerns regarding feasible but unlikely supply chain relationships remaining in the sample. Second, I construct instrumental variables from predicted rather than actual portfolios. The strategy focuses on companies and investors with more stable ownership structures and portfolios based on panel data on shareholdings, additions, and deletions from the S&P 500 index.

Two reasons justify the call for new instruments rather than employing previous identification strategies in the literature. First, vertical relations entail two-sided decisions. Therefore, techniques aimed at market outcomes from unilateral company choices, such as prices, entry, or investment, fail the exclusion restriction when implemented in the supply chain. Second, these approaches rely on shifts in the degree of overlapping ownership but cannot capture changes in the relative concentration of ownership structures. Meaning that they are inadequate for exploring asymmetric incentives among managers.

Overall, increasing the similarity between ownership structures among feasible customer-supplier dyads by one standard deviation raises the unconditional probability of an active trading partnership by 18% to 23%. Vertical overlapping shareholders reminisce features of *vertical integration* and *vertical control*. Thus, it is only natural that previous studies focus on mechanisms closely related to the tropes of partial vertical integration, such as contractual and informational frictions. Not surprisingly, I observe similar patterns when companies operate in markets with higher degrees of double marginalization and holdup.

More interestingly, trading partnerships become more likely when they primarily benefit one side of the relationship. Increasing the similarity between ownership structures by one standard deviation has disparate effects, depending on the relative concentration of shareholders across the two firms. For instance, increasing the relative concentration from the bottom to the top decile of the distribution raises changes in the unconditional probability from 8.25% to 50.82%.

In many cases, overlapping owners privately benefit from relatively diluted ownership structures. In other words, conflicted managers, i.e., the ones weighing externalities the most, engage in trading partnerships that transfer resources out of the company. Consequently, multiple choices may result in direct losses or foregone profits to the detriment of non-overlapping shareholders at the firm appointing the managers.

My paper contributes to the literature on common ownership. The concept dates back to a theoretical framework in Rotemberg (1984), where companies act collusively in favor of shareholders with diversified portfolios. Nonetheless, the topic seized everyone's attention when papers started showcasing significant losses in competition and welfare. For example, increasing market concentration (He and Huang, 2017) and prices (Azar, Schmalz and Tecu, 2018; Park and Seo, 2019; Torshizi and Clapp, 2021), or negatively affecting employment, wages (Azar, Qiu and Sojourner, 2021), and market entry (Newham, Seldeslachts and Banal-Estañol, 2019; Xie and Gerakos, 2020).

Other studies back the positive aspects of overlapping owners, such as spillovers on research and development (R&D) activities (Anton et al., 2021; López and Vives, 2019), an increasing product variety (Aslan, 2019), or a faster diffusion of innovation (Kostovetsky and Manconi, 2020). In particular, articles on vertical relations stand out as their most substantial supporters. For example, firms achieve larger loans with lower interest rates (Ojeda, 2018) or are more likely to strike a deal with syndicated loans (Cici, Gibson and Rosenfeld, 2015) in the presence of vertical overlapping shareholders. Similarly, they increase the likelihood of companies joining strategic alliances (Lindsey, 2008), discourage suppliers from engaging in upward earnings management (Gao et al., 2022), boost upstream partner-specific investments (Deng and Li, 2022), and extends the lifetime of existing trading partnerships (Freeman, 2021).

I add to the literature in two different ways. First, methodologically, by presenting an identification strategy capable of targeting overlapping ownership measures at the dyad level. Using predicted shareholdings does not rely on shifts in the average similarity in ownership structures and serves for two-sided decisions, too. Furthermore, the instrument circumvents the critique concerning other sources of exogenous variation. For example, Berger (2023) challenges fire sales resulting from mutual fund scandals while Lewellen and Lowry (2021) discusses issues related to mergers of financial institutions and index additions.

Second, empirically, by uncovering an unfavorable mechanism behind the part played by overlapping shareholders along the supply chain. My findings add to a long list of cautions posed by researchers regarding the adverse effects of common ownership. However, my work is the first to expose the negative impacts of vertical overlapping shareholders, as the literature has primarily focused on solutions akin to those offered by partial vertical integration.

The remainder of the paper proceeds as follows. Section I describes the data, the sample, and the overlapping ownership measures. Section II discusses the empirical approach, the use of weights in my analysis, and the identification strategy to address usual concerns about endogeneity. III reports baseline results while Section IV explores how asymmetric incentives across managers can give rise to private benefits for overlapping shareholders. Finally, Section V concludes.

I. Data

The analysis centers on publicly listed companies in the United States and Canada from 1999 to 2013, excluding those in the financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) sectors and combines several publicly available data sources regarding ownership ties and supply chain relationships.

Publicly listed companies I use *Compustat North America – Fundamentals*, which provides quarterly information about firms, including outstanding shares, market value, closing price, net sales, total assets, and research and development (R&D) investment. In addition, I compute the company age from the first report of book assets since

1976 and include the Herfindahl-Hirschman Index (HHI) from the text-based network industry classification (TNIC) 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.

Ownership ties The ownership network of the US relies on two publicly available datasets from previous studies. I compile 13F filings with the SEC between 1999 and 2017 from Backus, Conlon and Sinkinson (2021*b*) and 13D and 13G filings from 1998 to 2016 from Schwartz-Ziv and Volkova (2021).[1] The SEC requires that investment managers holding over USD 100 million in North American securities file 13F forms quarterly, irrespective of the fraction of shares they own in the companies. Blockholders, on the other hand, must file 13D and 13G forms once upon acquiring at least 5%

Active trading partnerships The supply chain network data stems from Barrot and Sauvagnat (2016).[2] Publicly traded companies file 10K forms to the SEC every year. Following the Statement of Financial Accounting Standard (SFAS) N°131, which supersedes SFAS N°14, companies must disclose the identity of any customer contributing at least 10% to their total annual sales. The *Compustat North America – Customer Segment* collects this information but does not provide customer identifiers. However, the authors combine a phonetic string-matching algorithm with manual identification[3] to recover trading partnerships among publicly listed companies in the United States and Canada from 1976 to 2013.

Vertical upstream relatedness Identifying the subset of feasible supply chain links relies on the *vertical upstream relatedness* measure assembled by Frésard, Hoberg and Phillips (2020). The authors map product descriptions from 10K filings to a broad range of US commodities, combine them with input-output intensities across commodities, and report yearly directed measures of how one firm's products could serve as inputs for the rest between 1989 and 2021[4]

A. *Sample*

Compustat reports 112,382 annual financial records between 1999 and 2013 that involve 15,433 unique publicly listed companies in industries other than the financial and utility sectors. Panel A in Table 1 provides a snapshot of the cross-year average characteristics of publicly listed companies.

