Mergers and Market Power

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Abstract

Can mergers and acquisitions (M&A) explain recent trends in rising market power? While existing literature primarily focuses on the direct effects of mergers on acquirer markups, we propose a novel approach by examining the impact of M&A through the lens of revenue transfers. We introduce a unique methodology to quantify such transfers, revealing how they significantly shape industry composition and market power. Our analysis indicates that M&A activities, often involving substantial revenue shifts, play a crucial role in the rise of aggregate markups, explaining all of the increase in concentration and accounting for 40-80% of the markup rise. These findings offer new insights into the factors driving market power trends, emphasizing the need to consider broader revenue implications of M&As.

JEL: D4, G34, L11, L16, L4, L5

Keywords: *markups, mergers, M&A, company valuation, reallocation, competition, concentration*

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1 Introduction

The invisible hand of competition is essential for a flourishing economy. Higher competition leads to greater efficiency and resource allocation, while lower competition reduces welfare and decreases input demand, such as labor and capital investment. Increased market power additionally leads to higher inequality and hinders innovation, curtailing potential economic growth. Measuring and understanding the degree of competition is of first-rate importance to both academics and policymakers.

A growing literature has documented a decline in competition across the U.S. economy over the past few decades (Gutiérrez and Philippon, 2017; Barkai, 2020; Decker et al., 2014). De Loecker et al. (2020) trace the evolution of market power by measuring the markup of prices over marginal costs. They find aggregate markups have steadily increased from around 1.2 in 1980 to over 1.6 in 2016. Similarly, Grullon et al. (2019), Autor et al. (2020b), and Covarrubias et al. (2020) show rising industry concentration ratios since the late 1990s. While the effects of increased markups and concentration on other macroeconomic trends, such as declining labor and capital share, lower business dynamism, and lower innovation, are well understood, it is less clear what is behind the rise in markups and concentration.

Mergers and Acquisitions (M&A) have been proposed as one potential explanation for the observed trends in market power.[1] The M&A as a potential driver is both appealing from theory and from data point of view. Theoretically, mergers may lower competition and lead to higher markups and concentration. Given the almost-exponential increase in the number of M&A activities from 1980's onward (Figure 1), these activities could explain the rising market power trends across many industries.[2] However, the empirical evidence on the effects of M&A on market power is mixed. While the prior literature has primarily looked at whether mergers affect acquirer markups, they have mostly neglected to account that any such potential changes are also accompanied by large revenue changes for the acquirers. Post-merger, acquirers become larger entities, sometimes substantially so. Their increase in size, even if the acquirer markups do not change, can still impact the aggregate markups.

To illustrate our intuition, let's examine the 2013 merger between American Airlines and US Airways. Before merging, American Airlines reported \$26.7 billion in revenue with a markup of 1.16, while US Airways had \$13.8 billion in revenue and a markup of 1.04. In 2014, post-merger, American Airlines' revenue jumped to \$42.6 billion, a more than 50%

[1] Other potential explanations include changes in technology, globalization, the rise of intangible assets, among others (Philippon, 2019).

[2] According to *WSJ*, M&A deals exceeded \$4 trillion globally in 2015, https://www.wsj.com/articles/2015-becomes-the-biggest-m-a-year-ever-1449187101, accessed November 8, 2023.

increase primarily attributable to the addition of US Airways' revenue.[3] The new entity had a markup of 1.2. To assess the merger's impact on overall markups, consider two approaches: First, comparing American's pre- and post-merger markups shows an increase from 1.16 to 1.2, a 0.04 increase.[4] However, when comparing the post-merger markup of 1.2 against the pre-merger weighted average markup of 1.12,[5] shows an overall effect of 0.08. This significant difference stems from the revenue shift from US Airways, which had a lower markup, to American Airlines, which had a higher markup. This case illustrates that revenue transfers during mergers can substantially influence aggregate markups.

In this paper, we examine how the M&As influence aggregate markups, focusing not on their effect on the acquirer's markups but rather on the *revenue transfer* to the acquirer. The revenue transfer channel will have a large impact on aggregate markups if: 1. the revenue transfers themselves are large, and 2. they largely work by moving revenues from targets with lower markups to acquirers with higher markups. We find that both these factors are significant. M&As typically involve large revenue transfers. The second factor encompasses two processes: the transfer of revenues to the acquiring firm and the exit of the target from the market. For the majority of M&A deals in our study, target companies are not in the dataset, leading us to first measure the impact on aggregate markups of the revenue transfer to the acquirer. However, where data on the target company is available, we extend our analysis to encompass the full impact of the transfer of the acquirer and target exit.

We set out to document all M&A activities that the US publicly traded firms are involved in and measure the revenue transfers for each M&A deal with know transaction price. In doing so, we establish six facts:

i) M&As are large revenue transfer activities. In fact, by looking at the impact of the M&As on the revenues of the acquirers, we can account for *all* of the rise in concentration as documented in the prior literature.

ii) Firms with higher markups are more likely to merge, and their revenue transfers are larger. This effect also holds for larger firms, in line with prior literature indicating that larger firms have higher markups Autor et al. (2020b).

iii) Combining Facts **i** and **ii**, we find that M&A activities explain nearly 40% of the rise in markups, as documented in De Loecker et al. (2020) (DLEU). Our approach corroborates the DLEU decomposition, showing that increase in aggregate markups

[3] The combined pre-merger revenue of both companies was \$40.5 billion.

[4] This effect on aggregate markups would be lower when using American's pre-merger revenues.

[5] Calculated as $\frac{26.7}{26.7+13.8} \times 1.16 + \frac{13.8}{26.7+13.8} \times 1.04$.

are largely driven by the reallocation effect: the overall markup increases primarily because firms with higher markups grow more than the average. We find that this growth is largely driven by M&A activities: the revenue transfer can explain over 60% of the reallocation term.

iv) Targets are more likely to have lower markups. The effect holds both across firms and within a firm over time. For the targets for which we can measure markups, we combine the target exit with the reallocation term to measure the overall revenue transfer effect of the M&A activity. This total effect is more than twice as large as the reallocation effect alone. Extending this ratio to the full sample, M&A activities can explain over 80% of the rise in markups.

v) Mergers and Acquisitions also increase firms' own markups. Motivated by the observation of merger waves occurring across industries, we leverage our revenue transfer approach to propose a leave-one-out instrument. Here, the size of the M&A is instrumented with the average size of revenue transfers across other industries. We find that firms' own markups increase both in an event study and in the IV specification.

vi) M&As also raise markups for other firms in the same industry.

We present a simple theoretical model in line with these facts. The intuition of the model is that while mergers and acquisitions tend to raise profits, the effects are stronger the bigger is the firm or the bigger is the acquiring target.

The main innovation of the paper is to measure revenue transfers that occur during M&As. To do so, we leverage the large database of M&A activities from SDC Platinum. SDC contains a comprehensive information on mergers and acquisitions, and has been used extensively in prior literature (Barrios and Wollmann, 2022; Barnes et al., 2014). From SDC we are interested in several key variables: which targets firms are acquired or merged with, their revenues, and the shares acquired. SDC aims to provide comprehensive information for each merger and acquisition. For many transactions, it also includes financial information of the target firms that are acquired. However, this financial information is missing for the majority of the transactions.

To utilize the entire set of mergers and acquisitions, we establish a robust linear relationship between the (log) sale price paid for the transaction and the (log) revenue of the target. Based on this relationship, we propose a novel method for predicting target revenues. This single variable, combined with the share acquired, explains 56% of R^2 in the linear specification. The coefficient estimate remains stable to the inclusion of host of fixed effects, such as geographic, time, and industry fixed effects, at varying degrees of granularity. These results alleviate concerns about potential omitted variable bias in the specification (Altonji et al., 2005; Oster, 2019). They are also in line with the "multiples" approach to firm valuation (Kaplan and Ruback, 1995; Liu et al., 2002). This approach has not been validated on private firms and on such a large scale. We use this relationship to predict missing target sales using other relevant information about the mergers. Our preferred specification utilizes the transaction value, shares acquired, US state/foreign country identifier, year of the merger, and 3-digit industry codes in a random forest specification. The findings robust to using alternative specifications, such as linear prediction or Lasso.

We next verify that our calculated revenue transfers from targets to acquirers are, in fact, reflected in the revenues of the acquirers. To do so, we calculate the acquirer excess revenue, defined as the difference between the current revenue and the expected revenue, based on prior periods' growth trends. We find that acquirer excess revenues grow 1-1 with target revenues.

We conduct a series of robustness checks to ensure that our results are not driven by specific assumptions regarding predicted revenues. As mentioned earlier, the results are robust to alternative prediction algorithms such as a linear specification or Lasso. We also find similar results when we use alternative sources for target revenues. Finally, for a set of deals, we manually verify how well our prediction algorithm corresponds to actual target revenues and find that our predictions align with the actual figures. Overall, these results confirm the validity of our approach.

Our findings imply a significant impact of M&As on rising markups and higher concentration. These effects may extend beyond the reallocation term. Facts ii), v), and vi), taken together, suggest that mergers and acquisitions could have a reinforcing effect. As a merger by a firm in an industry increases its own markup as well as the markups of other firms in the industry, this then increases the likelihood of future mergers, further amplifying the overall effect of M&As on markups over time. Such potential dynamic effects should be carefully considered by regulators and policymakers.

Related Literature. Our work relates to several strands of literature in economics, finance, and antitrust. A large and growing body of literature has documented the rise in market power and declining competition in the US and other countries (De Loecker et al., 2020; Grullon et al., 2019; Gutiérrez and Philippon, 2017; Gutierrez and Philippon, 2023; Philippon, 2019; Autor et al., 2020b). De Loecker et al. (2020) document rise in markups in the US from 1980 onwards, while Grullon et al. (2019) show increasing concentration from the late 1990s. Further, Autor et al. (2020b) document falling labor share in the major industries across the US and other countries. Several hypotheses have been put forth what is behind the rise in markups and concentration: changes in technology, globalization, rise in intangible assets or mergers and acquisitions (Philippon, 2019). While the intuition behind the M&As is theoretically straightforward, and prior work has found that M&As lead to higher profits (Grullon et al., 2019), higher markups for rival firms (Stiebale and Szücs, 2022), and more lobbying (Cowgill et al., 2023), the direct empirical evidence on the effects of M&As on markups has been mixed (Blonigen and Pierce, 2016; Chen, 2019; Cao and Zhu, 2022; Arnold et al., 2022). We contribute to the literature by proposing a new way to measure M&As by documenting the revenue transfers that occur from targets to acquirers.

Additionally, a robust finding in decomposing the aggregate trends in rising market power, or falling labor share, is the significance of the reallocation term (De Loecker et al., 2020; Foster et al., 2022; Autor et al., 2020b). Economy-wide markups increase as the firms with higher markups grow larger, while the media markup remains the same. The same intuition also holds for declining labor share. We contribute to these findings by providing a channel for the increase in the reallocation term: mergers and acquisitions. Higher markup firms do not necessarily grow faster internally, but do so by acquiring other firms. The raises the overall economy-wide markup.

There has been growing discussion on the increase in mergers and acquisitions in the economy (Wollmann, 2019; Barrios and Wollmann, 2022; Eeckhout, 2022). However, to date the literature has not analyzed how the overall size of the M&As has affected other observed trends in the economy. We contribute to this by showing that not only the number of M&As but also the size of the deals, as measured by revenue transfers, has been increasing.

We also contribute to the literature on the empirical findings of firm valuation. The "multiples" approach establishes a link between the value of a firm and its revenues. This theoretical result has been tested only with publicly traded firms, where revenue and firm valuation information are readily available (Kaplan and Ruback, 1995; Liu et al., 2002). We contribute to this literature by empirically testing the effect for private firms and on a much larger scale than has been done in previous analyses.

Finally, in analyzing the aggregate effect of mergers on the economy we contribute to the literature on capital misallocation, pioneered by the seminal work of Hsieh and Klenow (2009). Recent applications identify the sources of capital misallocation in declining real interest rate (Gopinath et al., 2017), capital liberalization (Bau and Matray, 2023; Varela, 2018), international trade (Xu, 2022), business cycle (Kehrig, 2015), and bank lending (Delatte et al., 2020). We show how mergers relocate capital to firms with higher market power, leading to a significant increase in aggregate markups.

