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 transfers, 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&A activities. JEL: D4, G34, L11, L16, L4, L5

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I. 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 in the U.S economy over the past several decades (Gutiérrez and Philippon, 2017; 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 that aggregate markups have steadily increased from around 1.2 in 1980 to more than 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 rising market power (De Loecker and Eeckhout, 2018).[1] The role of M&A as a potential driver is appealing both theoretically and from a data perspective. Theoretically, mergers can reduce competition, leading to higher markups and increased concentration. Additionally, there has been a significant increase in the number of M&A activities since the 1980s that mirrors the rise of market power, as shown in Figure I. However, the empirical evidence on the effect of M&A on market power is mixed. While studies have examined specific mergers or industries, the research on the effect of M&As on acquirer markups has shown varying results (Blonigen and Pierce, 2016; Chen, 2019; Cao and Zhu, 2022; Arnold et al., 2022).

One aspect that has often been overlooked on aggregate trends is the effect of mergers and acquisitions on the target firm being acquired. If high-markup acquirers buy low-markup targets and impose their pricing strategy, industry-wide markups could increase.

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

More importantly, the impact of this channel on aggregate markups depends not only on the relative markup differences between the acquirer and the target but also on the pre-merger revenues of the target firm and the extent of *revenue transfer* that occurs as the target is integrated into the acquirer during the M&A process. Significant revenue transfers could also substantially impact industry concentration. Therefore, quantifying revenue transfer during M&A transactions is critical to accurately assess the impact of M&A activity on industry concentration and aggregate markups. Analyzing M&A through this lens also corroborates existing evidence showing that reallocation is driving the rise in markups (De Loecker et al., 2020): while the median markup has remained stable, higher markup firms have experienced greater growth, accounting for a larger share of the economy and consequently raising aggregate markups.

To illustrate our intuition, let us 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, after the merger, American Airlines revenue increased to $42.6 billion, a more than 50% increase primarily attributable to the incorporation of US Airways revenue. The new entity had a markup of 1.2. There are two possible approaches to assess the impact of the merger on markups. The first one evaluates acquirer markups alone: comparing American Airlines pre- and post-merger markups shows a change from 1.16 to 1.2, a 0.04 increase. The second approach focuses also on the change in target's markup, providing a comprehensive overview on the entire market share of the joint firm. Comparing the post-merger markup of 1.2 against the pre-merger weighted average markup of 1.12,[2] shows an overall effect of 0.08. This additional 0.04 increase in markups stems from the revenue transfer from US Airways, with a lower markup, to American Airlines, with a higher markup. This case illustrates that large revenue transfers from low-markup targets to high-markup acquirers during mergers and acquisitions can have a large impact on aggregate markups.

In this paper, we examine how M&A activities influence aggregate market power, focusing on the impact of *revenue transfer* to acquirers, as a complement to the direct effect on acquirers' market power. Our approach, akin to a merger review process conducted by antitrust authorities, aims to assess the size of the joint entity post-merger and its relevance

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

for the industry and the economy. To do so, we document how much the acquirer firm grows from mergers and acquisitions relative to organic growth by accounting for the revenue transfer from the target firm to the acquirer. The revenue transfer channel will have a significant impact on aggregate markups if: 1) the revenue transfers themselves are large, leading to increased concentration, 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 and often relocate revenues from targets with low markup to acquirers with higher ones.

We set out to document all M&A activities that US publicly traded firms are involved in since 1980 and measure the revenue transfers for each M&A deal with known transaction price. In doing so, we establish six facts:

I. M&As are large revenue transfer activities. By looking at the impact of M&As on the revenues of the acquirers, we can account for *all* of the rise in concentration among publicly listed firms, and over 60% among public and private firms.

II. Firms with higher markups are more likely to engage in M&A activities as acquirers.

III. Combining Facts I) and II), we find that M&A activities can explain nearly 40% of the rise in aggregate markup. The effect is due to the reallocation effect stemming from revenue transfers.

IV. Target firms typically exhibit lower markups, suggesting that the effect estimated in fact III is a lower bound for M&As' total effect.

V. Acquiring firms raise their markup after a merger, with the increase being more pronounced for larger revenue transfers.

VI. M&As also raise markups for other firms in the same industry, with the effect being higher for larger revenue transfers.

Our approach, borrowing from the literature of the firm as a "bundle of units" analyzes the share of the revenue of the acquirer firm given the relative sizes of the acquirer and the target firms before the merger (Bradley et al., 1988; Cuñat et al., 2020; Dessaint et al., 2017; Fich et al., 2018; Wang and Xie, 2009). A crucial input in this analysis is the pre-merger revenue of the target firms, which we take from SDC Platinum (Barrios and Wollmann, 2022;

Barnes et al., 2014). SDC Platinum provides comprehensive information on mergers and acquisitions, including key variables such as the identity of the target firms, their revenues, and the shares acquired. However, for many transactions, comprising roughly 29% of deals by value-weighting, the target's financial information is missing.