Nonetheless, the empirical section analyzes the dyads of customers and suppliers among these publicly listed companies. In particular, the study focuses on whether a higher degree of overlapping ownership increases the likelihood of active trading partnerships among feasible supply chain links.

Feasible trading partnerships In 2011, Nokia Oyj announced it would ditch its flagship operating system, Symbian, and license Windows 7 and Bing from Microsoft Corporation. In this example, I am interested in capturing the fact that Microsoft was a potential supplier of Nokia before 2011. Following the reasoning, my sample should capture all potential supply chain relationships, irrespective of whether I observe them

[1] Accessible at `https://www.dropbox.com/s/yp2r7graixxus7r/Blocks.csv`.
[2] Accessible at `https://sites.google.com/hec.fr/jnbarrot/data`.
[3] The methodology employed by the authors follows the approach of previous studies in the literature. See, for example, Fee, Hadlock and Thomas (2006), Wu and Birge (2014), or Cheung et al. (2020).
[4] For a publicly available dataset, see `https://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite/index.html`.

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	7,492	222	11.24	2,847.41	2,270.46	1,819.59	25.37%	3,212	-0.10
Panel B - Feasible supply chain links									
Customers	3,690	127	15.06	4,362.03	3,762.88	2,732.82	12.11%	3,212	2.77
Suppliers	3,715	128	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	60	14.59	3,642.25	2,340.77	2,082.19	13.78%	3,082	2.73
Panel D - Disclosing suppliers									
Customers	528	21	19.61	23,804.53	20,598.98	12,691.23	5.98%	2,759	3.14
Suppliers	1,420	40	15.41	3,757.86	2,450.71	2,095.14	13.34%	2,992	2.46
Panel E - Non-disclosing suppliers									
Customers	220	12	19.61	22,511.97	18,116.37	11,231.93	5.48%	2,749	3.82
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 number and 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 final sample of feasible trading partnerships. Panel C reports the same information for customers and suppliers in operational supply chain relationships. Finally, Panels D and E report separate cross-year averages for disclosing and non-disclosing suppliers and their respective customers.

or not taking place at some point in time. On the contrary, 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 them to engage in a trading partnership, independently of their degree of overlapping ownership, given the commodities they produce.

Unfeasible supply chain links, such as Activision Blizzard and Alexion Pharmaceuticals, can bias my results. However, determining the direction of such bias is not straightforward, as it would depend on the degree of overlapping ownership among these unfeasible dyads compared to that of active trading partnerships. To tackle the problem, I keep dyads with positive vertical upstream relatedness or observed trading partnerships.[5]

Thus, the final sample comprises 193,795,735 observations, representing 43,212,666 unique dyads among 7,798 customers and 8,014 suppliers with feasible supply chain links between 1999 and 2013. Panel B shows that, on average, around 3,690 customers and 3,715 suppliers operate in a single year, exhibiting longer lifespans and higher sales, assets, and market value than the average firm in Compustat. However, they have a lower R&D intensity and market-to-book ratio.

Active trading partnerships Following Barrot and Sauvagnat (2016), I define trading partnerships as being active in all periods ranging from the first to the last year a company reports another firm as a significant customer in a 10K filing. That way, I identify 29,413 active trading partnerships between 1999 and 2013, representing 8,081 unique dyads among 1,499 customers and 3,119 suppliers.

Notice that there are some limitations associated with the data. First, matching

[5]The distinction stems from the fact that Frésard, Hoberg and Phillips (2020) lose data when they map CUSIP to GVKEY identifiers, so supposedly unfeasible supply chain links appear in the Customer Segment. Nonetheless, Section B.B1 discusses whether results vary under different assumptions or when drawing on alternative criteria to identify feasibility from the original supply chain network.

customers by disclosed names can introduce noise into the data since firms with similar denominations could refer to unrelated organizations despite their shared historical roots.[6] Fortunately, 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.[7] In fact, Panel C shows an average of 1,949 active suppliers in a single year, with characteristics that do not differ, on average, significantly from potential suppliers in Panel B.

On the contrary, one could be concerned about relatively small companies relying on a few key suppliers, which would be significant operational trading partnerships to miss due to the wording of the Statement. Given their lower levels of purchases, these companies would rarely reach the 10% threshold. Indeed, Panel C shows that, on average, 670 customers remain active in a single year, reporting significantly higher levels of sales, market value, assets, and market-to-book ratio when compared to potential customers in Panel B. Although, they exhibit a lifespan of nearly five additional years and a lesser engagement in R&D activities.

Non-mandatory disclosure Despite the Statement not requiring to disclose customers below the 10% threshold, several companies include them when filing 10K forms. To assess whether differences between disclosing and non-disclosing suppliers could become an issue, I exploit observed sales across 20,613 (70%) trading partners. Thus, Panel D centers on trading partnerships involving suppliers who have listed customers below the threshold at least once since 1976, covering approximately three-quarters of all suppliers and customers. Meanwhile, Panel E displays information for the remaining dyads in the Customer Segment. Notably, there are no significant differences across Panel C, D, and E, reducing the concerns about this potential source of bias.

B. *Overlapping ownership*

I combine data sources on 13D, 13F, and 13G filings to construct annual overlapping ownership measures in the US from 1999 to 2013. The ownership network contains 10,781,778 annual observations of 3,316,767 unique ownership ties between 33,861 investors and 15,459 companies, indicating the fraction of outstanding shares owned by each shareholder in every company.

I can compute profit weight values for every feasible trading partnership within my sample, which originates in a microfundamented model by Rotemberg (1984). Notably, the predictions suggest that investors might not need to engage with managerial decisions actively but can still influence them passively. There, a manager does not focus solely on the profits of the firm that appointed her. Instead, the manager maximizes a weighted average of the portfolios held by all the shareholders in the company. As a result, a manager in firm a weighs the externalities that decisions can impose on the profits of firm b at time t by using

$$\kappa_{abt} = \overbrace{cos(\beta_{at}, \beta_{bt})}^{\text{Overlapping ownership}} \cdot \underbrace{\sqrt{\frac{IHHI_{bt}}{IHHI_{at}}}}_{\text{Relative concentration}} \tag{1}$$

[6] For example, A.T. Massey Coal Company spun off Massey Energy Co. in 2000 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.