Road-Map. The rest of the paper is organized as follows. Section 2 presents data. Section 3 presents our methodology for computing revenue transfers. Section 4 validates our methodology. Section 5 presents the theoretical model. Section 6 discusses our main findings. Section 7 addresses robustness of our findings, and Section 8 concludes.

2 Data

We use data from two main sources to study the effect of mergers and acquisitions on market power. First, we use Compustat to compute a measure of firm-level markups, which we then match to SDC Platinum for information on mergers and acquisitions.

Compustat contains the financial statements of U.S. publicly traded companies and several large private firms. It includes the Sales, Cost of Goods Sold (COGS), and other balance sheet information. We use Compustat to calculate markups and concentration ratios. In some concentration ratio specifications, we also use Census figures to determine the overall size of each industry, which includes public and private firms.

SDC Platinum provides information on mergers and acquisitions around the world, including share buybacks. This information is collected from various sources, such as media reports and regulatory filings. It is the most widely used dataset for analyzing mergers and acquisitions in both finance and economics (Barrios and Wollmann, 2022; Barnes et al., 2014). For each merger or acquisition, comprehensive detailed information is provided.[6] Relevant to us, it includes the Date of the Merger/Acquisition Announcement,[7] the Acquirer Name, Target Name, along with Acquirer and Target CUSIP numbers. The CUSIP numbers are provided in three categories: the Company, the Immediate Parent Company, and the Ultimate Parent Company.[8] Further, a brief synopsis of the merger is included. Additional details on the merger include the value of the transaction, and financial information on target (as well as information on advisors). A critical aspect of the target information includes "net sales", which is defined as "Primary source of revenue after taking into account returned goods and allowances for price reductions for the last 12 months ending on the date of the most recent financial information prior to the announcement of the transaction ($mil). If not available, total revenues are used. For banks, net sales equals interest income plus non-interest income." Broadly, this corresponds to the sales definition of Compustat, which is

[6] Throughout the analysis, we would refer to "target" and "acquirer", even in cases of mergers between two firms. That is because, in the SDC dataset, both under mergers and acquisitions, the acquirer and the target are clearly defined.

[7] As well as other relevant merger dates, such as the Effective Date, or the Date of withdrawal, if any.

[8] They are largely the same for most companies but may differ for some. We utilize all three CUSIP numbers in matching SDC mergers with Compustat.

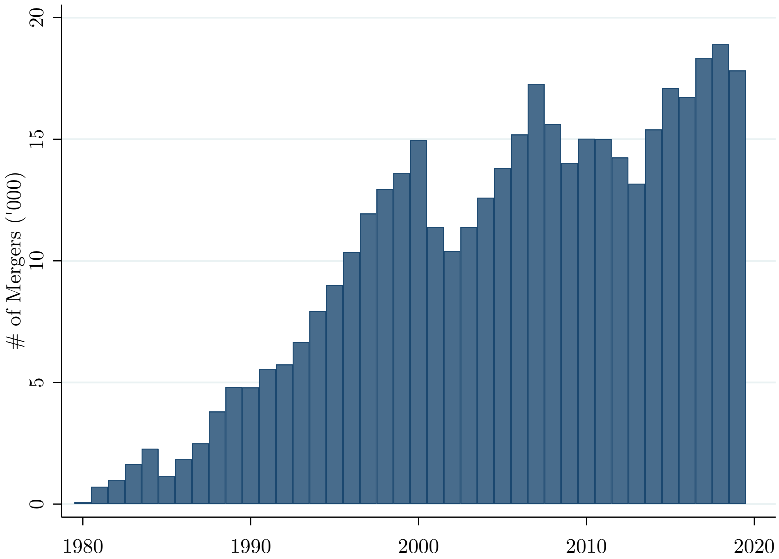


Figure 1: Total Number of M&A with Known Price

Notes: The graph shows the total number of mergers and acquisitions reported by the SDC, with known transaction value. The number of mergers is expressed in thousands.

"gross sales, the amount of actual billings to customers for regular sales completed during the period, reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers." We use this sales information, along with the shares acquired, to measure the revenue transfer from the target to the acquirer.

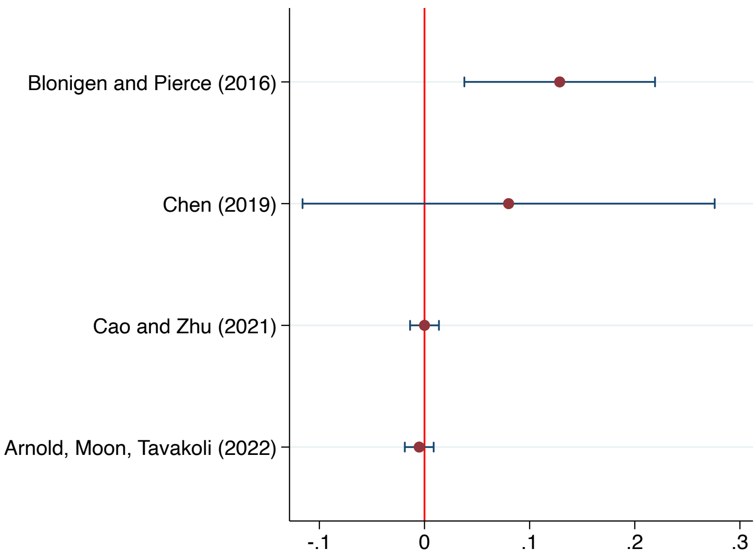


Figure 2: Literature Review

Notes: The figure shows the results of prior studies on the effect of M&A on markups.

Figure 1 presents the overall count of mergers and acquisitions in SDC dataset where the transaction price is known. For the early years of the sample, until late 1980's, the number of M&A activities is low. From then on, there is a steady increase in the number of overall cases, peaking in 2000. Following the burst of tech bubble and the ensuing recession, the number of M&A activity drops until 2002, with the next peak coming in 2007, right before the Great Financial Crisis and the Great Recession. The pace of M&A activity is picked up again from early 2010s, steadily increasing until the end of the sample. Figure A.2 in the appendix plots the same graph for all mergers and acquisitions. The total number of cases in the latter is about 4 times larger and shows the same pattern. We find larger effects of the contribution of the merger activity to the reallocation term during the periods of high overall merger activity.

2.1 Merging/Matching

We first match the acquiring firms in the SDC dataset to the firms in Compustat. We use CUSIP number as our primary matching identifier, as is typically done in the literature. For example, Cowgill et al. (2023) also combine Compustat with SDC using CUSIP identifiers, and it is reassuring that their total matches align with our results. To maximize the number of potential mergers and acquisitions in the data, we expand the matching algorithm to also include exact name matches, matches via ticker symbols, and commonality of search engine results. The latter has been shown to perform well in identifying different name variants and spellings of the same company (Autor et al., 2020a). Appendix B provides further details of our matching methodology. For all the matches that are not done via CUSIP or exact name matches, we manually check the results to account for any false positives.

Table B.1 provides the matching results. Out of 21,367 distinct firms in the Compustat dataset used for markup calculation, 15,919 of them have ever merged with or acquired another company. This is a somewhat skewed result, as these firms are involved in 70,428 merger and acquisitions, with many firm-years including multiple M&A transactions.

2.2 Markups

We use firm information from Compustat to compute a measure of firm-level markups. Compustat provides financial information for the universe of publicly listed firms in the U.S. from the 1950s onward. In addition to firm identifiers and sector classification, it includes revenues and costs of goods sold, which are necessary for computing markup indicators. We

Variable	Acronym	Mean	Median	No.Obs
Sales	SALE	1,925,342	147,737	247,845
Cost of Goods Sold	COGS	1,017,983	55,358	247,845

Table 1: Summary Statistics

Notes: All variables are expressed in thousands of Dollars deflated using the GDP deflator with base year 2010.

restrict the time period to 1980 - 2016 and follow the same data preparation as De Loecker et al. (2020). Table 1 hows summary statistics for the sample under analysis.

In order to compute markups, i.e., the ratio of price over marginal costs, we employ the production function approach pioneered by Hall (1988) and De Loecker and Warzynski (2012). This method is a structural approach based on a firm's optimizing behavior with respect to static cost minimization and derives a straightforward formulation for firm-level markups:

$$\mu_{it} = \theta_{it}^{v} \frac{P_{it} Q_{it}}{P_{it}^{V} V_i t}$$

with μ_{it} being firm i's markup in time t, θ_{it}^{v} the output elasticity with respect to the flexible input v, P_{it} and Q_{it} price and quantity of final product sold by firm i in time t and finally, P_{it}^{V} and V_{it} price and quantity of variable input v used. We leave the full derivation of this formula in Appendix C.

We use the 2-digit-sector-specific and time-varying output elasticities from De Loecker et al. (2020) to compute firm-level markups.

3 Target Sales

The key information necessary for our analysis is the revenue of the target firm. SDC tries to provide comprehensive information for each merger and acquisition event, including financial information of the target firm, such as revenues. The target revenue information, however, is more often missing than available. This is the case both in the overall SDC database, and also for the subset of transactions that are matched to Compustat. In the overall SDC sample, revenues are available in only 32% of M&A events. In the matched subset, it is slightly better at 37%. For the analysis of the revenue contributions of the target firms from all transactions, considering only transactions with non-missing revenues would discard the vast majority of merger and acquisition activities, potentially diluting our main object of interest. Trying to obtain the missing target revenue information from alternative sources is prohibitively expensive. We instead infer the missing revenues using other available data

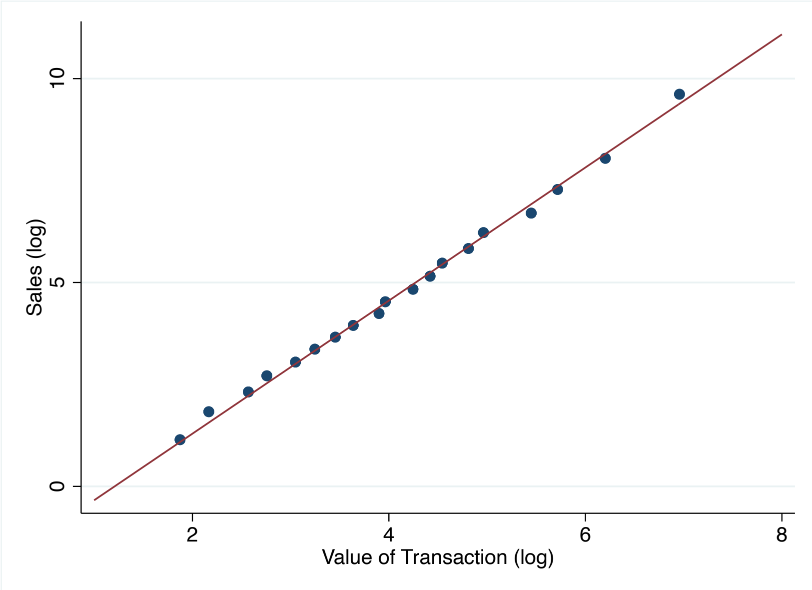


Figure 3: A Log-linear Relation

Notes: Binscatter between (the log of) target sales and (the log of) the transaction value.

on the event. In our main specification we use the transaction value - how much was paid for the merger, the shares of the company acquired, the year of the merger, the location and industry classification for the both the acquirer and the target to infer the revenues of the target firm.[9]

We first document a very robust linear relationship between the (log) revenue of the target firm and the (log) transaction value, while controlling for shares acquired. Figure 3 shows the binscatter plot of the log value and the log revenues in the matched SDC database when both information are available. The linear specification of Figure 3 is precise at all bins, and the explanatory power is also large: log value alone explains 56% of the variation of the regression, implying a correlation of 75% between the two variables.[10] Such a linear relationship is in line with a simple theory of the "multiples" approach, where the value of the firm reflects the present discounted value of future revenues, and the current revenue is an informative statistic of future revenues (Kaplan and Ruback, 1995; Liu et al., 2002). Then, in the absence of any financing frictions, the price paid is equal to the value of the acquisition and, thus, will be a multiple of firm revenue. Prior work has empirically tested this using a limited number of publicly listed firms, with information on both the value and the revenues of the firm available. To our knowledge, we are the first to empirically document

[9] As mentioned from Figures 1 and A.2, there are also many more cases where the price of the transaction is also not available.

