ONLINE APPENDIX

Appendix A: Data Appendix

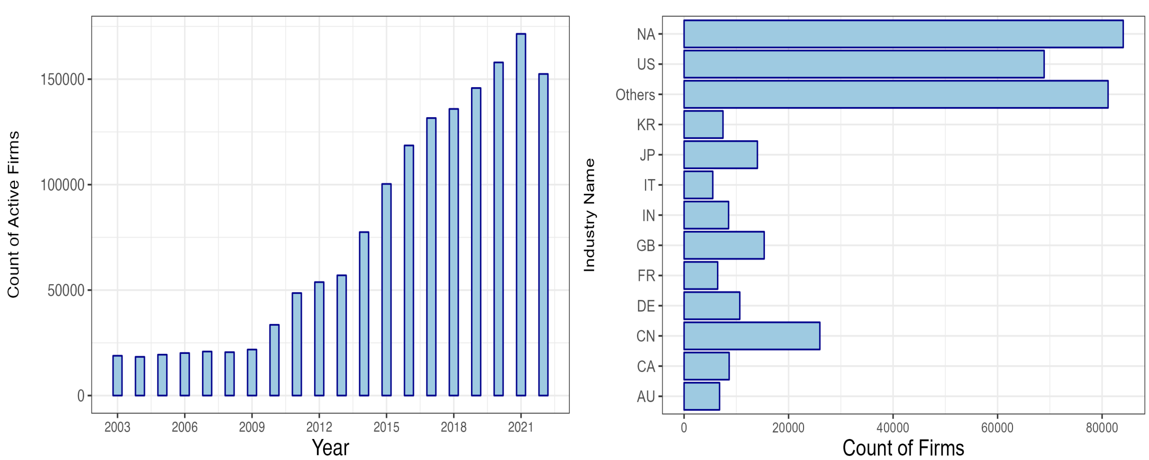
A.1. FactSet database

We present the summary statistics of the raw FactSet Revere data in this section. Table 1 shows the frequency of various relationships in the raw FactSet Revere database from 2003 to 2022. These statistics cover 13 distinct relationship types, organized into four main groups: 1) Customers, 2) Suppliers, 3) Partners, and 4) Competitors. Most relationship types belong to the customer category, as indicated in Table 1.

Relationship type	Total Relationships
Supplier	308,290
Customer	905,943
Competitor	425,133
Partner	636,020
Total	2,275,386

Table 1 Relationship types and total number of these relationships in the raw FactSet dataset.

Figure 1 (panel a) shows the total number of active firms over time in the raw FactSet dataset. We infer that a firm is active in a given year if it features in at least one of the active relationships in that year. We note that there has been an increase in the total number of active firms in the FactSet data over time. This is due to the increased coverage of FactSet to Asian and European countries over time. However, the increased coverage does not impact our results. Our sample mainly contains U.S. firms whose coverage has remained unchanged over time. Figure 1 (panel b) shows the total number of firms in the dataset corresponding to different countries. The United States is the largest country represented in the dataset.



(a) Number of firms in FactSet (b) Number of firms by country in FactSet

Figure 1 FactSet Descriptives

A.2. Data Cleaning Procedure

This section describes the data-cleaning steps for all the datasets used in the paper.

A.2.1. FactSet Revere The original FactSet Revere dataset contained 3.7 million rows of relationship data from 2003 to 2022. We filtered and cleaned the data in the following way:

1. We eliminated relationships that have the same start and end date. This results in a sample of 2.3 million records. Figure 2 provides an example of such a record for a relationship starting on 7/12/2005 and ending on 10/26/2005. We verified this with the FactSet team, and it turns out that these are not data errors but that "these records are included to help users easily identify when a record is terminated within its respective time series."

START$	END$	REV$	ID	
7/12/2005	10/26/2005	2129998471	CUST-2207840	
10/26/2005	10/26/2005	2130037211	CUST-2207840	start$ = end$ to identify the ending of the record in the time series beginning on 7/12/2005
8/26/2022	1/1/4000	2333157806	CUST-2207840	record resumes in new time series beginning 8/26/2022

Figure 2 Records with same start and end dates in FactSet.

2. We found 1.08 million relationship records with empty CUSIPs for the source or target company. Since creating a supply network requires both source and target firm IDs, we used the FactSet Fundamentals dataset to fill in as many CUSIPs as possible. This process resulted in about 1.5 million relationships, which we used to build the annual supply network and identify vertical integration cases.[1]

A.2.2. SDC Platinum

1. Even though the SDC Platinum database has over 400,000 deals, we focused on those between 2003 and 2022. We removed deals where the acquirer and target CUSIPS were not available. There were about 233,065 announced deals during this period, of which 200,401 were completed.
2. We selected only those deals categorized as mergers and acquisitions (M&A) from these completed deals, resulting in a sample of 27,669 M&A deals.

A note on potential biases arising from using SDC: Some prior studies suggest that SDC performs poorly with smaller firms or those with high book-to-market values. To test the presence of smaller firms, we provide demographics of the firms in both the SDC database and our final sample. This information provides a clearer picture of the composition of our dataset. Specifically, we calculate firms' book-to-market ratio and size (measured as log (market capitalization)). Book-to-market (BTM) ratio is calculated as:

$$BTM = \frac{\text{Book value of equity}}{\text{Market Value of Equity}} \tag{1}$$

where, book value of equity is calculated as stockholders' book equity (Compustat filed SEQ), plus balance-sheet deferred taxes (TXDB) and investment tax credit (ITCB), minus the book value of preferred stock.[2] Market value of equity is calculated as stock price times the number of shares outstanding (using the monthly stock file in CRSP). Table 2 shows the distribution of size and BTM in our final sample and SDC. We note from Table 2 that the overall distribution of BTM values is right-skewed (mean > median). This suggests that SDC indeed does cover firms with very high book-to-market values.

[1] the FactSet Fundamentals dataset comprises 3.5 million records, including company IDs, names, active status, and firms' identifier details like CUSIPs, ISINs, and SEDOLs.