[7] 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.

to weight the impacts, where β_{ft} and $IHHI_{ft} = ||\beta_{ft}||^2$ depict the ownership structure and concentration within firm f at time t, respectively. Importantly, profit weights are non-symmetric, resulting in two distinct values for every dyad within my sample: one for the supplier concerning the customer's profits and one for the customer with respect to the supplier's profits. For more details of the model and its derivation, see Section A.A1 in the Appendix.

Equation 1 also shows how to decompose profit weight values into the cosine similarity[8] of the ownership structures and the relative concentration of shareholders across firms. Notice that the second measure weighs the concentration of shareholders within the weighted firm with respect to the company appointing the manager. The term proves compelling because it incorporates the trade-off between incentives and influence within companies' boards, i.e., 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.

Throughout the paper, I denote the cosine similarity of the ownership structures as the degree of overlapping ownership. The measure ranges from 0 to 1, with higher values indicating an increased presence of common vertical shareholders and a strengthened alignment of their interests. For instance, consider the scenario where two shareholders, each controlling 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 the same shareholders. Similarly, when two vertical overlapping 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 ownership because their interests would become more aligned.

Nonetheless, if anything characterizes the literature on common ownership, it would be the ongoing debate on how to properly measure it. For that reason, Section B.B1 in the Appendix discusses alternative measures found in the literature and portrays the results of employing them.

II. Empirical strategy

The analysis consists of panel data regressions using a linear probability model. Specifically, I employ a two-way fixed-effects model to address whether the likelihood of trading partnerships among companies depends on their degree of overlapping ownership. Namely,

$$Link_{sct} = \delta_{st} + \delta_{ct} + \tau \, OvrOwn_{sct} + \varepsilon_{sct} \tag{2}$$

where $Link_{cst}$ identifies whether customer c and supplier s engage in a trading partnership at time t, and $OvrOwn_{cst}$ measures the degree of overlapping ownership between the two. I include time-varying company fixed-effects δ_{ct} and δ_{st} 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 if I add them directly to the empirical model. Alternatively, I also depict results using a more conventional approach by using separate time fixed-effects δ_t, controlling for time trends in the average likelihood of trading partnerships, and time-invariant supplier fixed effects δ_s and customer fixed effects δ_c. To facilitate the interpretation of the estimated results, I

[8] 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 $cos(A, B) = \dfrac{A \cdot B}{||A|| ||B||}$ comes from the polar notation of the cross product of the vectors.

report percentual changes in the unconditional probability of an active trading partnership given a one-standard-deviation increase in the degree of overlapping ownership, thereby avoiding the display of small-scale percentage point changes due to the large number of feasible but non-operational supply chain links in the sample.

The following subsections discuss potential biases arising from sample selection and endogeneity while describing workarounds to alleviate these concerns. First, using weights deals with biases from including feasible but unlikely trading partnerships. Second, constructing instrumental variables based on predicted shareholdings allows the implementation of a 2SLS approach.

A. *Feasible trading partnerships and weights*

Unlike other studies, I do not condition the sample based on the prior existence of the trading partnerships, allowing me to incorporate the extensive margin of whether companies with higher degrees of overlapping ownership prefer to trade among themselves over other potential customers and suppliers.

Despite focusing solely on dyads with positive vertical relatedness, only a tiny fraction hold active trading partnerships. Indeed, the unconditional probability of one is just 0.002%, which constitutes the first cue that the sample still contains many unlikely trading supply chain relationships[9], which can lead to biases in the estimates.

Let me illustrate it with an example by considering a generic linear regression

$$Link_{sct} = \alpha + \tau \, OvrOwn_{sct} + X_{sct} \, \beta$$

and assuming the empirical model is correctly specified. The OLS estimates (α, β) would originate from minimizing

$$\mathbb{E}\left[\left(Link_{sct} - \alpha - \tau \, OvrOwn_{sct} - \beta \, X_{sct}\right)^2 \pi\left(F_{sct} = 1\right)\right]$$

where $\pi\left(F_{sct} = 1\right)$ represents the likelihood of a feasible supply chain link since I cannot directly observe it.

The underlying concern is that trading partnerships do not arise from unfeasible relationships so that $Link_{sct}$ takes the value of zero when $F_{sct} = 0$. Therefore, I can rewrite the expression for the error term as

$$\mathbb{E}\Bigg[\mathbb{E}\left[\left(m_{sct} - f_{sct}\right)^2 \omega_{sct} \middle| F_{sct} = 1\right] \pi\left(F_{sct} = 1\right) \\ + \mathbb{E}\left[\left(\alpha + \tau \, OvrOwn_{sct} + \beta \, X_{sct}\right)^2 \omega_{sct} \middle| F_{sct} = 0\right] \Big(1 - \pi\left(F_{sct} = 1\right)\Big)\Bigg]$$

where m_{sct}, f_{sct}, and ω_{sct} represent the conditional mean, the best predicting function, and the weight of each observation, respectively.

To assess the source of the bias, let me abstract from weights for a second by setting them all equal to one. Since the estimation targets the first term, a correctly specified model should be enough to minimize its bias. However, estimates could suffer from a sizable and systematic bias due to the second term, i.e., when $\pi\left(F_{sct} = 1\right)$ becomes sufficiently low.

[9]A way to think about the issue is to notice that no firm within my sample produces a single commodity. Therefore, a dyad with a positive but close to zero vertical upstream relatedness, despite pointing out that the supplier produces at least one commodity employed by the customer for making at least one of its products, implies that companies hold multiple other input-output unfeasible options. Although I do not want to discard unlikely but feasible dyads, one could argue that firms seldom source single inputs across numerous companies, except when the specificity of the input justifies an exception.

While I do not directly observe this likelihood, I assume the vertical upstream relatedness is informative enough of $\pi(F_{sct} = 1)$. As a result, I can use its value as weights, ω_{sct}, driving the second expression towards zero and significantly reducing the bias.

B. *Identification strategy*

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, meaning that several institutional investors would follow rumors of changes in the supply chain, making my estimates suffer from reverse causality. Similarly, unobservable shocks could simultaneously affect the firm's ownership structure and trading partnerships, leading to biases due to omitted variables. For example, let us consider a substantial technological innovation from a company. On the one hand, the firm might engage in new trading partnerships to source inputs required to produce the new technology. On the other hand, a newly created patent could attract the attention of informed investors, increasing their holdings not only in the innovator but in companies they believe might benefit from the novelty along the supply chain network.

Although the ongoing debate regarding valid strategies for addressing the endogeneity of ownership structures[10], the literature has benefited from exogenous shifts in the similarity of the ownership structure to measure the impacts that overlapping owners can have in market- and firm-level outcomes (See Boller and Morton (2020) and Antón et al. (2023)).