[10] In the Figure and the specification we also include share buybacks - firms buying back a portion of their outstanding shares. We exclude share buybacks in the analysis. Share buybacks comprise about 5% of all M&A activities, and the results are robust to excluding them.

this relationship for private, non-traded set of companies and on such a large scale.

Table 2 presents the stability of the estimated coefficient, when an increasingly richer set of fixed effects are added. Column 1 presents the baseline specification with only log value and shares acquired as the explanatory variables.[11] Column 2 adds year-of-the-merger fixed effects.[12] Columns 3 to 9 gradually add more granular industry sector fixed effects, starting from two-digit information (around 60 in total), and increasing to four-digit information (around 900 in total). Columns 10 and 11 include the geographic location of both parties, which are either the foreign country or the U.S. state where the headquarters are located. Finally, column 12 provides the specification with all fixed effects combined. As can be seen, the coefficient of the log value barely changes with the inclusion of various fixed effects, while the R^2 increases from an initial level of 0.56 to 0.70. This also allays any concerns about the coefficient stability due to omitted variable bias (Altonji et al., 2005; Oster, 2019).

We use the above relationship to predict missing revenues.[13] We make use of all the controls in the specification: value of the transaction, shares of the target firm acquired, time, geographic, and industry fixed effects. Our baseline approach uses a random forest specification, with 3-digit industry fixed effects. The results are almost identical when using alternative approaches, including linear specifications with fixed effects or Lasso. In doing so, we document a novel empirical fact about mergers. While prior work has documented increase in the number or total deal value of the mergers over time, we also document that the revenue share, that is transferred during mergers, is also increasing over time.

4 Validation of Revenue Transfer

Before diving into the model and our main results, we set out to perform a validation check to test whether acquirer revenues do in fact increase after acquisition and how well this increase corresponds to the revenues of the target. If our approach holds, then there should be a close relation between the target's revenue and the increase in the acquirer revenue. To test this, we construct a measure of "excess" revenues for the acquirer, which measures the deviation from its recent growth trend. Formally, we define excess revenues as $A_{t+1} - A_t(1 + \bar{g_n})$, where A_t and A_{t+1} are acquirer revenues for t and $t + 1$, respectively, and $\bar{g_n}$ is the average growth

[11] The acquired shares can be incorporated in two ways: one as an explanatory variable, and the other by adjusting the revenues by shares acquired directly. We opt for the first approach as it is more general and, in the log-log regression, would also encompass the second approach.

[12] Defined as the effective date. The results are robust to other alternatives, e.g., the announcement date.

[13] We also use it to correct for any obvious errors in the revenue information in the SDC database, such as numbers reported in thousands instead of millions.

Table 2: Log-Sale Log-Price Relation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Value (log)	0.75***	0.78***	0.76***	0.76***	0.75***	0.76***	0.76***	0.76***	0.75***	0.75***	0.77***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Share Aquired	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	No	Yes	No	No	No	No	No	No	No	No	Yes
Acquiror 2d-Ind FE	No	No	Yes	No	No	No	No	No	No	No	No
Target 2d-Ind FE	No	No	No	Yes	No	No	No	No	No	No	No
Acquiror 3d-Ind FE	No	No	No	No	Yes	No	No	No	No	No	No
Target 3d-Ind FE	No	No	No	No	No	Yes	No	No	No	No	No
Acquiror 4d-Ind FE	No	No	No	No	No	No	Yes	No	No	No	Yes
Target 4d-Ind FE	No	No	No	No	No	No	No	Yes	No	No	Yes
Acquiror Geo FE	No	No	No	No	No	No	No	No	Yes	No	Yes
Target Geo FE	No	No	No	No	No	No	No	No	No	Yes	Yes
R^2	0.56	0.58	0.61	0.63	0.63	0.65	0.65	0.67	0.58	0.59	0.70
N	25,280	25,280	25,280	25,280	25,280	25,280	25,280	25,280	25,280	25,280	25,280

Standard errors are clustered at the acquiror level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

rate of the revenue calculated over the preceding n periods. For a merger or acquisition taking place at period t we regress the excess revenue on the target's revenue:

$$A_{t+1} - A_t(1 + \bar{g_n}) = \beta T_t + \varepsilon_t,$$

where T_t is the target's revenue. We are interested in the coefficient β, which by our intuition should be positive and close to 1. Table 3 presents the results. Columns 1-6 show the regression results in levels at different lags of growth rates, whereas Columns 7-12 do the same exercise in logs. For all specifications, we consider those firms that had M&A activity, but did not have a merger or acquisition in any of the previous lagged periods. We find a large positive coefficient for β, as predicted by our hypothesis. This effect increases and becomes close to 1 for longer lags, potentially eliminating any short-term fluctuations that might occur with smaller lags. The effect is present even with the specification that includes a constant term.[14] Since the result in levels might be driven by outliers of large M&A deals, we also look at the effect in logs.[15] The effect is also present in logs and is quite stable across different specification of lags. We again have a coefficient of 1 in the no constant specification. This confirms our intuition that mergers induce large revenue changes in acquirers, and these changes correspond to the target's revenue.

Table 3: Validation of Methodology

	Levels						Logs					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TSales	1.05	0.97	0.60	1.03	0.94	0.59	0.71	0.71	0.70	1.00	1.01	1.01
Constant	-141492	-200478	-170691				3.13	3.18	3.38			
Lags	4	3	2	4	3	2	4	3	2	4	3	2
N	5413	7527	11025	5413	7527	11025	3090	4296	6163	3090	4296	6163

Notes: The table presents the regression coefficients of the excess revenue of the Acquirer on the Target. The excess revenues are calculated as next period revenue minus current period revenue, multiplied relative to a growth rate. The growth rates are calculated as the average of prior 2, 3 0r 4 periods. Columns 1-6 report the estimates in levels, and columns 7-12 report in logs.

[14] Incidentally, the negative constant term indicates that, absent the effect of a revenue increase through a merger, acquirers would on average have lower revenue than their recent trend would indicate.

[15] The drawback of log specification is that it excludes firms with negative revenue changes.

5 Model

We provide a simple setup for the model that underlines the intuition of our results. The full model, that considers a more general demand specification, is in the appendix. Suppose there are n firms in a market, each producing one product. The consumer choice set is governed by the discrete choice logit utility setup:

$$u_{ij} = \beta x_j - \alpha p_j + \varepsilon_{ij}, \tag{1}$$

giving rise to the familiar logit shares:

$$s_j = \frac{exp(\beta x_j - \alpha p_j)}{\sum_k (\beta x_k - \alpha p_k)} \tag{2}$$

Further, assume each firm is producing only a single product. Then the solution to the firm's maximization will be given by:

$$p_j = mc_j + \frac{1}{\alpha(1 - s_j)}, \tag{3}$$

where mc_j is the marginal cost for firm j. It follows that the higher the firm's market share, the larger will be its price. Now suppose firms 1 and 2 merge.[16] If there are no synergies or other impact on marginal costs, then the joint profit maximization for them will solve for the new equilibrium prices p_1^m and p_2^m. In particular, for p_1^m, we'll have:

$$p_1^m = mc_1 + \frac{1}{\alpha(1 - s_1^m)} + (p_2^m - mc_2)\frac{s_2^m}{1 - s_1^m} \tag{4}$$

The difference between p_1^m and p_1 will be higher, the larger s_2^m is, and the larger s_1^m is. Thus, larger mergers lead to higher price increases. Further, the prices of the other, non-merging firms also increase. It is straightforward to show that this also leads to higher profits. This implies, ceteris paribus,[17] that a merger is more likely to take place for a larger firm, which is also more likely to merge with another large firm. This intuition also holds in a more general setting and aligns with the results of prior work that considers Bertrand-Nash competition with differentiated products Deneckere and Davidson (1985); Belleflamme and Peitz (2015); Werden and Froeb (1994).

[16] In this setup we consider a horizontal merger, that has an effect through the pricing equation. In a more general setting we also consider mergers that impact mc_j of the firms.

[17] For example, if the firm can be in only one merger at a time.

6 Empirical Facts About Mergers

Fact 1: Mergers Explain All of the Rise in Concentration

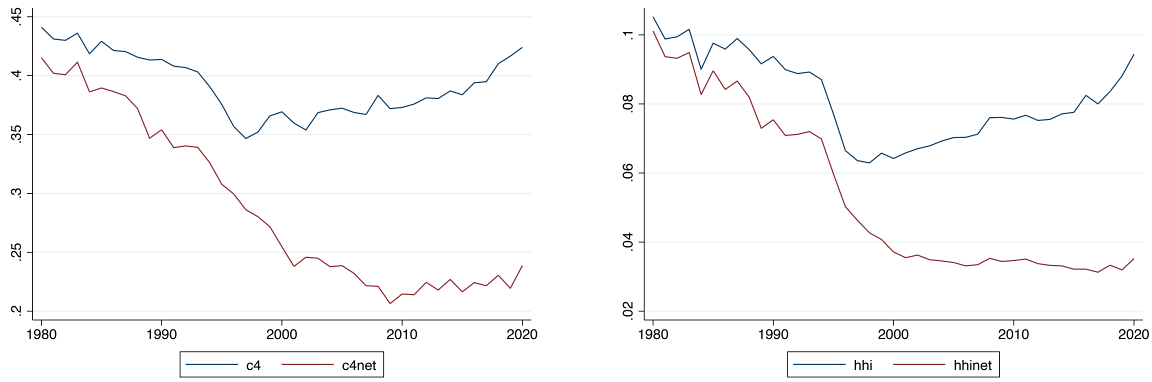
There has been a recent discussion on rise in concentration and its potential effect on market competitiveness (Autor et al., 2020b; Gutiérrez and Philippon, 2017; Grullon et al., 2019). In particular, using the Compustat dataset, (Grullon et al., 2019) documents rising industry-wide concentration in the US starting the late 1990s. Using Census data, Autor et al. (2020b) also show rising concentration across major sectors in the US. To measure the effect of mergers on changes in concentration, we first document in the Compustat data the same trend that Grullon et al. (2019) observe using both Herfindahl-Hirschman-Index (HHI) and the four-firm concentration ratio (C4) measures. For the HHI measure, we calculate HHI for each industry, at the 3-digit level, and then aggregate it to the overall US economy, using respective industry weights in the overall economy. The industry weights ensure that the smaller or declining industries have less impact on the overall economy-wide measure of concentration. Similarly, we calculate the C4 measure for each industry, taking the four largest publicly traded firms over all public firms. We again use the industry weights to aggregate industry concentration measures to the overall economy measure.

Figure 4a presents the results. As can be seen in the figure, we find overall increase in concentration measures across both specifications. For the publicly traded firms, we find increasing concentration from the late 1990s, in line with the findings of Grullon et al. (2019).

We next measure how much of each firm revenue change is due to M&A. For that, we construct a cumulative merger revenue measure that accounts for all target revenues acquired by the firm - each new acquisition's revenue is added to the cumulative measure for that year. We also scale this measure year-to-year with the growth rate of the firm, to ensure that the share of the firm that is due to a merger will not decrease as the firm grows and no future mergers take place. For example, if a firm acquires a target that represents 5% of its revenue and is not involved in any other mergers, then in all future years, the merger share of the firm relative to the firm's overall revenue will stay fixed at 5%. Finally, we subtract the cumulative merger revenue share from the firm's overall revenue and recalculate the concentration measures.[18] Figure 4a shows the results. As can be seen, without accounting for merger revenue, both concentration measures are much lower than the overall economy-wide measures. Moreover, the recent rise in concentration measures is severely diminished

[18] There is also the issue of what to do with the subtracted merger revenue amount. One may treat them as individual firms and recalculate the C4 and HHI measures with them included, or one may exclude from the sample. Our results are robust to either approach.

when taking away the merger revenues, and in the case of the HHI and the C4 measures with the publicly traded firms, it disappears completely.