[2] The book value of preferred stock is calculated based on availability in the following order: redemption value (pstkrv), liquidating value (pstkl), or convertible value (pstk).

Source	Variable	1%ile	1st Qu.	Median	Mean	3rd Qu.	99%ile
Sample	Size	4.1395	7.3471	8.7957	8.7891	10.4192	12.6482
	BTM	-0.5997	0.2009	0.3584	**0.5047**	0.6064	4.6892
SDC	Size	4.8802	6.0748	7.4062	7.4788	8.8019	10.2210
	BTM	0.1382	0.2710	0.4670	**0.7840**	0.7538	1.1303

Table 2 Summary statistics for Sample and SDC data.

Having said that, we acknowledge that SDC may not capture all acquisitions. Specifically, if SDC underreports M&A activity among smaller or value-oriented firms, our findings may be more representative of transactions involving larger, more established firms. However, this is consistent with the literature as Mirzayev et al. (2025) note that "it is common in the literature to eliminated small and economically insignificant deals" while working with SDC. However, given that vertical mergers often involve firms with significant market presence, we believe that our estimates may be slightly overestimated if there was indeed a reporting bias in SDC. The only paper that estimates this bias is Barnes et al. (2014), and the authors found it to be very small. We have now added the discussion on this bias in the paper.

A.3. Compustat Data Imputation

Table 3 shows the summary statistics of the key variables used for markup estimation, extracted from the Compustat dataset. The variables include operating income (xopr), sales, total assets (at), net property, plant, and equipment (ppent), and gross property, plant, and equipment (ppegt). The average missing value for all variables is around 17%. The missing values in the dataset were imputed using linear interpolation. The interpolation was applied at the GVKEY level for cases with four or fewer missing observations. Table 4 presents the summary statistics after imputation. The % Imputation column indicates that only a small fraction of the dataset (2–2.5%) was altered. The distributions remain stable, with minimal changes in means and quantiles, suggesting that the imputation process preserved the overall structure of the data. Notably, variables with higher missing rates, such as PPENT and PPEGT, show the most adjustment post-imputation, yet their mean and quantile values remain close to the original.

The table 5 summarizes the distribution of missing values replaced after imputation at the GVKEY (firm) level. Only a small fraction of firms (top 1%) had missing values replaced, with no firm having more than four imputations per variable. This reinforces the minimal impact of imputation on our dataset, ensuring the robustness of our analysis.

Variable	1%ile	1st Qu.	Median	Mean	3rd Qu.	99%ile	% Missing
XOPR	2.90	13.34	66.33	1441.66	395.27	1973.60	17.30
SALES	1.44	13.10	76.30	1776.08	481.36	2427.82	14.65
AT	3.72	17.77	117.41	5900.02	864.88	4549.39	14.69
PPENT	0.21	2.03	15.01	854.35	131.55	1014.36	16.46
PPEGT	0.46	3.78	27.75	1605.24	255.1	1857.27	22.92

Table 3 Summary statistics of the raw data from Compustat.

Variable	1%ile	1st Qu.	Median	Mean	3rd Qu.	99%ile	% Missing	% Imputation
XOPR	2.84	12.97	64.06	1411.04	382.45	1920.71	14.71	2.59
SALES	1.37	12.66	73.87	1741.17	467.69	2364.72	12.50	2.16
AT	3.61	17.14	113.06	5777.37	839.63	4428.58	12.62	2.07
PPENT	0.202	1.944	14.47	837.32	126.97	984.21	14.33	2.13
PPEGT	0.44	3.57	26.41	1569.82	244.64	1796.28	20.66	2.26

Table 4 Summary statistics of the data after Imputation from Compustat.

Variable	Min	1%ile	1st Qu.	Median	Mean	3rd Qu.	99%ile	Max
XOPR	0	0	0	0	0.34	0	1	4
SALES	0	0	0	0	0.28	0	1	4
AT	0	0	0	0	0.27	0	1	4
PPENT	0	0	0	0	0.28	0	1	4
PPEGT	0	0	0	0	0.30	0	1	4

Table 5 Summary statistics of the transformed data from Compustat.

A.3.1. Vertical Mergers To identify vertical merges, we matched the FactSet Revere and the SDC Platinum databases using the source and target firms' CUSIP codes (as identified by FactSet) with the CUSIP codes of both acquirer and target firms (as identified by SDC) for the same year. This initial matching process yielded 236 vertical integration cases from 2003 to 2022.

A.3.2. Focal firm markup panel We started by selecting acquirer firms involved in the 236 vertical integration cases from 2003 to 2022. To create our panel of firms, we match the financial data of these firms from Compustat, incorporated the estimated year-level markup details, and included network-level information, such as in/out degree, centrality, etc., from FactSet. After merging these three datasets and removing any missing information, our final sample consisted of 213 vertical integration cases across 168 firms.

A.3.3. CRSP Mutual Fund Data

- The original monthly CRSP mutual fund data contains 6,895,890 observations from 2003 to 2022. While linking `crsp_fundno` to WFICN, we lost some observations and were left with 5,407,216 observations. We aggregated the monthly data to a quarterly level to calculate total net assets and fund returns.
- We keep only those funds with net assets greater than 0.1 million dollars, aiming to mitigate any biases associated with smaller funds. Similarly, we remove any unusually large inflows or outflows, possibly from data anomalies. In the end, our sample contained 614,809 fund quarter observations.

A.4. Supply network based variables

This section describes the supply network variables used in our analyses. We use an unweighted directed graph $G(V_t, E_t)$ to represent the supply chain network in period t, where the set of nodes and edges are denoted by V_t and $E_t = \{(i,j) : i,j \in V_t\}$. An individual node corresponds to a firm, while each directed edge denotes the supplier→customer relationship.