To utilize the entire set of mergers and acquisitions, we leverage the robust log-linear relationship between the transaction price and the target's revenue, in line with the "multiples" approach to firm valuation (Kaplan and Ruback, 1995; Liu et al., 2002). Target's revenue, combined with the shares acquired, explains 56% of the variation in the log-linear specification.[3] Therefore, we predict missing target sales in a random forest specification using transaction values, shares acquired, geographic identifiers (US state/foreign country), years of the merger, and 3-digit industry codes.[4] We provide extensive validation for this exercise and verify the extent to which target revenues are actually transferred to the acquiring firms, and our results are robust to restricting the analysis to transactions with specified target revenues.

Having quantified the size of the revenue transfers during mergers and acquisitions, and correspondingly, by how much the acquirer growth due to M&A, we proceed to investigate the impact of these transactions on industry concentration and aggregate markups as laid out in Facts I-IV. Additionally, we document an increase in own markups, as laid out in Fact V, when a firm merges or acquires, and also when accounting for the relative size of the revenue transfer compared to the size of the acquirer. The relative size of the revenue transfer in the joint firm, coupled with the observation of merger waves occurring across industries, allows us to propose a leave-one-out instrument for a firm's merger, where we exclude the entire industry (Cowgill et al., 2023). This instrument, the motivation of which is prevalent in the corporate finance literature, allows to use underlying economy-wide trends determining mergers, while disregarding firm (and industry) idiosyncratic factors that might lead to endogeneity concerns. We then adjust this approach by instrumenting the revenue transfer with the average size of revenue transfers for all other industries, finding that the markup increase is positively related to the size of the merger. Finally, we find that when a merger takes place in a sector, it has spillover effects to the non-merging firms as

[3]Moreover, the coefficient estimate remains stable even after including a host of fixed effects, such as geographic, time, and industry fixed effects, alleviating concerns about potential omitted variable bias (Altonji et al., 2005; Oster, 2019).

[4]The findings are robust to using alternative specifications, such as linear prediction or Lasso.

well (Fact VI).

Next, we conduct several tests to verify the validity of our findings. The results are robust to alternative estimations of the imputed revenue. Since most of the effects are due to reported revenues, the results are significant even with dropping all mergers with imputed revenues. They also hold after accounting for divestments and using alternative measures for target revenues.

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 the decline in competition in the United States 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 U.S. from 1980 onward, while Grullon et al. (2019) show an increasing concentration from the late 1990s. In addition, Autor et al. (2020b) document the decreasing share of labor in the major industries in the U.S. and other countries. Several hypotheses have been put forward about 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), 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 analyze M&As by focusing on revenue transfers that occur from targets to acquirers.

Our work is also related to the rise in concentration (Grullon et al., 2019; Gutiérrez and

Philippon, 2017). Measuring concentration is a critical input in antitrust analysis, requiring precise definitions of the product market. Prior literature has documented rising concentration ratios using NAICS industry codes (Grullon et al., 2019; Autor et al., 2020b), as well as with IRS data Kwon et al. (2024). However, there is disagreement on recent trends in concentration depending whether product markets are defined at a local and national level (Benkard et al., 2023; Rossi-Hansberg et al., 2021). Additionally, Benkard et al. (2023) identify product markets from survey, finding very high concentration measures, but also declining over time. The role of M&A has been highlighted as a potential driver for rise in concentration. Grullon et al. (2019) show that M&A's are associated with higher returns and Benkard et al. (2023) present evidence of persistent and positive annual contribution of mergers to concentration ratios. However, to date we are not aware of a prior study that looks at the cumulative effect of M&A on the overall economy-wide concentration. We aim to fill this gap by presenting how mergers cumulatively affect the rise in concentration.

Further, there is a growing discussion on the increase in the M&A activity (Wollmann, 2019; Barrios and Wollmann, 2022; Eeckhout, 2022). Most of this literature has focused on the *number* of deals, while we also document that the *size* of the deals, as measured by revenue transfers, is also critical. Our analysis is related to post-merger reviews, most important of which, are the price effects. Recent work looking at the meta-analysis of the post-merger study has found a positive correlation between the combined concentration before merger and the increase in the post-merger price (Stöhr, 2024).

Additionally, reallocation has been significant when trying to understand aggregate trends in rising market power or falling labor share (De Loecker et al., 2020; Foster et al., 2022; Autor et al., 2020b). De Loecker et al. (2020) show that economy-wide markups have increased as the firms with higher markups have grown larger, while the median markup remains the same. Similar intuition is also prevalent in the decomposition of declining labor share Autor et al. (2020b). 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.

Our paper also closely relates to the impact of mergers and acquisitions on target firms' markups and productivity (Blonigen and Pierce, 2016; Demirer and Karaduman, 2022).

Studying 500 acquisitions in the U.S. electricity generation industry, Demirer and Karaduman (2022) find an increase in the efficiency of the acquired plant after a merger. We show a similar mechanism according to which acquirers increase target markups for the universe of M&A deals including publicly listed firms. While this allows us to study aggregate markups, a common limitation in using large datasets is that we cannot identify efficiency improvements. We leave it to future research to address this in a large-scale dataset, possibly using census data.