(a) C4

(b) HHI

Figure 4: Concentration and Mergers

Notes: The figure shows the concentration ratios of the 3-digit industries, and measures the concentration without the revenue transfers from the mergers.

Fact 2: Large Firms Are More Likely To Acquire

Our next fact deals with which firms are more likely to be involved in M&A deals. Guided by our theoretical result, we test whether higher markup firms are more likely to merge and acquire other firms. Autor et al. (2020b), using Census data, have shown that larger firms are more likely to have higher markups. We find the same effect using Compustat data. The binscatter plot in Figure 7 confirms the finding. We further verify this by running the following specification:

$$\mathbb{1}[\mathrm{A}]_{ist} = \beta_0 + \beta_1 s_{ist-1} + \beta_i + \beta_{st} + \varepsilon_{ist}$$

with $\mathbb{1}[\mathrm{A}]_{ist}$ being a dummy that takes the value 1 if firm i in sector s engages in a merger as an acquirer at time t. s_{ist-1} are firm i's (log) sales at time t-1 and β_i and β_{st} are firm and time-varying sector fixed effects, respectively. In an alternative specification, we also run:

$$\mathbb{1}[\mathrm{A}]_{ist} = \beta_0 + \beta_1 \mu_{ist-1} + \beta_i + \beta_{st} + \varepsilon_{ist}$$

with μ_{ist-1} being firm i's markups at time t-1 and the other variables as defined before. Table 4 presents the results of the effect of lagged sales on markup. The effect shows a strong positive effect of larger firms on the probability of being engaged in M&A. The coefficient estimate indicates that roughly doubling the firm's size increases the likelihood of M&A activity in that period by about 3%. This is a sizeable effect, given that out of all possible firm-years, roughly 14% have M&A activity. The coefficient doesn't change with the inclusion of finer levels of fixed effects, including industry×year ones. In Column 5, we find that the effect even holds with the inclusion of firm fixed effects. The coefficient decreases by about 40% but remains highly statistically significant. This shows that within a given firm, the likelihood of a merger occurring increases if the firm's revenue was higher in the prior period.

Further, Figure 5 shows that the effect is not driven by outliers but rather holds for all firms, as the entire distribution of the revenues is shifted to the right for those firms that are engaged in M&A in the next period.

Table 5 conducts the same analysis, this time using lagged markups as the main explanatory variable. We find similar effects: the coefficient on lagged markup is significant, and stable with the inclusion of varying degrees of fixed effects, including industry×year and firm fixed effects. Figure 6 shows that the results are not driven by outliers as the entire distribution of the markups is shifted rightward for those firms that merge.

Table 4: Mergers and Sales Correlation

	(1)	(2)	(3)	(4)	(5)
Sales	0.033	0.031	0.035	0.035	0.021
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)
Constant	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes	Yes
Sector x year FE	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
r2	0.049	0.064	0.078	0.085	0.281
N	1.84e+05	1.84e+05	1.84e+05	1.84e+05	1.84e+05

Notes: Standard errors are clustered at the industry level.

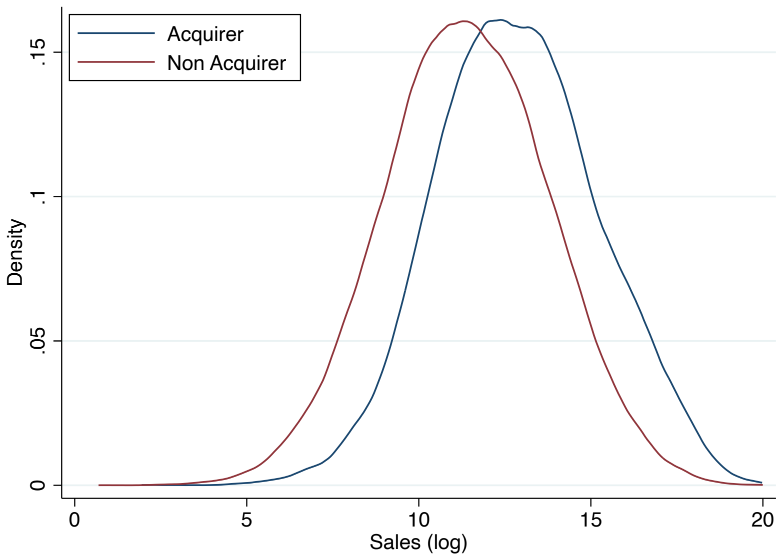


Figure 5: Comparing sales before merger

Notes: The figure presents the kernel density of log(Sales) of the acquirers and the non-acquirers before the merger.

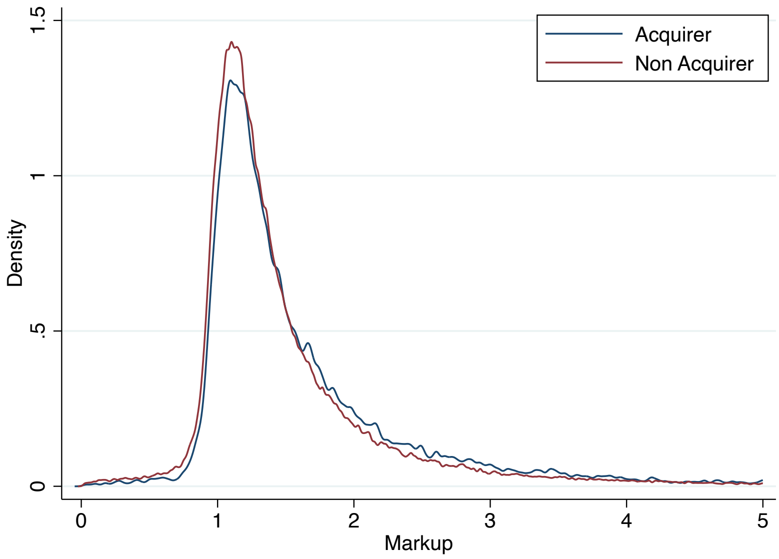


Figure 6: Comparing markup before merger

Notes: The figure presents the kernel density of markups of the acquirers and the non-acquirers before the merger.

Table 5: Merger dummy on LAGGED markup

	(1)	(2)	(3)	(4)	(5)
Markup	0.021	0.017	0.013	0.013	0.015
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes	Yes
Sector x year FE	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
r2	0.003	0.025	0.031	0.037	0.280
N	1.84e+05	1.84e+05	1.84e+05	1.84e+05	1.84e+05

Notes: Standard errors are clustered at the industry level.

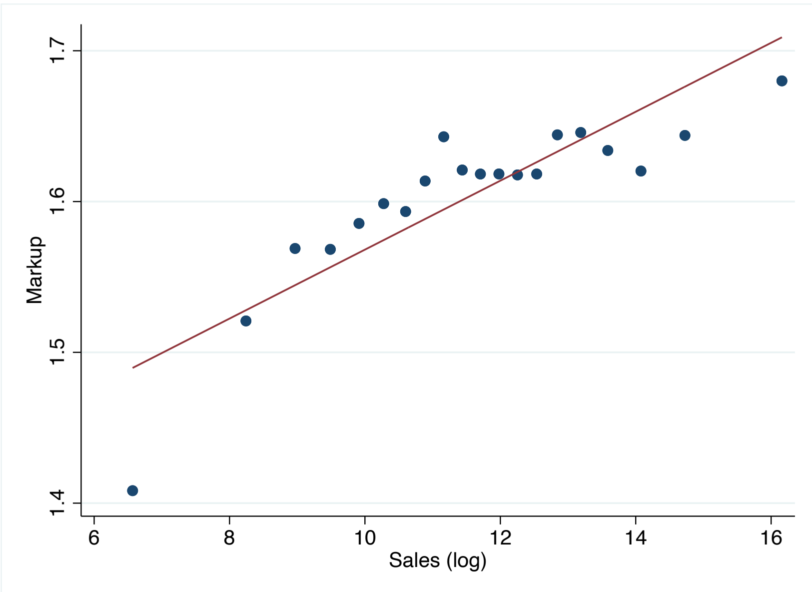


Figure 7: Markups vs logsale

Notes: The figure shows the binscatter plot, along with fitted linear line, for log(Sales) and Markups.

Fact 3: Mergers Are Key Driver For Reallocation and Aggregate Markup

Facts i) and ii) establish that there is a large number of mergers taking place and that higher markup firms are more likely to be involved in mergers. Furthermore, these firms are more likely to have mergers that are larger in size, comprising a higher share of their pre-merger revenues. These facts, taken together, imply that M&A could potentially raise overall markups, as higher markup firms grow through mergers and acquisitions, thereby raising the overall economy-wide markups. To examine this, we measure how much of the overall rise in economy-wide markups is due to M&A. To help understand the effect, we look at the decomposition effect as specified by DLEU. We decompose growth in sales-weighted markups into three components measuring the within-firm growth, the change due to reallocation of resources, and the contribution of entrants and exiters:

$$\mu_t - \mu_{t-1} = \underbrace{\sum_{i \in C} s_{it-1}(\mu_{it} - \mu_{it-1})}_{\text{within}} + \underbrace{\underbrace{\sum_{i \in C} \tilde{\mu}_{it-1}(s_{it} - s_{it-1})}_{\text{between}} + \underbrace{\sum_{i \in C}(s_{it} - s_{it-1})(\mu_{it} - \mu_{it-1})}_{\text{covariance}}}_{\text{reallocation}}$$
$$+ \underbrace{\underbrace{\sum_{i \in E} s_{it}\tilde{\mu}_{it}}_{\text{entry}} - \underbrace{\sum_{i \in X} s_{it-1}\tilde{\mu}_{it-1}}_{\text{exit}}}_{\text{net entry}} \tag{5}$$

with μ_t, μ_{it}, s_{it} being sales-weighted aggregate markup in time t, and firm i's markup and sales in time t, respectively. C, E, X represents the group of firms active in $t-1$ and in t, entering in t, and exiting in $t-1$. Finally, $\tilde{\mu}_{it} = \mu_{it} - \mu_t$ and $\tilde{\mu}_{it-1} = \mu_{it-1} - \mu_{t-1}$ (Haltiwanger, 1997).

Replicating DLEU, we use this decomposition to compute theoretical counterfactuals in which we restrict the growth of aggregate markup to only one of the terms of the decomposition, keeping the others unchanged, thus isolating each individual contribution. Figure D.1 shows the different components of the decomposition. The blue dashed line shows the counterfactual aggregate markup we would observe if changes stemmed only from within-firm growth. The black short dashed line shows the counterfactual markup due to only resource reallocation across firms, without internal growth. Finally, the green long dash and dot line shows the markup changes due solely to firm dynamics.

We then conduct the same exercise as we did in Fact i) to calculate a firm's revenue derived from all its merger activities. We measure how much of the revenue is attributable solely to mergers. Figure 8 presents the outcome of this exercise, the main result of Fact iii).[19] It first replicates the decomposition results of DLEU, including showing the cumulative effect of the reallocation component. It also shows the effect of mergers on the overall reallocation term - our main contribution. In the initial part of the sample, for the 1980-2000 period, mergers contribute a small share to reallocation, explaining at best 20-30% of

[19]Table A.1 shows the importance of the merger effect on the reallocation term and on aggregate markup in each year.

the overall contribution. The modest effect of the merger contribution is partially driven by the small number of mergers taking place (Figure 1). As the overall quantity of mergers and acquisitions increases from 2000 on, the impact of the mergers on the reallocation term also grows. In the second half of the sample, the M&A activity explains over 60% of the reallocation.

We can also look at how much of the overall increase in the markups is explained by the merger effect. We again find that the merger effect explain a small share of the overall effect of the rising markup, about 10-15% (Table A.1). However, as both the number and the size of merger activities increases, their effect on the overall rise in markups also grows, explaining close to 35-38% of the total effect.