1. Betweenness Centrality: Betweenness centrality helps to assess the importance of a firm i in a supply network by counting how often it appears on the shortest path connecting any two nodes p and q. We measure the betweenness centrality for firm i in the supply network as follows:

$$CB_i = \sum_{p \neq q, i \notin \{p,q\}} \frac{\sigma_i(pq)}{\sigma(pq) \cdot (n-1)(n-2)}$$

   Where $\sigma(pq)$ denotes the total number of shortest paths from node p to node q in the network, and $\sigma_i(pq)$ is the total number of shortest paths that contain node i.

2. Layer: To measure upstreamness, we construct a layer measure, which captures a firm's position within the supply network relative to final demand. Specifically, following Gofman et al. (2020) and Osadchiy et al. (2021), we assign firms that directly serve final consumer demand—those classified under GICS sectors 25 (Consumer Staples) and 30 (Consumer Discretionary)—to Layer 1. For all other firms, the layer is defined as the minimum number of buyer-supplier links (shortest-path distance) that separates them from any Layer 1 firm.

A.5. Summary statistics of the variables used from the mutual fund datasets

Table 6 shows the summary statistics of the key variables across the CRSP and CDA/Spectrum datasets. The CRSP mutual fund dataset consists of 14,028 mutual funds and approximately 600,000 fund-quarter observations from 2003 to 2022. On average, funds manage approximately 1.7 billion dollars in assets. There is significant cross-sectional variation in fund flows, with an average net flow of 1.64 million dollars per quarter. Funds in the lowest quartile experienced a flow of around -0.04 million dollars. The mean share price across all holdings of the funds is about $30. The mean number of shares held at the fund-quarter level is around 603,000.

Variable	Source	Type	Obs	Mean	Std. Dev.	Min
TNA ($ mill)	CRSP MF	Quarterly	606,141	1737.3	10788.6	0.1
Return	CRSP MF	Quarterly	599,973	0.02	0.16	-0.98
Inflow ($ mill)	CRSP MF	Quarterly	588,379	1.6	136.1	-13.3
Share price (prc) ($)	CDA	Quarterly	1,170,659	29.2	160.6	0
# Shares	CDA	Quarterly	423,439	5027118	8.19e+07	1
Normalized MFHS	Constructed	Yearly	168,064	-0.09	3.92	-1048.9

Table 6 Summary statistics of the key variables used from the mutual fund datasets.

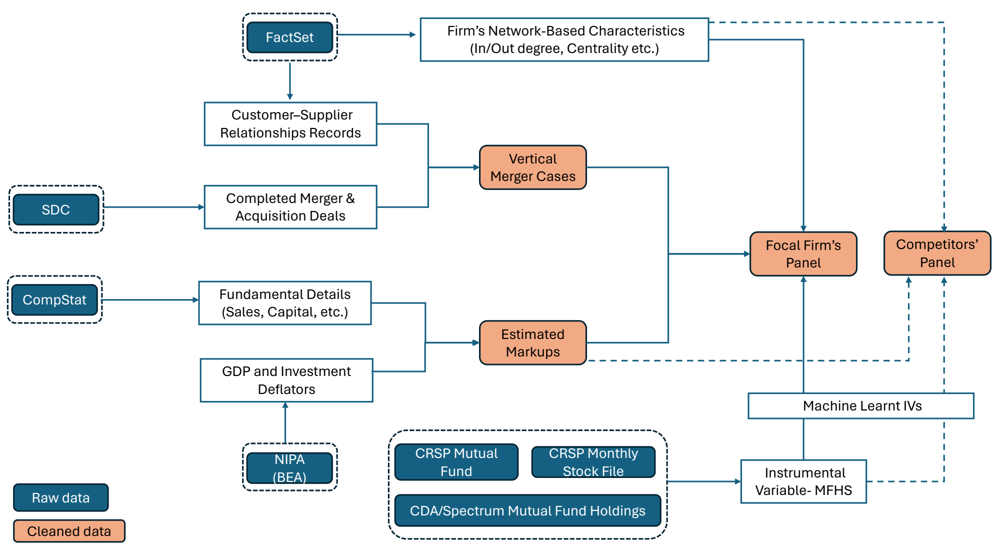


Figure 3 Schematic of all the datasets used in the paper and how they feed into our analyses.

A.6. Compustat Variables and derived metrics

This section (Table 7) describes the compustat variables (and the metrics derived from them) that we use in the paper.

A.7. Production Costs and Their Inclusion in Financial Indicators

Table 8 summarizes key production-related cost components and indicates whether they are captured under commonly used financial indicators—COGS, SG&A, and OPEX. While COGS includes core production costs such as direct materials, labor, and factory overhead, it omits important variable expenses like selling and administrative costs. SG&A captures those operational costs but excludes direct production inputs. In contrast, OPEX offers the most comprehensive coverage, making it a more suitable input proxy in production function estimation, especially in modern firms where variable costs extend beyond traditional manufacturing inputs.

Variable	Definition
INVT	End of year total inventory. Sum of finished goods inventory raw materials inventory, work in progress inventory, and other inventory.
SALES	Yearly gross sales, the amount of actual billings to customers for regular sales reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.
XSGA	All commercial expenses of operations incurred in the regular course of business pertaining to the securing of operating income. Includes advertising expense, bad debt expense, commissions, engineering expense marketing expense, freight-out expense, strike expense, directors' fees and remuneration research revenue, parent company charges for administrative services.
XOPR	Sum of Cost of Goods Sold (COGS) and Selling, General and Administrative Expenses (XSGA)
GM	Calculated as (SALES-COGS) divided by SALES

Table 7 Compustat variables and derived variables along with their definitions.