However, these strategies do not work in vertical settings, where the trading partnerships require both parties to agree on the conditions of the transaction, invalidating the assumptions of these identification strategies.

Instead, I propose a novel empirical approach to construct instrumental variables from predicted shareholdings. The idea intuitively works on the concept that sufficiently lagged values of overlapping ownership could provide a good instrument as long as the persistence in the outcome falls faster than the covariate. I construct the same overlapping ownership measures from predicted shareholdings based on panel data on institutional investors' portfolios across US companies and differences in the market value of annual additions and deletions from the S&P 500 index.

The previous examples concerning the endogeneity of ownership structures described sudden shifts in shareholding positions caused by investors anticipating changes in the supply chain. A way around this would be to focus on shareholders with less shifting portfolios or companies with more stable ownership structures. Therefore, I exclude institutional investors purchasing shares in a company for the first time and treat them as retailing shareholders when computing ownership structures for that year. Furthermore, I exclude companies entering and exiting the S&P 500 index when computing portfolios for that year, given that they would probably attract the attention of numerous institutional investors.

For the remaining shareholders and companies, I model portfolios by using a simple Markovian process

$$\beta_{if,t} = \alpha + \rho\, \beta_{if,t-1} + \tau\, W_{f,t} + u_{if,t} \tag{3}$$

where $\beta_{if,t}$ denotes the fraction of shares owned by investor i on company f at time

[10] For example, Berger (2023) highlights the challenges associated with using fire sales resulting from mutual fund scandals, and Lewellen and Lowry (2021) discusses issues related to mergers of financial institutions and analyzing companies added to indexes.

t, and $W_{f,t}$ depicts shifts in the index-weights that company f faces during period t. Intuitively, S&P 500 additions and deletions affect the weight of the remaining constituents in the index because of differences in the market value of companies. For instance, if the market value of entering companies were higher than that of exiting ones, index weights for the remaining companies would adjust proportionally downwards to make room for the higher index weights of the entrants. The opposite would hold as well[11]. Thus, τ should capture how institutional shareholders rearrange their passive investments due to index-weights shifts. For more details, Section A.A2 in the Appendix extensively describes the use of additions and deletions from the S&P 500.

I argue that $u_{if,t}$ captures most of the endogeneity in portfolios; however, one crucial identification assumption is that time-varying supplier and customer fixed effects, δ_{st}, δ_{ct}, in Equation (2) can accurately absorb persistence in supply chains. An argument against it would be that persistence depends on idiosyncratic characteristics of the trading partnership itself; however, it would be impossible to control for that flexibly in the empirical model.

A second threat to identification arises from the inherent non-linearities in the overlapping ownership measures, as they may capture unintended interactions between shifts in index weights. I address the issue by implementing a first-order Taylor expansion to linearize the expressions. For more details, Section B.B1 in the Appendix discusses and reports results using a second-order Taylor expansion and the entire functional form.

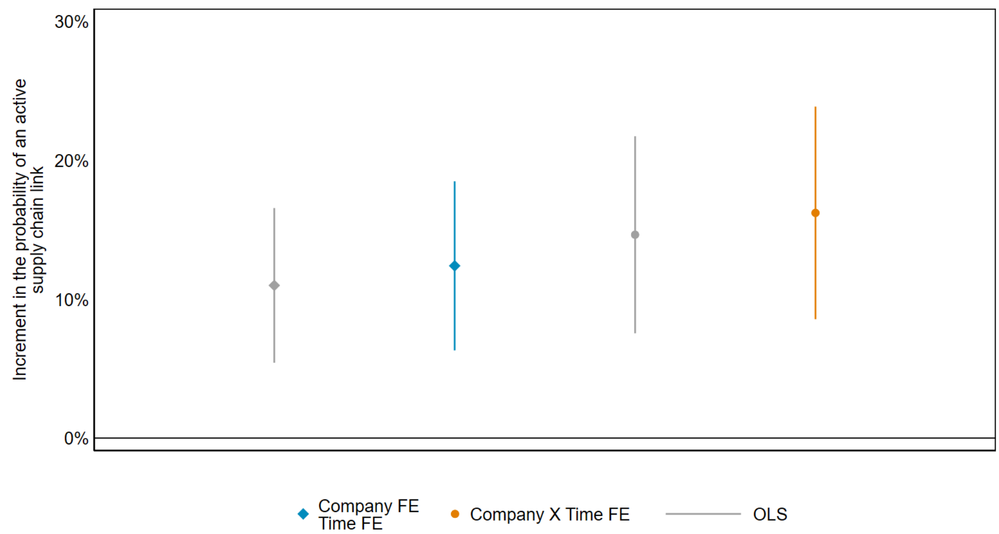
III. Results

I estimate the OLS and 2SLS models using the sample of feasible supply chain links between 2000 and 2013. Figure 1 indicates 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 by 14.93% to 16.21%. Furthermore, coefficients are slightly higher for the 2SLS model, though they do not statistically differ from OLS. For more details, see Table B1 in the Appendix, which reports OLS and 2SLS estimates, including the corresponding first stages.

Notice that 2SLS estimates capture local effects, i.e., average effects among compliers weighted by the strength of the first stage. Let's break this down gradually to understand it better. First, the instrument excludes from the shareholding prediction changes in supply relationships for firms entering or exiting the S&P 500 and shareholders acquiring their first shares in a firm during the same year. Second, the 2SLS approach puts a lower weight on observations substantially deviating from the predicted instrument. In other words, coefficients emphasize the effects among customers and suppliers with more stable ownership structures over time.

[11]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 one addition with its corresponding deletion. 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 net market value of the constituent's change. 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. Likewise, 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.

Figure 1 — 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 B1 in the Appendix.

The characterization fits the description of passive indexing investors, whose holdings track and replicate known indices in the market. However, it might include other institutional shareholders with stakes in the long run, such as strategic alliances, conglomerates, etc. Thus, results do not imply that endogeneity concerns were unsubstantiated or that active investment funds do not care about customers and suppliers among firms in their portfolios.

On the contrary, the reported coefficients suggest that similar results in the literature would be driven by shareholders not considering trading partners when choosing a portfolio, but still affecting managerial decisions through their holdings. Not necessarily because they directly persuade executives to do so but because managers tend to please pivotal shareholders and factor in how their choices affect other companies in the shareholders' portfolios.

IV. Private benefits in supply chain relationships

Following Rotemberg (1984), one can interpret the previous findings as institutional shareholders influencing managerial decisions through profit weight values κ_{fgt}, which in turn can affect upstream and downstream market outcomes from internalizing the effects on other firms, namely, $\pi(x_{ft}, x_{-ft})$.