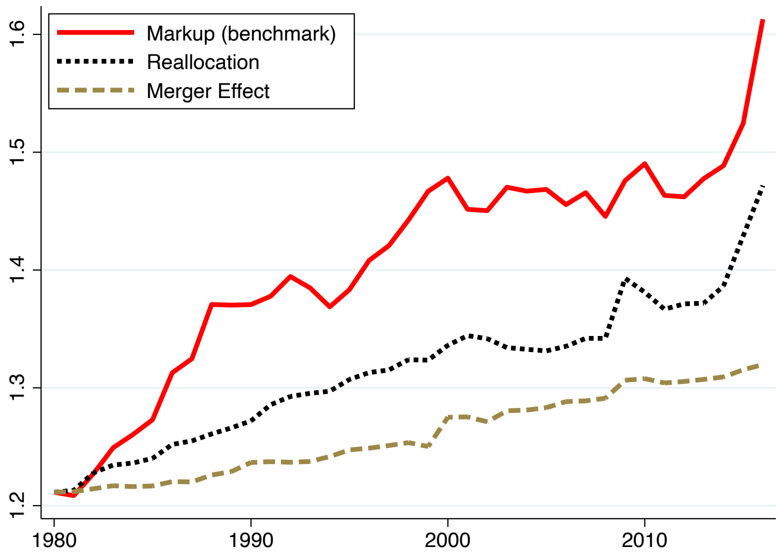


Figure 8: The Importance of Mergers for Aggregate Markups

Notes: Sales-weighted aggregate markup relies on firm-specific markup indicators based on sector-specific and time-varying output elasticities. The reallocation term comes from the decomposition of aggregate markup growth (equation 5). The merger effect measures the importance of M&A activities for aggregate markup growth and shows a theoretical experiment in which all other terms are set to zero.

We next analyze what share of the overall effect is driven by horizontal mergers. We take mergers and acquisitions to be horizontal if the target is in the same 3-digit industry sector as the acquirer. In an alternative specification, we also consider the impact of mergers if the target and acquirer are in the same 2-digit industry sector. Figure 9 presents the results for the horizontal mergers, showing that they explain 60-70% of the overall effect of mergers. In Figure A.1 we find that looking at 2-digit industry sectors explains 80% to 90% of the overall merger effect. Moreover, we see a relative increase in mergers in the same 2-digit industries in the latter part of the sample, indicating that firms are increasingly acquiring not only their competitors but also other firms related industries. The share of horizontal mergers in the overall merger contribution has important policy implications, and further raises the question whether the mergers also affect acquiring firm markups, through changes in competition.

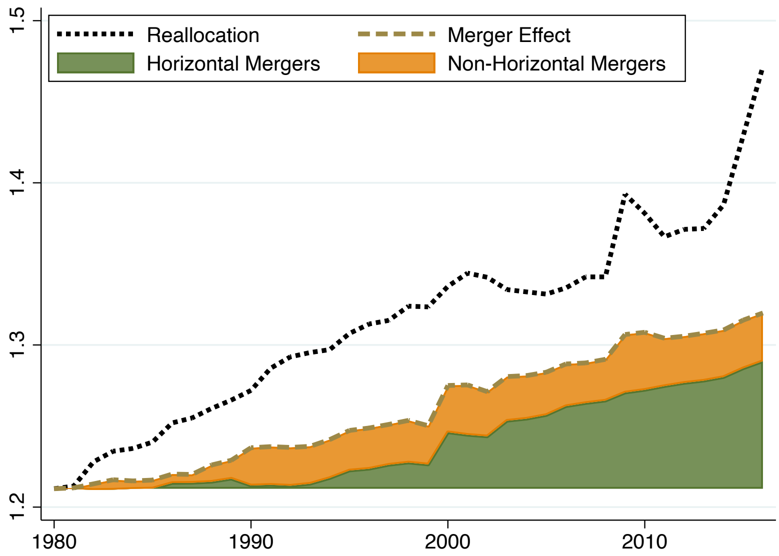


Figure 9: The Importance of Horizontal Mergers (3d-industry)

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 5). The merger effect measures the importance of M&A activities for aggregate markup growth and shows a theoretical experiment in which all other terms are set to zero. The green area measures the increase in aggregate markups due to horizontal mergers and the yellow area the effect of other mergers. We define horizontal mergers as mergers between firms in the same 3-digit sector.

Fact 4: Target Firms Have Low Markups

The decomposition formula shows that the mergers and acquisitions can affect the overall aggregate markups two ways: first, they increase acquirer revenues and impact overall markups through the reallocation effect. Second, they can also affect markups through the exit effect as the target firms leave the economy. Up to now we have calculated the effect of M&A through the reallocation and exits effect only. However, to measure the full impact of merger and acquisitions, we also take into account the effect of the exit of the targets in the decomposition formula. For the subset of acquisitions, where the target is also in Compustat, we relate our measured markup effect to the overall effect, by accounting for target exit. Figure 10 shows the ratio of our estimate to the true estimate for the cumulative sum of the mergers, starting with total mergers up to 1990 and extending further. The graph shows that our estimated merger effect on markups is between 40 to 50% of the total effect. This is consistent with the observation that targets are more likely to have lower markups. To check, we run the following specification:

$$\mathbb{1}[\mathrm{T}]_{ist} = \beta_0 + \beta_1 \mu_{ist-1} + \beta_i + \beta_{st} + \varepsilon_{ist}$$

with $\mathbb{1}[\mathrm{T}]_{ist}$ being a dummy that takes value 1 if firm i in sector s engages in a merger as a target at time t. μ_{ist-1} is firm i's markup at time t-1 and β_i and β_{st} are firm and time-varying sector fixed effects, respectively.

	(1)	(2)	(3)	(4)	(5)
Markup	-0.002	0.011	-0.004	-0.007	-0.046
	(0.014)	(0.014)	(0.018)	(0.017)	(0.023)
Constant	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes	Yes
Sector x year FE	No	No	No	Yes	Yes
Firm FE	No	No	No	No	Yes
R2	0.00	0.01	0.01	0.05	0.193
N	183,836	183,836	183,836	183,836	183,836

Table 6: Target dummy on markup

Notes: The table reports the coefficient estimate of the target dummy regressed on markups. The regression controls for sector-by-year fixed effects, and firm fixed effects. Standard errors are clustered at firm level.

Table 6 shows that indeed targets are more likely to have lower markups. The effect holds in a within-firm specification, where a firm is more likely to be acquired the lower its own markup is. Extending these results to all targets[20] implies that, if anything, we are *undercounting* the full effect of mergers on markups. If we were to extend Figure 10 results to *all* targets we would find that the M&A activities could explain as much as 80% of the rise in markups.

[20]For those not in Compustat.

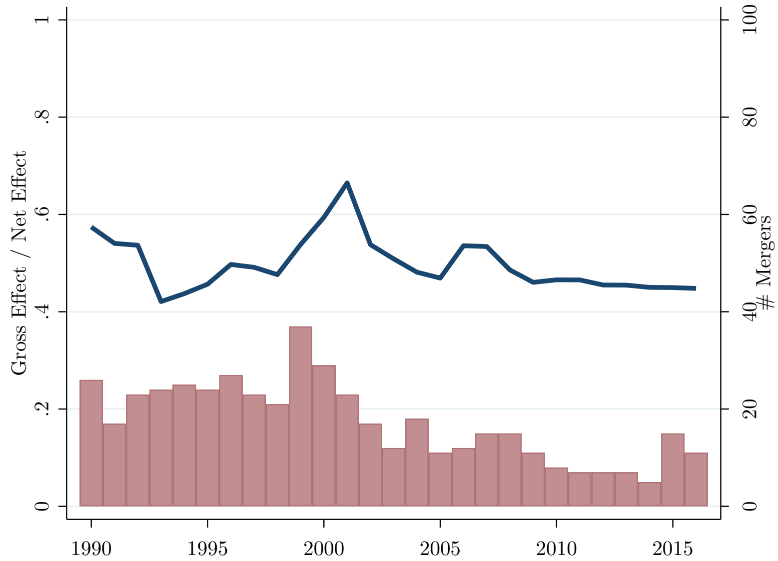


Figure 10: Total Merger Effect for Compustat Targets

Notes: The graphs shows on the left axis the ratio of the gross effect of mergers over the net effect for mergers with known target markup. The gross effect is defined as the contribution of target sales to the growth of revenues of the buyer weighted by the demean buyer markup, while the net effect is the difference between buyer's and target's markup weighted by buyer sales share. On the right axis, the number of mergers per year in thousands.

Fact 5: Firm Markup Increases After Mergers

We have established that through the reallocation effect, the impact of the mergers on the rise in concentration and markups is significant. But does the merger also have a direct effect on the acquirer? And also does the magnitude of the merger matter? This will also provide a rationale for the mergers taking place, in line with our model. We then look at the effect of the merger on actual markups. Guided by the theoretical prediction, the mergers should increase own profits, and consequently markups.[21] As such, we examine whether the merger also increases firm's markup. We use the following specification:

$$\mu_{ist} = \beta_0 + \beta_1 X_{ist} + \beta_i + \beta_{st} + \varepsilon_{ist}$$

with μ_{ist} being firm i's markup at time t in sector s and β_i and β_{st} are firm and time-varying sector fixed effects, respectively. X_{ist} is the merger treatment and in the first specification (Column 1) it is a dummy taking value 1 if firm i engages in a merger as an acquirer in time t. In the second specification (Column 2), we use a continuous treatment in which we interact the merger dummy with the share of target revenues over acquirer revenues as a measure for

[21]In that simple example, we mainly look at the change in profits through increased prices. The same intuition would apply under cost efficiencies as well.

how important the merger is for the acquirer. In the last specification, we instrument the continuous treatment with the *merger wave instrument.* This instrument, already prevalent in the corporate finance literature (Cowgill et al., 2023) uses the number of mergers in other sectors weighted by the revenue transfers as an instrument for firm i's merger.

Table 7 presents the results. Column 1 takes a similar approach to the prior literature, where we measure the effect of the merger through an event study-type of approach. It shows that the dummy coefficient of whether the firm is involved in M&A has a significant effect on its current markups. In our baseline sample, we take the control group as all the firms that have not been engaged in a merger. In robustness, we also take the control group as the failed mergers, in line with the prior literature (Seru, 2014; Savor and Lu, 2009). As Column 1 shows, the firm merging increases the markup of the firm by about .02. Given, that the average merger growth per year economy is about 0.01, this is a very sizable effect, and in line with the prior literature (Stiebale and Szücs, 2022). The results are robust to including sector$\times$time dummies, and also firm fixed effects. The latter effect indicates, that the company experiences a higher merger in the year that it is merging compared to non-merging years.

We then consider whether the size of the merger itself affects firm markups. While the merger dummy presents findings for the average effect of the firm, we instead measure whether the size of the effect also plays a role. This approach is in line with the main intuition of the paper, that mergers are different in size and will have heterogeneous effects: by our intuition, larger mergers will have a bigger effect. We indeed find the case. Column 2 presents the results for the merger share, defined as the revenue acquired during M&A relative to the overall revenue. We again find a large and statistically significant effect on the markup share. One percent increase in the merger share would increase the markup by 0.15%.

Finally, Column 3 presents the IV specification. We instrument for the merger share for a merging firm with the average merger share in all *other* industries in that year. This leave one-out instrument, popular in IO and other fields (Hausman et al., 1994; Marinescu et al., 2021), is based on the intuition that there are economy wide merger waves, where many mergers, including larger size mergers, are common in the industry. However, in creating our instrument, we do not include not only the firm, but the entire industry that firm is in.[22] We have a strong first stage, and Column 3 shows that the OLS result in column 2 holds with the IV specification.

[22] Cowgill et al. (2023) also motivate a similar approach.