Cost Category	Included in COGS?	Included in SG&A?	Included in OPEX?
Direct Materials	✓	✗	✓
Direct Labor	✓	✗	✓
Factory Overhead	✓	✗	✓
Indirect Labor	✓	Sometimes(e.g., admin staff)	✓
Depreciation (Production)	✓	✗	✓
Rent (Production)	✓	✗	✓
Depreciation (Non-Production)	✗	✓	✓
Rent (Non-Production)	✗	✓	✓
Selling Expenses	✗	✓	✓
General & Admin Expenses	✗	✓	✓
Inventory Costs	Partial	✗	Partial

Table 8 Production Costs and Their Inclusion in Financial Indicators

Appendix B: Additional Analyses

B.1. Non-parameteric First-Stage Regression

Weak instrumental variables can pose a challenge in estimation because they can lead to biased estimates of causal relationships (Stock and Yogo 2005). To address the weak IV issue, we adopt the MLIV procedure outlined in Singh et al. (2020) and Chen et al. (2021), and construct a stronger instrumental variable.[3] The main idea in Singh et al. (2020) is that if z is a valid instrument, then any choice of the transformation $H(\cdot)$ of the instrument z also corresponds to valid instrument for the below GMM problem:

$$\mathbb{E}\left[\xi\left(x_i;\theta\right) \mid Z\right]=0 \Longrightarrow \mathrm{E}\left[\xi\left(x_i;\theta\right)\cdot H\left(z_i\right)\right]=0$$

The problem faced by the researcher is to choose an "efficient" rule $H(\cdot)$, and the most efficient set of instruments are optimal instruments. Following the algorithm in Singh et al. (2020), we perform the below steps to strengthen our instrument:

- **Outer Loop:** Split the data $\mathcal{D}$ (roughly) equally into a 2-fold partition, such that each partition $\mathcal{C}_s (s \in \{1,2\})$ has size $\lfloor \frac{n}{2} \rfloor$ or $\lfloor \frac{n}{2} \rfloor + 1$. For each partition s, define $\mathcal{D}_s^c$ as the excluded data.
- **Inner Loop:** For each partition s, learn the optimal instrument function $f_s\left(\cdot;\zeta_s\right)$ to predict the vertical indicator variable using the excluded data $\mathcal{D}_s^c$. Specifically, $f(\Delta;\zeta)$ is a class of instrumental variable functions

[3] Similar machine learning methods to strengthen the instruments have been applied by operations management researchers (Arora et al. 2023, Lou et al. 2021).

parameterized by ζ, where Δ are hyperparameters. The pool of possible f functions consists of XGBoost, Lasso, Ridge, and Elastic Net. The hyperparameters pertinent to f are tuned by 2-fold cross-validation.

- **Prediction Step:** Compare the prediction accuracy of each of the two instrument functions $f_s(\Delta;\zeta_s)$ and choose the one that has the lower RMSE. Denote the selected function and hyperparameter by $f_*(\Delta;\zeta_*)$.
- **IV Generation:** Now, for the entire dataset $\mathcal{D}$, obtain the new instrument $f_*(\Delta,\zeta_*)$. Use the generated IV to obtain 2SLS estimates for post-integration markups.

We run the first-stage regression of the vertical indicator on the constructed MLIV and report the corresponding F-stats in Table 9. The F-stats are 143 and 498 for the focal firm and rival firms, respectively, indicating that our constructed IVs are strong and pass the weak IV tests.

	Dependent Variable: Vertical_Indicator	
	Focal Firms	Rival Firms
	MLIV	MLIV
MLIV	0.503*** (0.064)	0.580*** (0.023)
Controls	✓	✓
Firm Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
F-statistic	**143.429**	**885.363**
Observations	2,511	28,139
R^2	0.120	0.280

Table 9 First stage results with MLIVs for focal and rival firms.

B.2. Post-integration markup increase over the last two decades: Has FTC's antitrust policy become too lenient over time?

This section investigates whether post-merger markups have increased over the last two decades. This is an important question because even though antitrust authorities like the Federal Trade Commission (FTC) try to regulate vertical mergers to ensure these cases do not harm competition and consumer welfare, antitrust intervention has become less strict over time (Wollmann 2019). Hence, we study whether the reduced antitrust enforcement over the last two decades is associated with increased post-merger markups. To answer this question, we construct a variable POST2003, which takes the value $t-2003$ for the years $t \geq 2003$. Using this variable, we estimate the following model to study changes in firms' post-merger markups over time:

$$\mu_{it} = \alpha_i + \alpha_t + \beta_1 d_{it} + \beta_2 POST2003 \times d_{it} + X_{it}\Theta + \epsilon_{it} \tag{2}$$

where, the coefficient β_2 captures the effects of vertical integration on markups over time from 2003. We estimate the above equation for both the focal and the rivals using 2SLS models. We instrument for the vertical integration dummy d_{it} and the interaction term using machine learnt instruments. The estimated values of β_2 for the focal and the rival firms are 0.103 and 0.040, respectively (Table 10, columns 2 and 3).

$\beta_2 > 0$ indicates that post-merger markups have steadily risen over the last two decades. This striking finding has direct implications for consumers and sheds light on important debates related to high-profile antitrust cases on vertical mergers. Based on our results, we advocate for higher scrutiny of vertical integration cases in the future.

	Dependent Variable: Markups	
	Focal Firm	*Rivals*
Vertical_indicator	-0.889^{***} (0.302)	-0.340^{***} (0.107)
Vertical_indicator × POST2003	0.103^{***} (0.029)	0.040^{***} (0.012)
In_degree	0.0001 (0.0002)	-0.0002^{**} (0.0001)
Out_degree	-0.0005^{***} (0.0002)	-0.0001 (0.0001)
Betweenness Centrality	4.238^{**} (2.030)	0.095 (1.488)
Capital	0.044^{***} (0.009)	-0.002 (0.004)
Size	-0.030^{***} (0.009)	-0.012^{**} (0.005)
Firm Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Observations	2,511	28,139
R^2	0.370	0.677
Adjusted R^2	0.319	0.636

Table 10 2SLS estimates showing the increase in firms' markups over the last two decades. (*,,*** indicate statistical significance at 10%, 5%, 1% levels, respectively.)**

B.3. Markup vs Gross Margin: Which is a better measure of market power?