By their very nature, vertical relationships should have underlying mechanisms closely related to the tropes of partial vertical integration. Indeed, the literature explores some of these features by leveraging alternative data sources and exogenous variations, finding that overlapping owners can help overcome informational and contractual frictions between customers and suppliers. Correspondingly, Section A.A3 in the Appendix documents similar interpretations regarding holdup and double marginalization.

Nonetheless, I focus on an alternative mechanism in which overlapping shareholders can employ trading partnerships to extract private benefits at the expense of one company. The exact mechanism can take many forms. For example, upstream or downstream markets could exhibit the foreclosure of companies not belonging to the portfolio of shareholders, tighter market-entry barriers, or straight 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.

While unable to pin down the channel of value transfers, the following subsection shows indirect evidence of how the influence of institutional shareholders on managerial decisions can give rise to tunneling opportunities across firms. When a firm has a more concentrated ownership structure than a potential trading partner, the degree of overlapping ownership affects the likelihood of a supply chain relationship by four times than results in the baseline. Interestingly, these situations coincide with managers among companies with more diluted ownership structures weighing heavily on the effects of their decisions on the firms with the relatively concentrated ones.

A. *Relative concentration of ownership structures*

The idea that overlapping shareholders privately benefit from managerial decisions at the expense of one of the companies reminisces the concept of *tunneling* (Johnson et al., 2000; Atanasov et al., 2007), where a company can 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.

As Ehrhardt and Nowak (2015) highlights, tunneling can take many forms and does not necessarily convey money transfers if shareholders also pursue asserting a higher degree of control in the future or affecting either 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 mergers and acquisitions increase the likelihood that integrated firms would foreclose rival companies. Overlapping shareholders could play a similar role by affecting managerial decisions to prefer certain trading partners over others or acting as a deterrent to potential entrants who anticipate the likelihood of foreclosure.

I explore these disparate incentives among managers by exploiting differences in the relative concentration of ownership structures across potential customers and suppliers. Backus, Conlon and Sinkinson (2021*b*) suggests that profit weight values above one would make managers prioritize the profits of a competing firm over those of the company that appointed them. Unlike product markets, where managers compete by making unilateral decisions, vertical relations provide a compelling setting to explore asymmetric incentives among managers. Not only do trading partnerships require both parties to agree on the conditions of the transaction, but they can create worth, meaning that profit weight values below one can convey practical information about the willingness of managers to split gains disproportionately.

As shown in Equation (1), changes in the cosine similarity affect profit weight values in the same direction; however, changes in shareholdings can accentuate or reduce differences in the relative concentration of shareholders across companies. Therefore, increases in overlapping ownership would disproportionately affect profit weight values unless the relative concentration is precisely 1. Hence, I estimate the following model using 2SLS

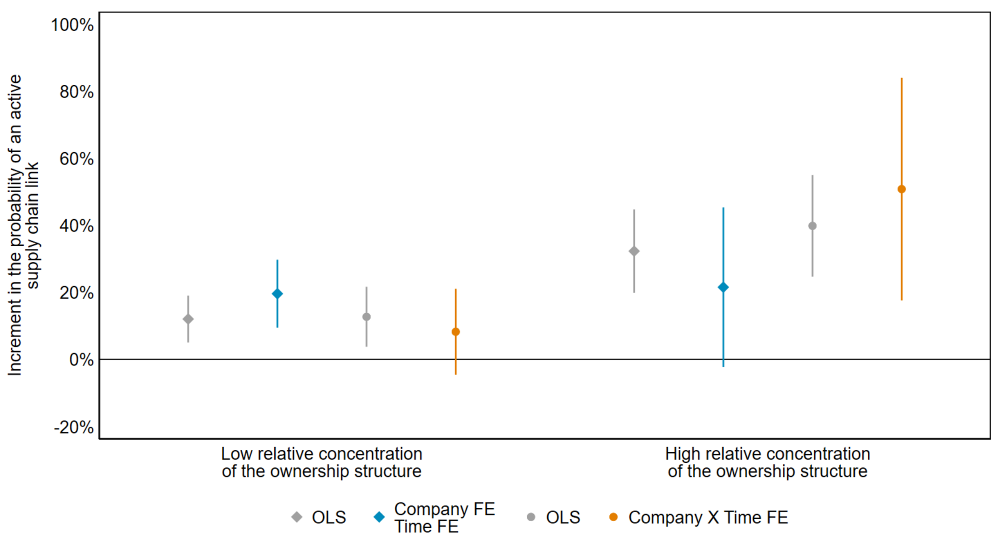
$$(4) \quad Link_{cst} = \delta_t + \delta_c + \delta_s + \tau_0\ cos_{cst} + \tau_1\ maxRelCon_{cst} + \tau_2\ maxKappa_{cst} + \varepsilon_{cst}$$

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. Unlike other identification strategies, which rely on shifts in the average measures of overlapping ownership, my approach allows me to construct instruments for any measure that is a known function of shareholdings and simultaneously explore the role and interaction between the similarity and the relative concentration of ownership structures.

Figure 2 compares the effects of increasing the cosine similarity of the ownership structure by one standard deviation for the lowest (1.0838) to the highest (3.4820) decile of relative concentration. Since the specification with time-invariant company fixed effect reports non-significant coefficients for all variables, it comes as no surprise that there is no statistically significant difference in the effects. However, the specification with time-varying company fixed effects depicts that effects amplify from 8.25% to 50.82%. For a more comprehensive description of results, please refer to Table B4 in the Appendix.

Intuitively, trading partnerships become more likely when managers weigh heavily on the externalities imposed on the other company, but more so when their peers do not respond in kind. These decisions harm the shareholders of the firm that appointed the

Figure 2 — 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 B4 in the Appendix.

conflicted managers, irrespective of whether they suffer from losses or unrealized gains. As mentioned above, supply chains allow for value creation. However, overlapping owners can accrue private benefits from the unequal distribution of gains.

V. Conclusions

In this paper, I explore whether diversified overlapping shareholders can affect the US supply chain network by creating incentives for managers to internalize how their decisions affect potential trading partners.

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 use panel data on shareholdings and additions and deletions from the S&P 500 index to assemble predicted portfolios for institutional shareholders, which I use to construct several measures related to overlapping ownership from known formulas.

My work finds that the degree of overlapping ownership between potential customers and suppliers affects the likelihood they would engage in a trading partnership. While the literature has emphasized its role in mitigating contractual and informational frictions, my findings reveal that it can also harm firms and non-overlapping shareholders by enabling value transfers across companies or influencing the distribution of the gains from the trading partnership.