Table 7: Merger Effect on Own Markups

	(1)	(2)	(3)
	OLS	OLS	IV
Merger	0.019		
	(0.004)		
MergerShare		0.149	0.212
		(0.038)	(0.040)
Constant	Yes	Yes	Yes
Sector x year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
F-Stat	18	15	28
N	207,543	207,543	207,543

Notes: The table reports the coefficient estimate of the merger on own markups. Column 1 specifies Merger as 1 if the firms merged or acquired and 0 otherwise. Column 2 uses instead the share of the revenue that is transferred from the target to the acquirer. Column 3 specifies the IV regression where the MergerShare is instrumented with the share of the revenue transfer for other firms in other sectors. The regressions control for sector-by-year fixed effects and firm fixed effects. Standard errors are clustered at firm level.

Fact 6: Merger Effect on Others' Markup

Given that the mergers increase own markups, what is the effect on other firms in the same industry sector? We then run the sector weighted average markup, excluding the merging firm(s) and calculate its effect on merger events. Table 8 presents the results. The effect shows that a merger not only increases the markup of the firm initiating the merger, but also has an effect on overall sector markups. The effect holds both when we look at the mergers as event studies, and also as shares of acquirer revenues. As the markups of other firms are increasing, and higher markup firms are more likely to be engaged in M&A, this finding indicates that mergers may spur additional mergers by other firms in the industry.

Table 8: Merger Effect on Other Firms in the Sector

	(1) Competitors Markup	(2) Competitors Markup
Merger	0.019	
	(0.011)	
MergerShare		0.514
		(0.158)
Constant	Yes	Yes
Sector x year FE	Yes	Yes
R2	0.62	0.62
N	10,761	10,761

Notes: The table presents the regression coefficients of the merger effect on other firm's markup in the same sector that have not merged. Column 1 presents the results for the merger dummy, with 1 if the firm merged and 0 otherwise. Column 2 presents the estimate for the share of the revenue transfer from the target to the acquirer. The coefficients control for year and sector fixed effects. The standard errors are clustered at sector level.

We use the following specification:

$$\mu_{st}^{-M} = \beta_0 + \beta_1 X_{st} + \beta_s + \beta_t + \varepsilon_{st}$$

with μ_{st}^{-M} being the sales-weighted markup in sector s at time t, excluding firms engaging in mergers. β_s and β_t are sector and time fixed effects, respectively. X_{st} is the merger treatment, and in the first specification (Column 1) it is a dummy taking the value 1 if any firm in sector s engages in a merger as an acquirer at time t. In the second specification (Column 2), we use a continuous treatment in which we interact the merger dummy with the share of target revenues over sector revenues as a measure for how important the merger is for the sector.

7 Discussion

7.1 Assumptions Underlying the Merger Effect

Critical to our analysis is calculating the revenue share that take place during M&A activity. To measure this effect, we make several simplifying assumptions. First, we take all target firm revenues transferring one-to-one to the acquiring firm. We also ignore any potential synergies that may arise from mergers, further increasing joint revenues. If there are significant synergies, as a result of mergers, our estimates provide if anything, a lower bound of the overall merger effect. Additionally, we assume there is no cost-cutting activities that may follow acquisitions. However, SDC also reports any divestment, and the results are robust to accounting for them. We further assume, that the entire revenue of the merging firm is realized in the year the merger is completed.[23] While this may hold true for most mergers, larger mergers might take several years to be fully internalized. The results are robust to considering longer time period for the mergers to be completed, such as three years. However, in the latter case, the reallocation term will be impacted by the markup of the acquiring firm also changing during those years, potentially due to mergers. We study this effect in detail and our preferred specification then takes all merger gains being realized in the year of the merger.[24]

7.2 Selection into Missing

Figure 11 breaks down the overall contribution of mergers in Fact iii) based on reported vs imputed revenues. The imputed revenues comprise a large share of the overall merger contribution, roughly in line with their share in the matched merger dataset. It then becomes important whether missing revenues are consistently imputed from existing merger transaction information or whether there is a potential bias in the estimates. While we document a stable relationship between log price and log revenue, our approach hinges on the assumption that mergers with missing sales are comparable to mergers with existing sales. That is, there is no selection into missing target sales, which could potentially bias our predictions. Perhaps, the targets with missing sales are younger and/or smaller firms, and hence no reliable information is available for the revenues at the time of merger. But also, their revenue contribution to the acquiring firm is also likely to be small. As a robustness, we rerun the analysis where we exclude the predicted sales where merger value was less than \$100 million, and the overall results hold. This is in line with the intuition that our results are driven by large mergers.

More concerning could be the cases of missing sales in the SDC database with large merger values. The predicted sales for those transactions may then greatly differ from their actual sales, potentially biasing their contribution. While checking for all possible missing revenues in the matched sample is not feasible, we approach this question several ways. First, we plot

[23] Given by the effective date of the merger.

[24] This may also explain, that for some firm-year observations, the revenue increase from mergers alone may be more than the overall acquiring company revenue change. This may happen when mergers take several years to be internalized, and indeed, disappears when considering longer time horizons.

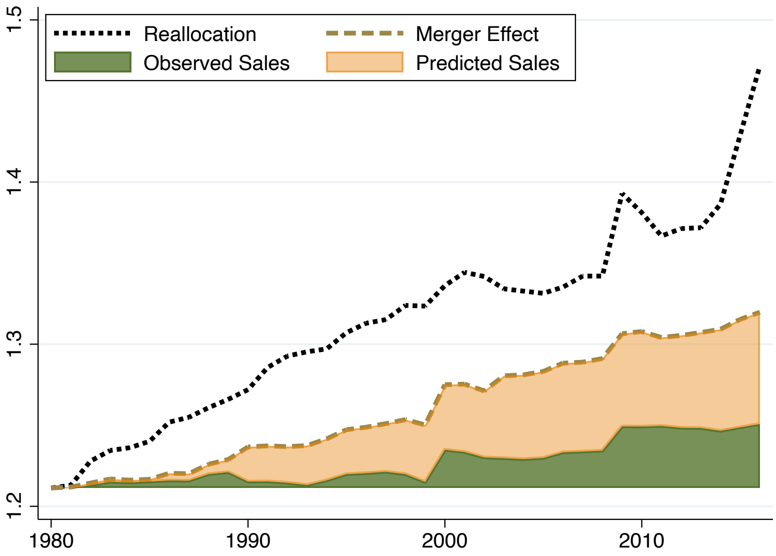


Figure 11: The Importance of Predicting Sales

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 5). The merger effect measures the importance of M&A activities for aggregate markup growth and shows a theoretical experiment in which all other terms are set to zero. The green area measures the increase in aggregate markups due to mergers for which target sales are available and the yellow area the effect of mergers with imputed sales. More details on predicting target sales in Section 2.

the kernel densities of (log) of transaction value for both targets with reported and missing sales in Figure 12. As expected, the distribution of transaction values with known revenues are to the right of those with missing revenues - targets with known revenue are more likely to have a higher transaction price. However, there is a significant overlap between the two distributions, which lends credence to our prediction algorithm, in that there are sufficient observations at each transaction level to infer the average revenue for the targets.

Next, we manually check the validity of imputed revenues for the largest transactions. Table 9 lists the ten largest merger value transactions with missing target sales. For each transaction, it includes the merger announcement date, the acquirer, the target and the merger value. While the target revenue information is missing in the SDC database, we were able to find the sales figures from other sources.[25] Column 6 in Table 9 shows the revenues figures that we obtain and Column 7 shows the predicted sales from our baseline specification. As can be seen, the predicted sales are in line with reported sales for most of the estimates, there is no systematic upward or downward prediction for the predicted sales.

The one example where the prediction is significantly different from the actual sales is Facebook's (now Meta) acquistions of WhatsApp, where close to $19.5 billion price paid

[25] Sometimes, the target firm, e.g. Covidien, is also publicly traded, and so its financial information is also available in Compustat.

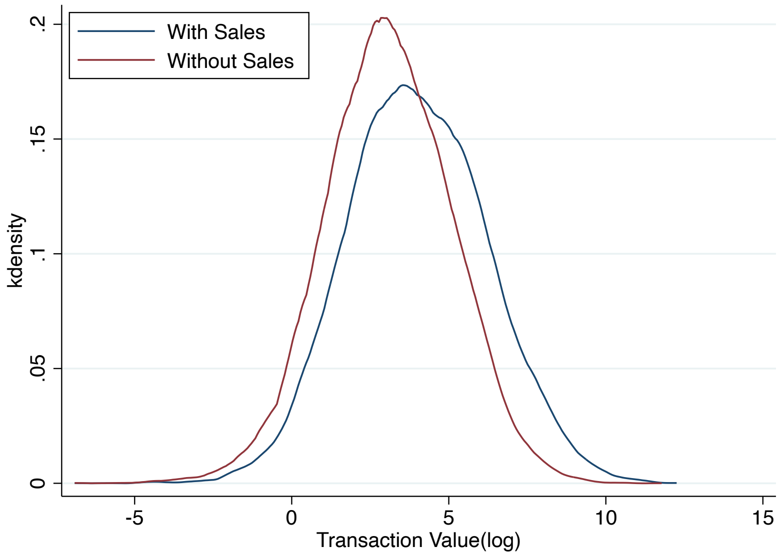


Figure 12: Kernel Densities

Notes: Kernel densities for the distributions of transaction values of mergers with information on target sales and not.

Table 9: Observed and Predicted Sales for Top 10 Mergers with Missing Information

Acquirer	Target	Year	Merger Value	Target Sales	Predicted Sales
Medtronic Inc	Covidien PLC	2015	42,729	10,200	12,391
Teva Pharm Inds Ltd	Allergan PLC, Generic Drug Bus	2016	38,750	15,071	11,727
Berkshire Hathaway Inc	Burlington Nrthn, Santa Fe Llc	2010	36,724	14,835	13,246
Facebook Inc	WhatsApp Inc	2014	19,467	10	3,784
Novartis AG	GlaxoSmithKline PLC, Oncology	2015	16,000	2,063	4,598
Continental AG	Siemens VDO, Automotive AG	2007	15,648	10,000	5,905
Coty Inc	Procter & Gamble Co, Beauty Business	2016	14,917	11,477	5,151
Vodafone Group Plc	Hutchison Essar Ltd	2007	12,748	2,600	5,093
Ito-Yokado Co Ltd	Seven-Eleven Japan Co Ltd	2005	12,483	23,416	20,238
Nestle SA	Pfizer Nutrition	2012	11,850	2,400	4,531

Notes: Comparison between imputed and manually collected target sales for the 10 largest mergers for transaction value.

implies that WhatsApp's revenues should have been close to \$3.8 billion, while it was nonexistent at the time. We are less concerned about it for several reasons. The fixed effects specification accounts for the target industry and thus the predicted sales of young firms in a given industry are estimated from the acquisition of more mature firms in the same industry, with established revenues. This means that the predicted revenues combine both current but also any potential future revenues into the imputed revenues, as may be the case for young startups. To take another example, when Facebook acquired Instagram in 2012 for $1 billion, there was hardly any reported revenues for Instagram at that time. However, in subsequent years Instagram ad revenues became a lucrative part of Meta's overall revenues: in 2016 it is reported to have $26 billion in revenues, comprising half of Meta's total revenues.[26] (These figures are most likely estimates, as Meta does not split the total revenues across its different platforms). Instagram, if it were a standalone company, was valued at more than $100 billion in 2018 based on the revenues it generated.[27] Our predicted specification applies to these situations, since we contribute the target's predicted revenues to the acquirer's total sales in the year of the merger alone, and assign no further contribution in the future years. The present discounted value of the Instagram revenues are much larger than the predicted revenues from our estimation, and while the actual revenues were negligible at the time of acquisition, if anything, our methodology undercounts the total revenue contribution of the Instagram acquisition. Alternatively, an additional source for predicted sales would be the synergies, where the revenues of the core business for Facebook would be increased by the predicted revenues. This would apply for acquisitions such as WhatsApp, where the no future revenues were generated until the end of our sample.