One may argue why we do not use gross margin to measure market power in our analyses. Although gross margin is more straightforward to calculate using standard financial data, it is, at best, a noisy signal of a firm's market power. This is because it only focuses on the difference between revenue and Cost of Goods Sold (COGS) and excludes other variable costs like Selling, General, and Administrative expenses (SGA) and other operating costs that can vary with output. This exclusion can make gross margins less representative of a firm's true economic costs. Conversely, markups are a better measure of market power because they consider the broader scope of variable costs and directly relate to a firm's ability to set prices above marginal costs, capturing the essence of market control.

Since gross margins ignore other variable costs like selling and administrative expenses, they could overestimate the extent of market power when these costs are significant. We demonstrate this in Figure 4. We track industries with varying proportions of variable costs (over COGS) and report the differences between gross margins and our estimated markups (firm-time level) for these industries. Specifically, for each industry, we (i) calculate the average of (SGA/COGS) over all firms, (ii) divide the industries into four quartiles based on this measure, and (iii) report the distributions of the differences between gross margin and estimated markups for these four quartiles. We note from Figure 4 that as the proportion of variables costs increases (going from Q1 to Q4), the mean of the distribution steadily increases, meaning that we may grossly overestimate market power if we were to use gross margin as a metric, especially for industries with a higher proportion of variable costs.

B.4. Robustness using Gross Margins

We test the robustness of our results by running the model with gross margin (GM) as the dependent variable instead of markups. Table 11 shows the corresponding 2SLS results for focal firms. The estimated coefficient in this specification is 0.146^{*}. Economically, this states that focal firms' gross margins increase by about 14.6% following vertical integration. Note that we use the same instrumental variable for this specification as our main results.

Table 11 indicates that the our main results are similar when using gross margins. The corresponding coefficient estimated from using markups is around 0.130 whereas the coefficient estimated using gross margins is 0.146. In other words, the two specifications perform similarly with slight differences in bias correction. Specifically, the coefficient using gross margins appears to be slightly overestimated. We think that this could be due to multiple reasons. (1) Given the fact that gross margin ignores other variable costs like selling and administrative expenses, they could overestimate the extent of market power when these costs are significant. (2) This overestimation may also arise due

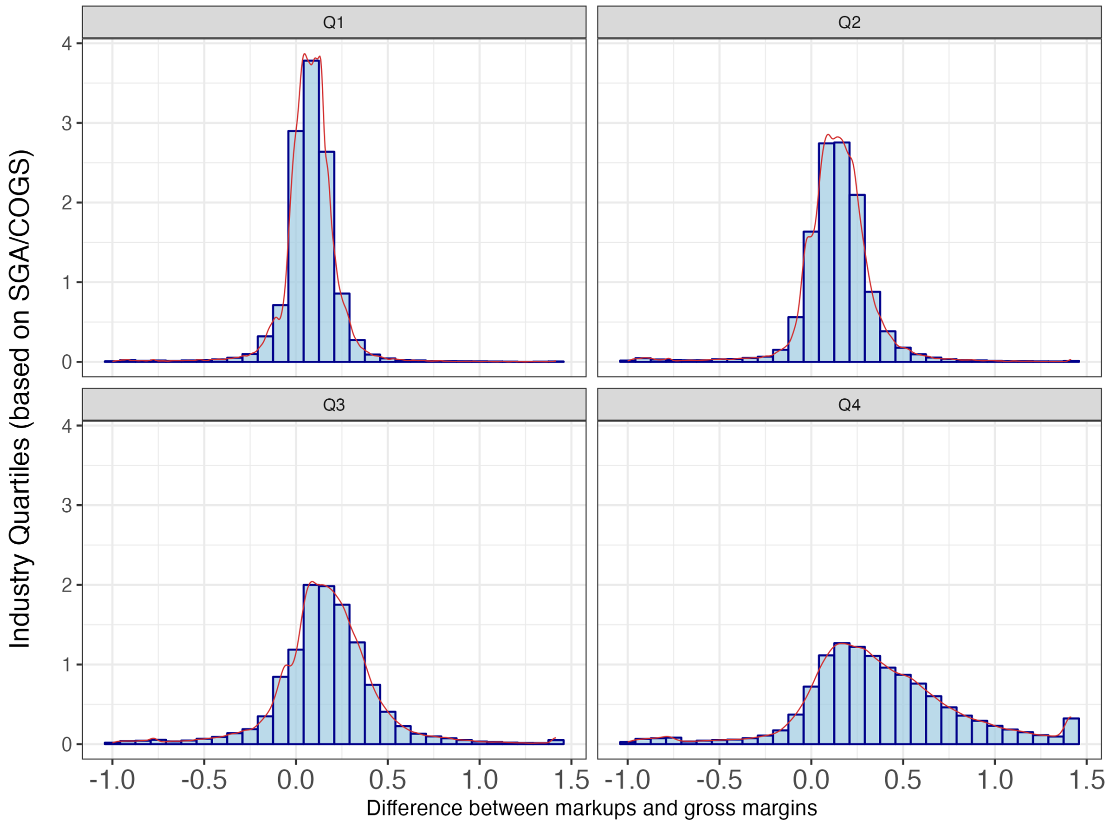


Figure 4 **Distribution of the difference between gross margin and our estimated markups**

	Focal Firm's Gross Margins
Vertical_Indicator	0.146^{*} (0.083)
In_degree	-0.0002 (0.0010)
Out_degree	0.0020 (0.0011)
Centrality (CB)	-15.25 (16.57)
Capital	0.296^{*} (0.118)
Size	-0.207^{**} (0.067)
Firm Fixed Effects	✓
Year Fixed Effects	✓
Observations	2,482
Adjusted R^2	0.01

Table 11 **2SLS estimates for the impact of vertical integration on focal firm's gross margins.**

to differences in scale between markup and gross margin or potential omitted factors that differentially impact the two measures. Overall, our results remain robust when using gross margin as the outcome variable. However, our recommendation would be to still use markups, as they are a more accurate measure of market power.