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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[12]: 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[13].

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

[12]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)

[13]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

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

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

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

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[14], 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

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

[14]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. Additions and deletions from S&P 500

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 replicating their strategy to acquire equity of companies entering the index and to sell shares of companies leaving it.[15] However, Lewellen and Lowry (2021) suggests 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[16], whose decisions might be affected by a company's most recent performance. In particular, the committee's members might be awaiting the entering company's business relationships to improve and the opposite for companies leaving the index. 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 included in 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 the degree of overlapping ownership prove to be completely exogenous. The proposal stands out in horizontal settings, where managers make 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.

Nevertheless, 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. However, 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.

S&P 500 index weighting The missing piece that bridges S&P 500 additions and deletions with portfolio decisions lies in the index-weight changes taking place because of

[15] 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 contrary, Aghion, Van Reenen and Zingales (2013) and Kwon (2016) have opted for S&P 500 additions.

[16] 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".

differences in the market value of companies entering and exiting the list of constituents. 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 one addition with its corresponding deletion. 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 net market value of the constituent's change.[17] Besides, 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 should adjust proportionally downwards to make room for the higher index weights of the entrants. The opposite holds as well.

Shareholdings and index weights For the identification strategy to work, it requires addressing other potential sources of endogeneity that may influence the chain of effects linking additions and deletions with the ownership structure of companies. For instance, institutional shareholders may exhibit varied responses based on their portfolio composition, e.g., whether they own shares in the companies involved in the additions or deletions, the stocks they hold in the remaining companies, the market capitalization of the portfolio, and so on.

The first step focuses on the computation of index weights from fixed variables, 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 excludes shares held by long-term strategic shareholders, such as insiders, private equity, or the government, although I cannot make the distinction.[18] Thus, I compute weights $\omega_{f,t}$ as follows

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

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.[19] 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 fixed variables, i.e., past index aggregate values and differences in the market capitalization of additions

[17] 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. Likewise, 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.

[18] 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`.

[19] 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.

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

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

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

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

A3. 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[20].

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[21]. 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,

[20]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.

[21]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.

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.

Holdup 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 (**??**) and (2) to estimate a two-way fixed-effects linear probability model like the following

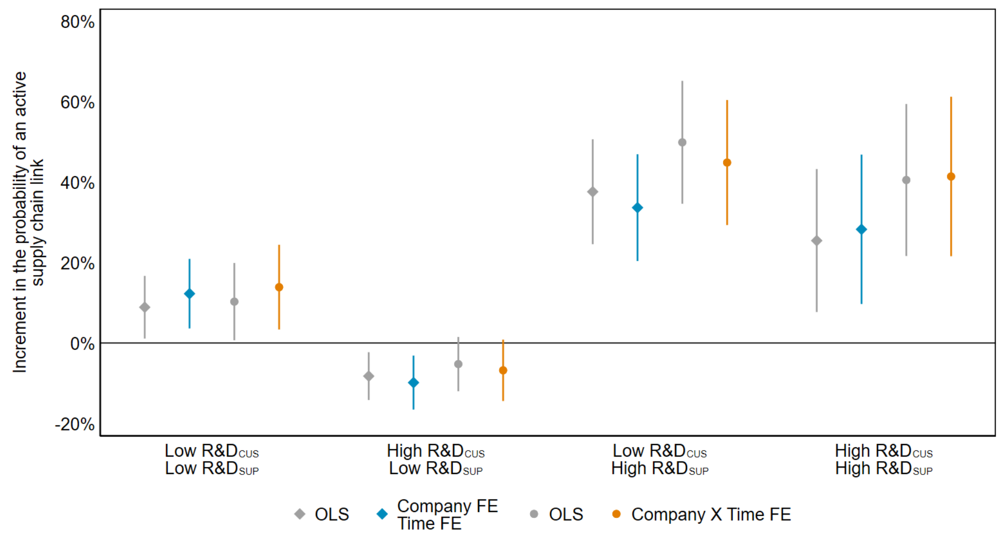
$$Link_{cst} = \delta_t + \delta_c + \delta_s + \sum_{i \in L,H} \sum_{j \in L,H} \tau_{i,j}\, \mathbb{1}_{\{R\&D_c = i\}} \mathbb{1}_{\{R\&D_s = j\}}\, cos_{cst} + \varepsilon_{cst} \tag{A4}$$

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

Figure A1 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 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 B2 in the Appendix.

Double marginalization Companies operating in less competitive markets apply successive markups to their marginal costs, giving rise to double marginalization. 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.

Figure A1 — 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 B2 in the Appendix.

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

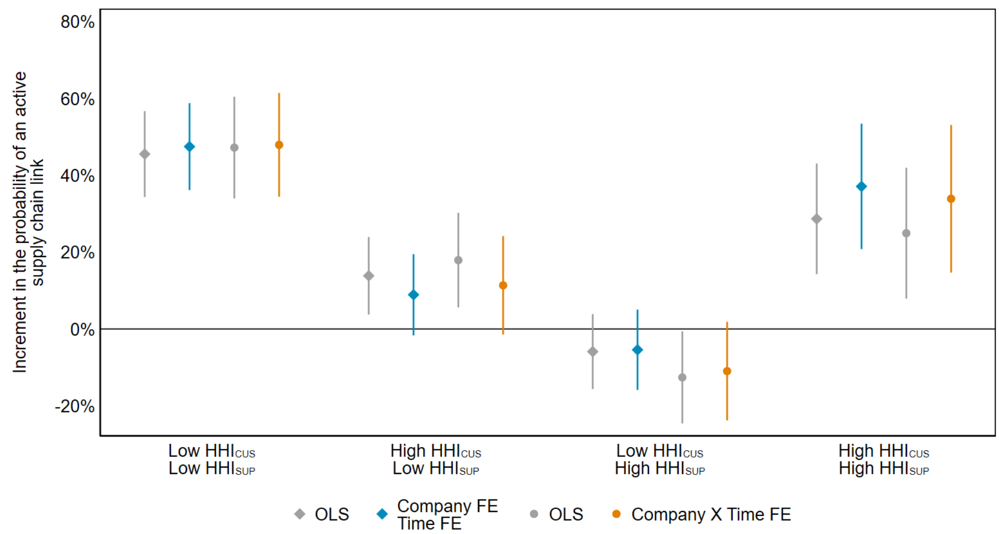
$$Link_{cst} = \delta_t + \delta_c + \delta_s + \sum_{i \in L,H} \sum_{j \in L,H} \tau_{i,j} \, \mathbb{1}_{\{HHI_c = i\}} \mathbb{1}_{\{HHI_s = j\}} \, cos_{cst} + \varepsilon_{cst} \tag{A5}$$

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

Figure A2 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 B3 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 so-

Figure A2 — 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 B3 in the Appendix.

lution 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 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.