More worrisome for us are the so-called "killer acquisitions" (Cunningham et al., 2021), where companies acquire young firms just to shut them down, eliminating future potential competition. Under this setup, we will incorrectly contribute target revenues to the acquirer and may over-attribute revenue increases from mergers and acquisitions. We do not think, however, that killer acquisitions are a concern in our context for several reasons. First, as Cunningham et al. (2021) report, only about 5-7% of the acquisitions are classified as killer acquisitions. If these are drawn randomly from the entire target revenue distribution, our results are robust to considering only the 93-95% of transactions. Second, and perhaps more important, we do not think that killer acquisitions will be drawn uniformly from the entire revenue distribution, but will be overwhelmingly concentrated among young firms, reporting low or zero revenues, and also acquired at a low value. In fact, as Cunningham et al. (2021) report, some killer acquisition transaction values are set at a sufficiently low level to avoid reporting, and thus evade any potential regulatory scrutiny. Our results are instead driven by mergers with large transaction values (both reported and imputed), with the target firm revenues significantly contributing to acquirer's revenues. It is highly unlikely that for such

[26] https://www.yahoo.com/entertainment/instagram-now-makes-more-half-140500679.html

[27] https://www.bloomberg.com/news/articles/2018-06-25/value-of-facebook-s-instagram-estimated-to-top-100-billion

transactions, the acquiring firms will spend significant amount to acquire a well-established company or a very promising young startup, just to shut it down.[28] Though, potentially shutting down potential competitors might have long term consequences and impact on markups in a longer horizon.[29]

7.3 Revenue Figures

The other concern for the analysis is how accurate are the reported revenue figures in the SDC database. This is especially relevant since the reported revenues are also used for the imputed revenue prediction. We find that a portion of the targets are publicly traded and thus, for 15% of targets, revenue figures are also available in Compustat.[30] We compare the revenue reported by the SDC with those in Compustat.[31] This is not quite straightforward due to the potential differences in the variable definition: in Compustat, the revenues are for the most recent fiscal year, and in SDC it is for the last 12 months, less of any returned goods and allowances. (See Section 2 for detailed definitions of revenues in each of the datasets.) As our baseline, we compare SDC revenue figures to the Compustat revenues that correspond to the fiscal year prior to the merger announcement, i.e., the latest available fiscal year revenues when the merger or the acquisition was announced. Since the SDC figures are constantly updated, as a robustness we also consider a window of $+/-2$ years. Figure 13 shows the scatterplot of the SDC revenues with Compustat revenues. While many points lie along the 45° line, the majority do not. However, the observations seem to be evenly distributed around the 45° line. And if anything, some also lie *below* the 45° line, indicating, that the SDC *undercounts* the target revenues. This alleviates one concern that, to command a higher price, target revenues might be artificially inflated prior to its sale and may not correspond to the actual revenues. It also shows, the using the SDC revenues provides a lower bound for the overall merger effect.

As a robustness, we also impute revenue figures using Compustat revenues. We do it two ways. First, we use actual revenues for the targets with reported Compustat revenues and predict revenues for all other firms, including firms with reported SDC revenues, but no Compustat revenues. For the second case, we use the Compustat revenues whenever available, SDC revenues if SDC figures are available but Compustat is not, and imputed revenues for all remaining missing revenue cases. Thus for the second case the prediction

[28] Further establishing our point is that there does not seem to be an example of a killer acquisition involving a mature target.

[29] Though, it will be very difficult to quantify these effects.

[30] These also include share buybacks.

[31] We also use it to correct for any obvious errors in the revenue information in the SDC database, such as numbers reported in thousands instead of millions.

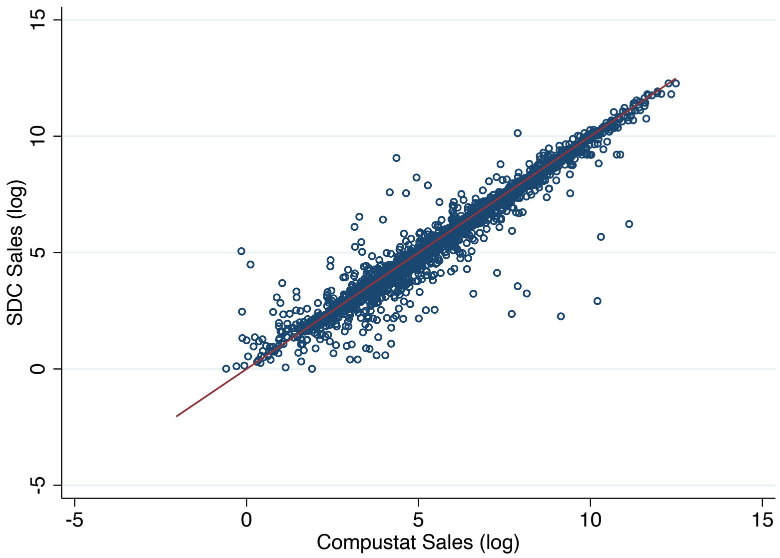


Figure 13: Comparing SDC and Compustat Sales

Notes: Scatterplot of (log) target sales from SDC Premium and (log) target sales from Compustat.

is done only for firms with missing SDC revenues, whereas in the first case we do it for all firms with missing Compustat revenues.

We first show that the linear relation between log value and log revenue also holds when restricting to the Compustat firms only (Figure 14). Figure 15 then presents the robustness results under both specifications for Fact iii). We find that the total merger effect, if anything, is larger, rising to as high as 70% of reallocation term. This confirms that the SDC revenues may be potentially under-reporting the contribution of mergers to the reallocation.

Finally, as an additional robustness check, we run a Heckman selection on both predicting revenues and selection. We run a double-lasso where a different set of fixed effects are selected to impute target sales and whether or not those sales will be reported. The results continue to hold.

7.4 Rise in Markups

We have taken "off-the-shelf" methodology of DLEU for markup analysis. Subsequent research considered whether the main findings of DLEU are robust to alternative specifications, such as including fixed costs (Traina, 2018), relaxing Cobb-Douglas production function specification (Raval, 2022; Demirer, 2022; Foster et al., 2022), or considering different levels of aggregation for input's output elasticity estimation (Foster et al., 2022). While in some

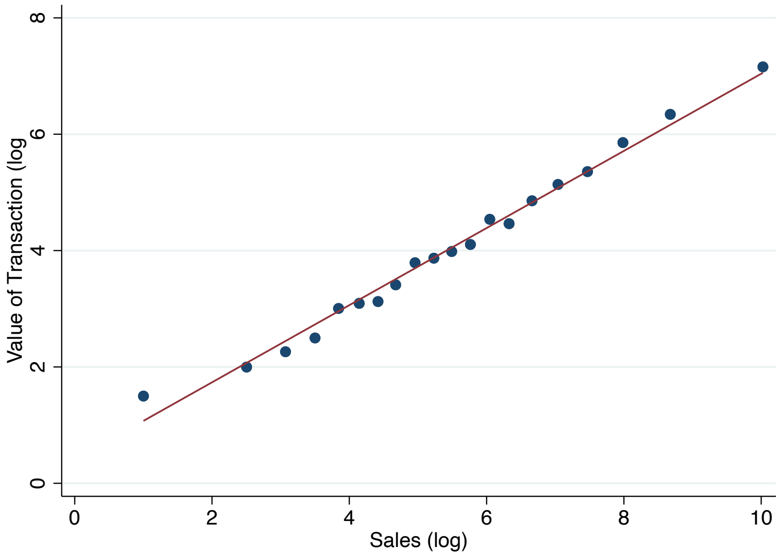


Figure 14: A Log-linear Relation in Compustat

Notes: Binscatter between (log) target sales and (log) transaction values using target sales from Compustat.

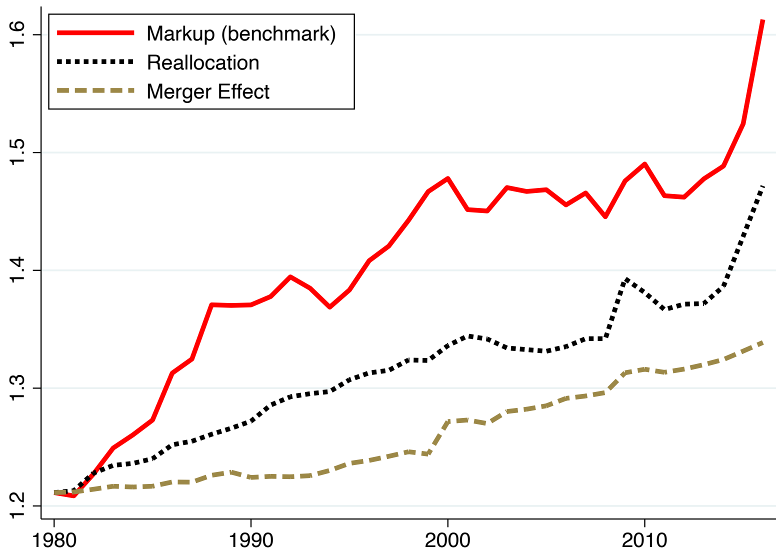


Figure 15: Merger Effect Based on Compustat

Notes: Sales-weighted aggregate markup relies on firm-specific markup indicators based on sector-specific and time-varying output elasticities. The reallocation term comes from the decomposition of aggregate markup growth (equation 5). The merger effect measures the importance of M&A activities for aggregate markup growth and shows a theoretical experiment in which all other terms are set to zero. Target sales are imputed from Compustat data.

specification the overall rise in markups might be dampened or even reversed, a robust finding is the rise in the reallocation term (Foster et al., 2022). That is, even if the overall level of markups may not increase, the evidence shows that the higher markup firms grow bigger.

We speak directly to the reallocation term, showing that the large part of the effect is driven by the merger and acquisition activity.

8 Conclusion

There has been increasing discussion on the rise of market power and declining competition in the US and other economies around the world (Gutiérrez and Philippon, 2017; De Loecker et al., 2020; Grullon et al., 2019). What is behind the rise in market power is of interest both to academics and also to policy makers. There have been several hypotheses put forward, including changes in technology, increased foreign competition, rise of intangible assets, or mergers and acquisitions (Philippon, 2019). The intuition behind the effect of the M&A on rising concentration is straightforward, but the empirical result has been mixed. We instead propose a novel way to measure M&A, not by an event study approach, but rather quantifying how much of the target revenues are transfered to the acquirer. In doing so we establish six stylized facts, including M&A explaining all of the rise in concentration and 38-80% of the rise in markups.

Perhaps more exciting is that we see the measurement of M&A via revenue transfers to have applications beyond the rise in market power. Many papers have looked at the effect of M&A on innovation and patents (Phillips and Zhdanov, 2013; Haucap et al., 2019; Bena and Li, 2014), product similarity (Fathollahi et al., 2022), corporate performance (Healy et al., 1992), and wages (Prager and Schmitt, 2021) to name a few. Further, many studies examine which factors contribute to a higher likelihood of M&A activity, such as stock price overvaluation (Shleifer and Vishny, 2003; Harford, 2005), or policy uncertainty (Bonaime et al., 2018). There is potentially added benefit in examining these question not just through the lens of mergers and acquisitions as 0/1 events, but also in terms of how large these acquisitions are. Such studies will provide a more complete picture on the overall impact of the M&A, and we think is a promising area for future research.

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A Additional Figures and Tables

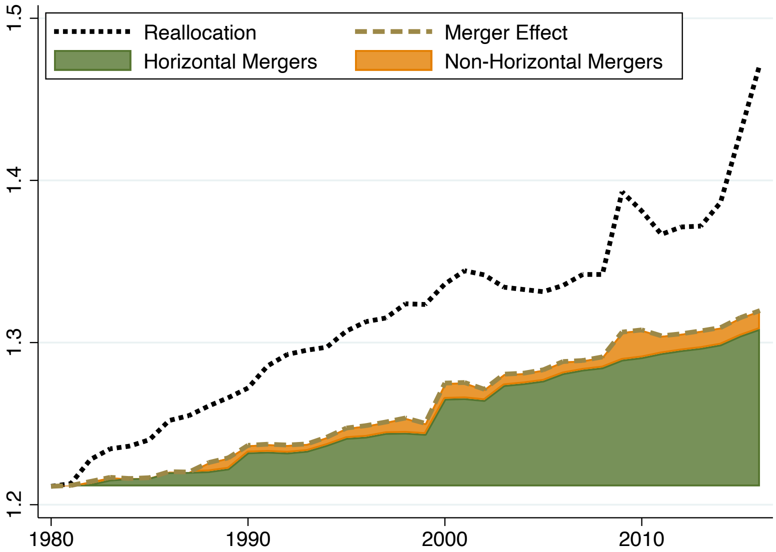

Figure A.1: The Importance of 2-digit Industry Mergers

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 5). The merger effect measures the importance of M&A activities for aggregate markup growth and shows a theoretical experiment in which all other terms are set to zero. The green area measures the increase in aggregate markups due to horizontal mergers and the yellow area the effect of other mergers. We define horizontal mergers as mergers between firms in the same 2-digit sector.