B.5. Validity of the Instrumental Variables Used

1. Falsification test using rumored mergers: To reinforce the validity of our instrumental variables and rule out confounding effects, we carried out falsification tests examining mergers that were rumored but ultimately unrealized. To do this, we constructed a dataset of rumored mergers by text-mining the historical descriptions of deals from the SDC Platinum database. We then identified rumored mergers that are of vertical nature and did not eventually go through. Table 12 shows some examples of such mergers along with the text descriptions.

Acquiror	Target	Deal Synopsis	Deal Status	History Event Description	Date Announced
30161N	744573	US - Exelon Corp (EXC) terminated its agreement to merge with Public Service Enterprise Group Inc (PSG), an electric utility holding company, in a stock swap transaction valued at $12.294 billion.	Withdrawn	Acquisition plans are rumored; Acquisition agreement is terminated;	20/12/04
037833	888706	US - Apple Computer Inc was rumored to be planning to acquire all the outstanding common stock of Tivo Inc, a provider of personal television services.	Dismissed Rumor	Acquisition plans are rumored;	23/02/05
842587	743263	US - Southern Co Inc was rumored to be planning to acquire all the outstanding common stock of Progress Energy Inc, a provider of electric services.	Dismissed Rumor	Merger plans are rumored;	22/03/06

Table 12 Examples of Vertical Merger Announcements and Rumors

To maintain consistency with our main analysis, we incorporated the same set of control variables and restrict the sample to our study period of 2003-2022.[4] Our difference-in-differences analysis indicates that the mere anticipation or rumor of a vertical merger has no significant impact on firms' markups (please see Table 13). This provides reassuring evidence that the markup effects observed in our main analyses can be attributed to the actual vertical integration process rather than to unobserved shocks or other confounding factors.

	Dependent Variable
	Markup
Rumor_Vertical_Indicator	-0.017 (0.017)
In_degree	0.0001 (0.0001)
Out_degree	-0.0001^{***} (0.00005)
CB	4.103^{***} (1.218)
Capital	0.066^{**} (0.027)
Size	-0.116^{***} (0.040)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	1849
Adjusted R^2	0.828

Table 13 OLS estimates for the impact of rumored vertical integration on firm's markups. (*, **, * indicate statistical significance at 10%, 5%, and 1% levels, respectively)**

2. Over-identification tests for instruments To formally assess the validity of our IV approach within the two-stage least squares (2SLS) framework, we conducted the Sargan–Hansen test, a standard procedure for evaluating instrument validity and over-identification. For this test, we constructed two separate instruments by applying different thresholds (5% and 10%) to identify extreme quarterly net mutual fund outflows, making our estimation setting over-identified by one. The test statistic had a p-value of 0.6338, indicating that we cannot reject the null hypothesis of instrument validity.

A note on the credibility of these IVs: Finally, we highlight that mutual fund flow-based IVs, initially introduced by Edmans et al. (2012), have subsequently been employed in several influential studies published in leading finance journals, including *The Journal of Finance* (Khan et al. 2012), *The Review of Financial Studies* (Phillips and Zhdanov 2013, Dessaint et al. 2019), and the *Journal of Financial Economics* (Lee and So 2017, Bonaime et al. 2018, Eckbo et al. 2018). Collectively, these studies demonstrate the effectiveness of Edmans-style IVs in isolating exogenous variation caused by mutual fund flows, thereby enabling researchers to credibly establish causal relationships.

[4] For this analysis, we treat the announcement year of the rumored merger as the "hypothetical treatment year."

B.6. Evidence of Vertical Foreclosure

Vertical or market foreclosure occurs when a company integrates with an upstream or downstream firm to harm its competitors. For instance, the integrated firm might block access to raw materials for its downstream rivals to gain monopoly power, which could reduce the rivals' production. It could also choose to sell its inputs at higher prices or provide low-quality inputs to its rivals. Thus, vertical foreclosure can create barriers to competitors' entry and reduce competition in the market, potentially leading to higher prices for consumers. Figure 5 depicts a foreclosure scenario where the focal firm F and its supplier S1 integrate, and S1 (now part of the integrated firm) decides to break its existing ties with the focal firm's competitor C. Here, competitor C is said to be foreclosed.

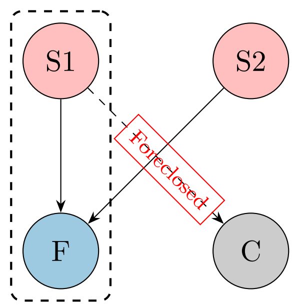


Figure 5 Illustration of vertical foreclosure: Focal firm F competes with firm C in the downstream market. Focal firm F and its supplier S1 (who supplies inputs to both F and C) integrate, and S1 (now part of the integrated firm) decides to break its existing ties with the focal firm's competitor C.

A large body of theoretical/analytical work has studied vertical foreclosure and firms' incentives to foreclose rivals (Ordover et al. 1990a, Hart and Tirole 1990, Rey and Tirole 2007, Chipty 2001). The foreclosure phenomenon has also been cited in many court cases. For example, in the United States, starting with *Terminal Railroad Association v. U.S. (1912)*, courts have established a doctrine on foreclosure (Boehm and Sonntag 2023). As a result, regulators and competition authorities closely monitor (and often intervene) cases presenting a risk of vertical foreclosure to protect consumer welfare. Antitrust and competition laws in various jurisdictions aim to prevent such practices when they significantly harm competition and consumer interests.[5] Despite the abundance of analytical work on foreclosure, the empirical evidence for foreclosure is quite limited due to the non-observability of vertical relationships.[6]

Estimating the extent of vertical foreclosure: We aim to measure the extent of vertical foreclosure by studying whether the supplier-customer link S1 $\rightarrow$ C in Figure 5 is more likely to break after S1 integrates with the focal firm F. In other words, we want to compare the probability of the link S1 $\rightarrow$ C breaking before and after S1 vertically integrates with F. To do so, we construct a set of all triples (s, c, t) where s and c have a supplier-buyer relationship in year t as identified through the FactSet dataset. We estimate the following linear-probability model to test for foreclosure:

$$\mathbb{1}\{\text{Link breakage}\}_{sct} = \beta\mathbb{1}\{s \text{ vertically integrates with c's competitor}\}_{sct} + \gamma_{sc} + \gamma_t + \gamma_{ct} + \epsilon_{sct} \tag{3}$$

where, $\mathbb{1}\{\text{Link breakage}\}_{sct}$ is a dummy that takes the value one if the link between the supplier and the customer is active in year t but not in $t+1$. $\mathbb{1}\{s \text{ vertically integrates with c's competitor}\}_{sct}$ is a dummy that takes value one if s

[5] Enforcement actions can include blocking mergers leading to vertical foreclosure, imposing conditions on mergers to ensure competitive markets, or taking legal action against firms abusing their dominant position.