Supplementary material

B1. Robustness

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.

Overlapping ownership measures 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,

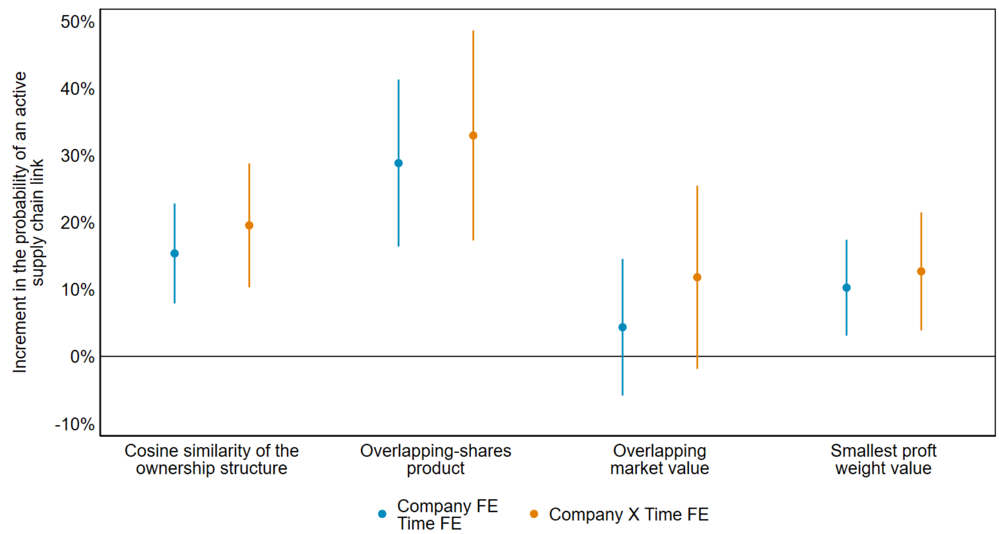
$$minKappa_{cst} = min(\kappa_{cst}, \kappa_{cst})$$

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

Figure B1 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 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 B5 in the Appendix.

Functional form of the instrument Continuing with the instrument, a potential threat to identification could originate in the non-linearities of the overlapping owner-

Figure B1 — Alternative overlapping ownership measures



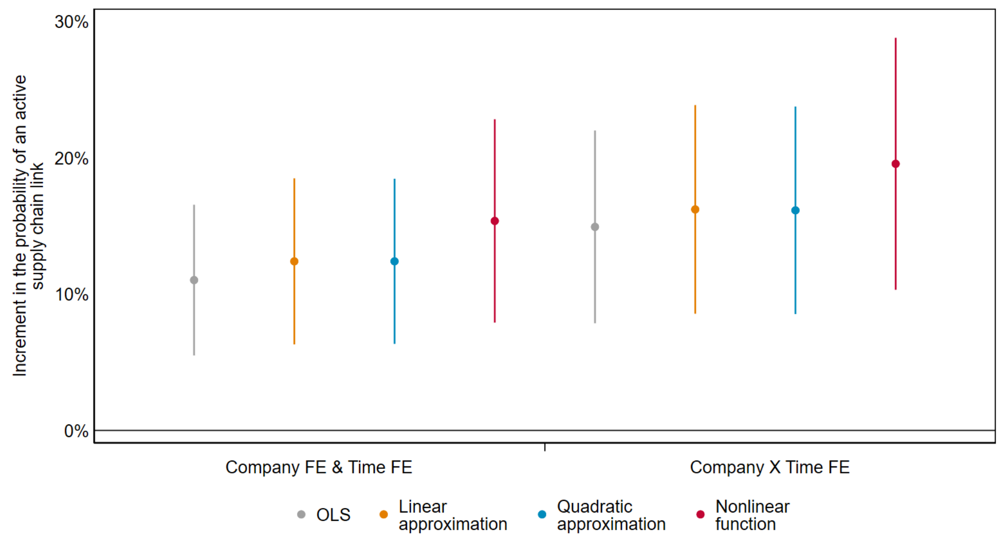
Notes: The figure depicts the coefficients and confidence intervals associated with OLS and 2SLS panel regressions of the likelihood of an active trading partnership on different metrics for the degree of overlapping ownership among publicly-listed companies in the US in industries other than the financial 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 B5 in the Appendix.

ship 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 **??**, and a second-order one. Furthermore, I include an estimation using the whole expression to construct the instrument. Opportunely, Figure B2 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, B6 in the Appendix offers more details about the estimations.

Sample definition 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 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,

Figure B2 — 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 B6 in the Appendix.

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.

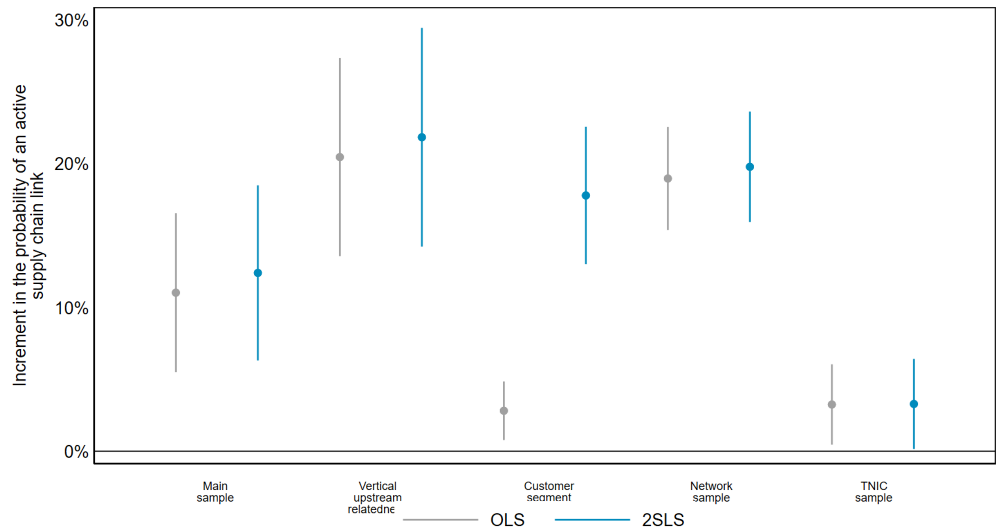
For example, I consider two distinct scenarios in which the source of the error comes solely from one of the datasets. Should inconsistencies arise from improper mapping between companies' names and GVKEY identifiers, I exclude all dyads without a vertical upstream relatedness, even if they appear in 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.