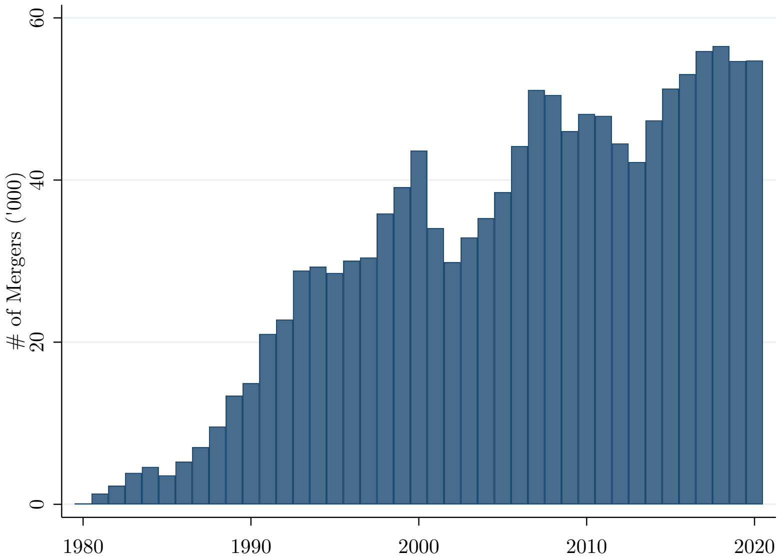

Figure A.2: Total Number of M&A

Notes: The graph shows the total number of mergers and acquisitions, reported by the SDC, both with known and unavailable transaction value.

Year	Effect on Reallocation	Total Effect
1981	32%	-19%
1982	18%	19%
1983	24%	15%
1984	19%	10%
1985	19%	9%
1986	22%	9%
1987	20%	8%
1988	30%	9%
1989	32%	11%
1990	42%	16%
1991	35%	16%
1992	31%	14%
1993	31%	15%
1994	35%	19%
1995	38%	21%
1996	37%	19%
1997	38%	19%
1998	37%	18%
1999	35%	15%
2000	51%	24%
2001	48%	27%
2002	46%	25%
2003	56%	27%
2004	57%	27%
2005	60%	28%
2006	62%	32%
2007	59%	30%
2008	61%	34%
2009	52%	36%
2010	57%	35%
2011	60%	37%
2012	59%	38%
2013	60%	36%
2014	56%	35%
2015	48%	33%
2016	42%	27%

Table A.1: Merger Effect by Year

B Additional Details on Matching

The first method includes merging with the CUSIP number. The Compustat data includes the 9-digit CUSIP of the companies, whereas the SDC Platinum includes only the the 6-digit CUSIP. This is not problematic, as the first 6 digits refer to the company and the last 3 digits of the CUSIP typically refer to the type of issuance. We then merge the SDC CUSIP with the first 6 digits of the Compustat CUSIP. We make use of all three company CUSIPs - actual company, the immediate parent and the ultimate parent. In case of multiple matches, the priority is given to actual then immediate then ultimate (the actual number of such matches is not frequent - several hundred). We match 55,909 cases this way.

When companies merge, their names, and CUSIP may change. For example, after Exxon merged with Mobil in 1999, the name was changed to Exxon Mobil, and the CUSIP of the corresponding company changed from 30229010 to 30231G10. The Compustat retroactively updates the company names and CUSIP to the new ones. Thus, Exxon, even before 1999 in Compustat will be listed as Exxon Mobil, with CUSIP number 30231G10. The SDC file however lists the name and CUSIP of that time: Exxon with CUSIP number 30229010. We further match new CUSIP numbers with old CUSIP using the CRSP linking tables. This provides a further 10,138 matches.

For the remaining companies, we match by exact name matches, we do so by changing all letters into capital letters, remove any punctuation, (such that "Inc." becomes "Inc"). We also remove the endings of the companies such as "Inc", "Corp", or "LLC". This allows for further 3,052 number of matches.

Finally, we do a matching by ticker symbol. In the SDC data, the ticker symbols are again given as three types - actual company, Immediate Parent, and Ultimate Parent. The tickers however are can refer to any of the worldwide exchanges, wherever the company is traded. In Compustat, however, the ticker symbols are primarily for US-based exchanges. After matching by the ticker symbol, we then take care that the matched companies are indeed the same, by checking their other identifiers, such as the headquarter location or the industry sector. We receive further 476 matches that way.

Finally, we also match using the URL method of Autor et al. (2020a). The approach utilizes the search engine algorithm of matching different version of companies. They use this approach to account for abbreviations or misspelling, and find that it works remarkably well. For instance, based on the large overlap of URL search results, IBM and International Business Machines are identified as the same company. The high overlap of the same searches also helps identify matches. We set the criteria of having an overlap of at least 4 matches from the first 10 search results on Bing, and find further 853 matches.

Table B.1 provides summarizes the total amount of matches between the two datasets, along with by which criteria are they matched. (The criteria is not exclusive, as if the company is matched by CUSIP, it could also be matched by ticker symbol or URL).

Criterion	Frequency	Share(%)
CUSIP	45,844	65.09
NewCUSIP	10,138	14.39
ImmediateParentCUSIP	8,200	11.64
Name	3,052	4.33
UltimateParentCUSIP	1,865	2.65
URLs	853	1.21
Ticker	404	0.57
ParentTicker	54	0.08
NewTicker	18	0.03

Table B.1: Matching by Criterion

C Markup Estimation

We use the so-called production approach to construct firm-level markups (Hall, 1988; De Loecker and Warzynski, 2012). The strength of this approach is that it does not rely on specifying a demand system or a specific competition framework. It requires firms to use a flexible input to produce and minimize costs.

Consider an economy with a discrete number of firms indexed by i, heterogeneous Hicks-neutral productivity, A_{it} and using a production function of $Q_{it} = A_{it}Q_{it}(V_{it}, K_{it})$, with V_{it} being a vector of flexible inputs and K_{it} a vector of predetermined inputs. Each period firms minimize the contemporaneous cost of production for given a target level of output to produce, $\bar{Q}_{it}$. Hence, the Lagrangian is:

$$\mathcal{L}\left(V_{it}, K_{it}, \lambda_{it}\right) = P_{it}^{V} V_{it} + r_{it}K_{it} + F_{it} - \lambda_{it}\left(Q(\cdot) - \bar{Q}_{it}\right)$$

with P_{it}^{V} being the price of input V and r the user cost of capital. F_{it} represents any potential fixed cost and λ_{it} is the Lagrangian multiplier associated with the target output level, i.e., the marginal cost. For simplicity, we assume only one flexible input and one predetermined one. Taking the first order derivative with respect to V yields:

$$\lambda_{it}\frac{\partial Q(\cdot)}{\partial V_{it}} - P^V_{it} = 0$$

Starting from this optimality condition, we can substitute both sides by $P_{it}\frac{V_{it}}{Q_{it}}$, and defining markups as the ratio of price over marginal costs, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, we obtain a markup formula that we can operationalize:

$$\frac{P_{it}}{\lambda_{it}} = \theta^v_{it}\frac{P_{it}Q_{it}}{P^V_{it}V_{it}}$$

The markup hence can be expressed as the product of the output elasticity of variable input, θ, and the inverse flexible input share. While we take the latter from the data, the output elasticity is unobservable and requires an estimation procedure. We do not estimate it ourselves but rather use the elasticities from De Loecker et al. (2020). These elasticities are estimated using the production approach initially proposed by Olley and Pakes (1996) and impose the assumption that firms produce according to a Cobb-Douglas production function with time-varying elasticities common across 2-digit industries.

D Industry Breakdown

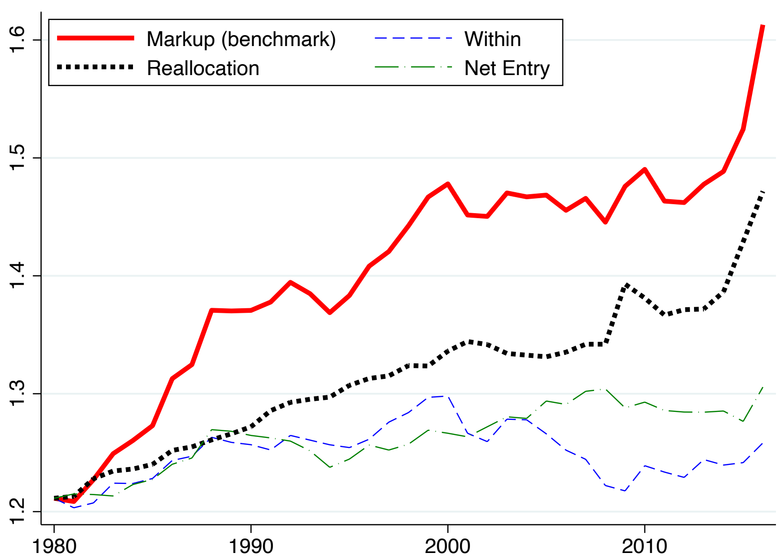

Figure D.1: DLEU Decomposition

Notes: Aggregate Decomposition into Reallocation, Within and Net Entry components.

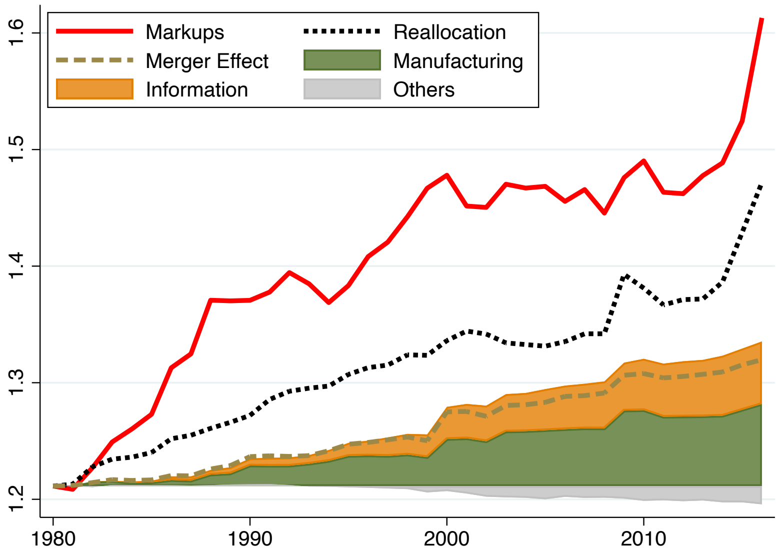

Figure D.2: Industry Breakdown

Notes: Firm-level decomposition of aggregate markup growth by industry. Manufacturing (NAICS codes 31-32-33) and Information (NAICS codes 51).

E Growth

Table E.1: Growth

	All	Non-Acquiror	Acquiror	Year of M&A
Growth (%)	0.10	0.07	0.11	0.20
M&A Growth (%)	0.06	0.00	0.09	0.39
N	184,410	63,228	121,182	29,264

Table E.2: Growth

	All	Non-Acquiror	Acquiror	Year of M&A
Growth (%)				
Mean	0.08	0.05	0.09	0.18
Median	0.05	0.03	0.06	0.13
M&A Share (%)				
Mean	0.05	0.00	0.08	0.34
Median	0.00	0.00	0.00	0.38
# Firms	21,237	11,505	9,732	9,732

Table E.3: Ratio

	Year		
	2010	2013	2016
Gross Effect / Net Effect (%)	0.53	0.54	0.60