[6] To our knowledge, Boehm and Sonntag (2023) is the only work that provides empirical evidence of foreclosure across a wide range of industries.

vertically integrates with c's competitor during year t (for example, with firm F in Figure 5) and β is the corresponding parameter of interest. We include a rich set of around 737,000 fixed effects in our model. Specifically, we include γ_{bs}, which are buyer $\times$ supplier fixed effects (479,404 in total), γ_{ct}, which are buyer $\times$ year fixed effects (257,531 in total) and γ_t, which are year fixed effects (20 in total).[7] We also include network-time-level characteristics for the supplier as controls in our model.

Table 14 shows the results of the estimated linear-probability model. We find that the probability of a supplier-buyer link breaking after the supplier vertically integrates with the buyer's competitor is about 35.3%. Our estimation results, which align with Boehm and Sonntag (2023), directly provide evidence for vertical foreclosure. By restricting competition through vertical foreclosure, vertically integrated firms might charge higher prices for their products or services, impacting consumers directly by harming welfare.

	Dependent Variable: $\mathbb{1}\{Link\ breakage\}_{sct}$
$\mathbb{1}$\{Supplier integrates with c's competitor\}	0.353^{***} (0.051)
In_degree	-0.0002^{**} (0.00007)
Out_degree	-0.0002^{*} (0.00009)
Betweenness Centrality	1.635 (2.286)
Year Fixed Effects	✓
Buyer x Year Fixed Effects	✓
Buyer x Supplier link Fixed Effects	✓
Observations	1,781,421
R^2	0.541

Table 14 Estimates of buyer-supplier link breakage probability when supplier vertical integrates with buyer's competitors. (*,,*** indicate statistical significance at 10%, 5%, 1% level, respectively.)**

B.7. Robustness to Hybrid Mergers

In our paper, we define vertical mergers as those mergers that occur between firms having a buyer-seller relationship. Horizontal mergers is when competitors combine to form one company (Viscusi et al. 2018). In this section, look more closely at the subset of mergers that may have both vertical and horizontal elements and test the robustness of our results to these "hybrid" mergers.

Specifically, we used data from FactSet and used the "competitor" relationship field to identify whether the acquirer and target firms in our vertical mergers had any direct product market competition—i.e., were they each other's competitors at the time of merger?. This exercise revealed 69 such mergers in our sample that exhibit both vertical linkages and horizontal overlap.

To test the robustness of our results, we re-estimated our main specifications after removing these 69 "hybrid" mergers. The key patterns—including the relationship between vertical integration and post-merger markup changes—remain statistically significant and qualitatively unchanged (please see Table 15, the result is actually a bit stronger with strict mergers- 13.9% vs 13.1%). This provides additional confidence that our findings are not driven by mergers that blur the vertical/horizontal boundary.

[7] We include buyer $\times$ year fixed effects to control for time-varying characteristics of buyers that affect their supplier relationships' breakage during a given year.

	Dependent Variable: Markup
Vertical_Indicator	0.139^{**} (0.063)
In_degree	-0.0001 (0.0001)
Out_degree	-0.00003 (0.0001)
CB	1.543 (1.073)
Capital	0.030^{***} (0.010)
Firm Fixed Effects	✓
Year Fixed Effects	✓
Observations	2,018
Adjusted R^2	0.668

Table 15 2SLS estimates for vertical integration on markup under strict case definition.

B.8. Effect of Vertical Integration on Firms' Cost Structures

To address the concern that higher markups do not necessarily reflect consumer harm, we conduct a more nuanced analysis that decomposes markup changes into price and cost components. This distinction allows us to assess whether observed markup increases stem from cost efficiencies—potentially beneficial from a welfare perspective—or from enhanced pricing power that could harm consumers.

Our core argument is that vertical integration leads to an increase in rivals' markups, which may indicate higher prices and thus potential consumer harm. However, an alternative explanation is also plausible: if the integrated firm becomes more efficient, it may pressure rivals to lower their costs, potentially raising rivals' markups without increasing their prices. To test this, we examine how vertical integration affects the cost structures of both rival and focal firms.

Effect on Rival Firms: We estimate a two-stage least squares (2SLS) regression, using the same instrumental variable strategy as in our baseline specification. The dependent variable is the log change in Cost of Goods Sold (COGS) for rival firms, and we estimate the specification separately for forward and backward integration cases (Table 16). In the case of backward integration, where the focal firm acquires its supplier, we find that rivals experience a statistically significant 2% increase in COGS on average. This positive coefficient suggests that vertical integration imposes cost externalities on competing firms, raising rather than lowering their costs. These findings are consistent with the Raising Rivals' Costs (RRC) theory originally proposed by Salop and Scheffman (1983). In contrast, for forward integration, we do not find conclusive evidence of any change in rivals' cost structures, supporting the interpretation that the observed markup increases are more likely due to price increases rather than cost reductions.