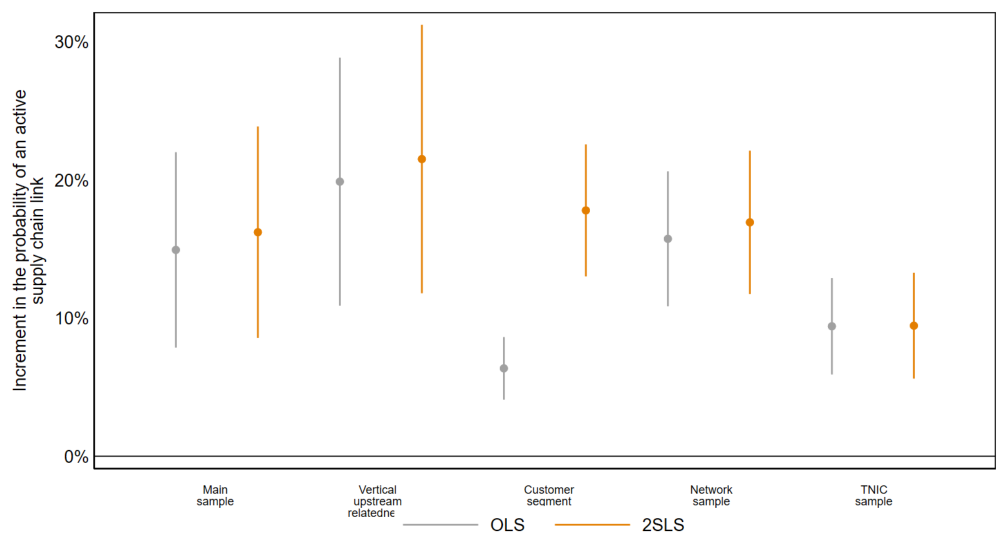
Second, by using the text-based network industry classification from Hoberg and Phillips (2016), I identify all competitors of customers and suppliers in the Customer Segment operating in industries other than the financial and utility sector. Then, for any given year and customer C_0, I define all of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

Figure B3 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.

Figure B3 — 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 B7 and B8 in the Appendix.

B2. Tables and figures

Table B1 — 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 B2 — 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												
$R\&D_{CUS}^{Low}$ $R\&D_{SUP}^{Low}$	0.0889*					0.1227**	0.1028*					0.1389**
	(0.039740)					(0.044128)	(0.049014)					(0.053715)
$R\&D_{CUS}^{High}$ $R\&D_{SUP}^{Low}$	-0.0824**					-0.0984**	-0.0525					-0.0679
	(0.030303)					(0.034250)	(0.034442)					(0.038965)
$R\&D_{CUS}^{Low}$ $R\&D_{SUP}^{High}$	0.3762***					0.3367***	0.4991***					0.4488***
	(0.066563)					(0.067756)	(0.077959)					(0.079340)
$R\&D_{CUS}^{High}$ $R\&D_{SUP}^{High}$	0.2547**					0.2827**	0.4053***					0.4141***
	(0.090724)					(0.094780)	(0.096413)					(0.101183)
Predicted overlapping ownership												
$R\&D_{CUS}^{Low}$ $R\&D_{SUP}^{Low}$		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)	
$R\&D_{CUS}^{High}$ $R\&D_{SUP}^{Low}$		-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)	
$R\&D_{CUS}^{Low}$ $R\&D_{SUP}^{High}$		-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)	
$R\&D_{CUS}^{High}$ $R\&D_{SUP}^{High}$		-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 B3 — 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												
$HHI^{Low}_{CUS}\ HHI^{Low}_{SUP}$	0.4548***					0.4743***	0.4717***					0.4788***
	(0.056967)					(0.057677)	(0.067517)					(0.068798)
$HHI^{High}_{CUS}\ HHI^{Low}_{SUP}$	0.1384**					0.0890	0.1790**					0.1135
	(0.051474)					(0.053876)	(0.062796)					(0.065265)
$HHI^{Low}_{CUS}\ HHI^{High}_{SUP}$	-0.0588					-0.0540	-0.1258*					-0.1096
	(0.049675)					(0.053287)	(0.061063)					(0.065409)
$HHI^{High}_{CUS}\ HHI^{High}_{SUP}$	0.2864***					0.3708***	0.2491**					0.3387***
	(0.073376)					(0.083199)	(0.086770)					(0.097887)
Predicted overlapping ownership												
$HHI^{Low}_{CUS}\ HHI^{Low}_{SUP}$		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)	
$HHI^{High}_{CUS}\ HHI^{Low}_{SUP}$		-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)	
$HHI^{Low}_{CUS}\ HHI^{High}_{SUP}$		-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)	
$HHI^{High}_{CUS}\ HHI^{High}_{SUP}$		-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 B4 — 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	0.0000				0.0003	0.0000				-0.0002
	(0.000076)				(0.000152)	(0.000091)				(0.000208)
Highest relative concentration	-0.0000				0.0000	-0.0000				-0.0000*
	(0.000003)				(0.000018)	(0.000004)				(0.000017)
Highest profit weight value	0.0001**				0.0000	0.0002***				0.0003*
	(0.000039)				(0.000087)	(0.000045)				(0.000122)
Predicted overlapping ownership		0.8379***	-0.9543***	1.2541***			0.8406***	-0.9976***	1.2377***	
		(0.000216)	(0.002049)	(0.000439)			(0.000205)	(0.002380)	(0.000555)	
Predicted highest relative concentration		0.0001***	0.0024***	-0.0001***			0.0002***	0.0062***	0.0007***	
		(0.000001)	(0.000021)	(0.000002)			(0.000002)	(0.000046)	(0.000004)	
Predicted highest profit weight value		-0.0105***	0.0676***	0.0033***			-0.0084***	0.0694***	0.0080***	
		(0.000099)	(0.000931)	(0.000116)			(0.000091)	(0.001113)	(0.000210)	
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		28,800	29,658	28,305	9,615		15,113	16,040	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 B5 — 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 B6 — 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 B7 — Robustness: Alternative sample definitions

Dependent variable: Active trading partnership

	Main sample			Vertical upstream relatedness			Customer segment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	2SLS
Overlapping ownership	0.1102***		0.1240***	0.2045***		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)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	OLS	FS	2SLS	OLS	FS	2SLS	OLS	FS	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 B8 — 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.