	Dependent Variable: log(COGS)	
	Forward Integration	*Backward Integration*
Vertical_Indicator	0.001 (0.007)	0.022^{***} (0.006)
In_degree	0.0005 (0.0006)	0.0003 (0.0005)
Out_degree	0.0007^{**} (0.0003)	0.0005^{*} (0.0003)
Centrality	20.073^{***} (5.842)	17.625^{***} (5.128)
Capital	0.316^{***} (0.022)	0.308^{***} (0.019)
Firm Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Observations	8,063	18,361
R^2	0.662	0.764

Table 16 2SLS estimates of the impact of forward and backward integration on rivals' cost structures. (*, **, * denote significance at the 10%, 5%, and 1% levels, respectively).**

Effect on Focal Firms: We also analyze whether vertical integration improves the cost efficiency of the integrating (focal) firm. Table 17 reports results from a similar 2SLS estimation. We find consistent evidence that vertical integration reduces the focal firm's COGS, with an average post-merger reduction of 4.2% for backward integration and 1.6% for forward integration. Given the log specification of the dependent variable, these coefficients reflect proportional cost savings. These results support classical theories of the firm, which posit that vertical integration can reduce transaction costs, improve coordination, and streamline procurement processes, thereby enhancing operational efficiency.

	Dependent Variable: log(COGS)	
	Forward Integration	*Backward Integration*
Vertical_Indicator	-0.016^{**} (0.006)	-0.042^{***} (0.005)
In_degree	-0.001 (0.001)	-0.002 (0.001)
Out_degree	-0.001 (0.0006)	-0.001 (0.0008)
Centrality	16.420^{*} (7.982)	19.540^{*} (8.326)
Capital	0.569^{***} (0.051)	0.583^{***} (0.048)
Firm Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Observations	1,204	1,595
R^2	0.769	0.773

Table 17 2SLS estimates of the impact of forward and backward integration on focal firm's cost structures. (*, **, * denote significance at the 10%, 5%, and 1% levels, respectively).**

B.9. Forward and Backward Integration

In this section, we classify vertical integrations into two categories-forward or backward-based on the direction of vertical integration. We then assess whether the effects differ across these two strategies. The identification of the two categories is straightforward - If the focal firm acquires their supplier, it is classified as backward integration. If the focal firm acquires their customer, it is classified as forward integration. We estimate separate treatment effects for forward and backward integration using our baseline regression model, instrumenting for vertical integration with MFHS instruments. The 2SLS estimates, reported in Table 18, indicate that backward integration has a stronger impact on post-integration markups than forward integration. Specifically, we find that backward integration leads to a 15% increase in markups, while forward integration results in a 10% increase, both statistically significant.

	Dependent Variable: Markups	
	Forward Integration	*Backward Integration*
Vertical_indicator	0.109^{*} (0.065)	0.152^{**} (0.076)
In_degree	-0.0002 (0.0002)	-0.00001 (0.0001)
Out_degree	0.00003 (0.0001)	-0.0001^{*} (0.0001)
Betweenness Centrality	4.107^{***} (1.278)	2.164^{**} (0.865)
Capital	0.056^{***} (0.021)	0.023^{***} (0.007)
Size	-0.069^{*} (0.036)	-0.018^{***} (0.007)
Firm Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Observations	1,204	1,595
R^2	0.619	0.790

Table 18 2SLS estimates for forward and backward vertical integration.

We note that the channels through which the two types of integrations help firms gain market power are possibly different. Backward integration typically confers greater market power than forward integration because it grants a firm control over essential upstream inputs—resources that are often scarce, costly to replicate, or critical to production. By acquiring suppliers, an integrated firm can raise rivals' costs or limit their access to key inputs, thereby weakening competitors and creating substantial entry barriers. This upstream leverage allows the firm to strategically foreclose input markets, denying competitors the scale or pricing needed to compete effectively (Salop and Scheffman (1983), Salop and Scheffman (1987). In contrast, forward integration—while it can enhance control over distribution and customer access—relies more on downstream dynamics that are often competitive and fragmented, making it harder to exclude rivals or raise prices unilaterally (Hart and Tirole (1990)). Theoretical models (Lin et al. (2014)) and empirical studies—such as those examining supply control in historical railroad and petroleum industries or healthcare consolidation (Lafontaine and Slade (2007))—suggest that while both forms of integration can affect competition, the ability to bottleneck supply through backward integration more reliably enhances market power across industries.

B.9.1. Raising Rival's Cost **Evidence from theoretical literature:** Salop and Scheffman (1983) first demonstrated that a firm with market power can profit by deliberately increasing its competitors' operating costs—such as by manipulating input prices or foreclosing distribution—thereby forcing rivals to raise prices. Krattenmaker and Salop (1986) extended this insight into the legal realm, arguing that vertical mergers can strategically raise rivals' costs by foreclosing access to key inputs or customers, and that such practices should be considered violations of antitrust law even when rivals remain in the market. Ordover et al. (1990b) formalized these ideas in a game-theoretic model, showing that foreclosure can emerge as an equilibrium outcome of vertical mergers in oligopolistic markets, where the integrated firm benefits by denying or degrading input access for its rivals, thus raising their costs and enabling higher prices.

Evidence from practice: Three prominent U.S. antitrust cases illustrate how vertical mergers can raise rivals' costs in ways that harm competition. In United States v. Ford Motor Co. (1972), the Supreme Court found that Ford's vertical acquisition of spark plug manufacturer Autolite could foreclose access to a key input for rival automakers and spark plug producers, effectively raising their costs by denying them an important supplier or forcing them to rely on less efficient alternatives. In United States v. Microsoft Corp. (2001), the D.C. Circuit found that Microsoft's exclusive contracts with computer manufacturers and Internet access providers raised Netscape's distribution costs by blocking efficient pre-installation and bundling channels. Similarly, in the DOJ's challenge to the AT&T–Time Warner merger (2018), the government argued that vertical integration would give AT&T the incentive and ability to raise content licensing prices for rival pay-TV providers—especially for "must-have" programming like HBO—thereby increasing competitors' input costs and weakening their ability to compete downstream. These examples illustrate how vertical mergers can have concrete, strategic effects on rivals' costs, echoing the empirical pattern we document in our setting.

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