We also contribute to the literature on the empirical findings of firm valuation. The "multiples" approach establishes a link between the value of a company and its revenues. This theoretical result has been tested only with publicly traded companies, 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 effect of mergers on firm growth, we contribute to the literature studying M&A, innovation and productivity. Cunningham et al. (2021)'s seminal contribution shows that incumbents buy innovative targets to preserve their future market share. Letina et al. (2024) and Fons-Rosen et al. (2022) provide theories to compare and evaluate the direct effect of "killer acquisitions" with the spillovers that result in the creation of startups, generally finding a net reduction in aggregate growth. Our study complements these findings by focusing on large acquisitions, showing how large mergers contribute to incumbent revenue growth and market power.

Road-Map. The rest of the paper is organized as follows. Section II presents the data and our methodology for computing revenue transfers. Section III discusses our main findings. Section IV addresses robustness of our findings, and Section V concludes.

II. 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 provides financial information for U.S. publicly traded companies starting

from the 1950s onward. In addition to firm identifiers and industry classifications, it includes revenues and costs of goods sold - necessary components for computing markups. We utilize the Compustat database for the 1980 - 2016 period and follow the same data preparation as De Loecker et al. (2020).[5] Table I shows summary statistics for the sample under analysis.

To calculate the markups, defined as the ratio of price over marginal costs, we follow the production approach pioneered by Hall (1988) and De Loecker and Warzynski (2012). This method leverages structural insights from firm optimizing behavior with respect to static cost minimization to derive a straightforward formulation for firm-level markups:

$$\mu_{it} = \theta_{it}^{v}(s_{it}^{v})^{-1} \tag{1}$$

with μ_{it} being firm i markup at time t, θ_{it}^{v} the output elasticity with respect to the flexible input v, and $s_{it}^{v} = \frac{P_{it}Q_{it}}{P_{it}^{V}V_{i}t}$ the flexible input share, with P_{it} and Q_{it} representing 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. Appendix A provides a more complete description of the approach. We compute the input shares taken directly from the data and use the 2-digit sector-specific and time-varying output elasticities of De Loecker et al. (2020) to compute firm-level markups.

SDC Platinum provides information on mergers and acquisitions around the world. This information is collected from various sources, including media reports and regulatory filings, and is the most widely used dataset to analyze mergers and acquisitions in economics and finance (Barrios and Wollmann, 2022; Barnes et al., 2014). For our analysis we take all completed mergers and acquisitions by a Compustat firm between 1980-2016 with known transaction price, meaning, it is reported in the SDC how much the acquirer paid for the target.[6] For each such transaction, comprehensive detailed information is provided, including the date of the Merger/Acquisition Announcement, Acquirer Name, Target Name, along with Acquirer and Target identifiers.[7] A brief synopsis of the merger is included, and, im-

[5]This is, in part, to have our results, such as Fact III, align with the key figures in De Loecker et al. (2020).

[6]Throughout the analysis, we would refer to "acquirer" and "target", even in cases of mergers between two equals. That is because even in mergers between two equals, there is typically an acquirer and a target, which are identified in the SDC dataset.

[7]The dataset includes other relevant merger dates, such as the Effective Date. The main identifiers that we implements are the CUSIP numbers. CUSIP numbers are provided in three categories: company, immediate

portant for us as we describe below, it may also contain additional details on the merger including financial information on targets. Appendix B provides details on matching Compustat firms with the mergers and acquisitions in which they were involved, primarily as acquirers, but also as targets.

II.A Target Revenues

A crucial component to measure revenue transfers is the pre-merger revenue of the targets. SDC provides comprehensive information for each merger and acquisition event, which often includes financial information on the target firm, including its pre-merger revenues.[8] However, target revenues are more often missing than available: in our matched sample target revenues are available for 38% of the sample. These are mostly transactions involving smaller targets, as the target revenue is available for 71% of the sample when weighting by transaction value.[9] If we were to consider only these M&A transactions with non-missing revenues, we would discard the vast majority of merger and acquisition activities, potentially underestimating its total effect. We instead infer missing revenues using other available data on the event.

We start by documenting a very robust log-linear relationship between target revenues and transaction value. Figure II plots the relation between log of target revenue and log of transaction value. The log-linear relation is precise at all bins and has large explanatory power: the (log) transaction value alone explains 56% of the variation of the regression, implying a correlation of 75% between the two variables.[10] In Table II we confirm the stability of the estimated coefficient also with more demanding specifications. 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 alleviates any concerns about the coefficient stability due to omitted variable bias (Altonji et al., 2005; Oster, 2019). This linear relation-

parent company, and ultimate parent company. They are largely the same for most companies but may differ for some. We utilize all CUSIP numbers to match the SDC mergers with Compustat.

[8] This is provided in the "net sales" column in the SDC database, 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." Broadly, this corresponds to the sales definition of Compustat, which is "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."

[9] In the overall SDC sample revenue information are even more scarce, covering only 32% of M&A events.

[10] In the Figure and the specification we also include share buybacks - firms purchasing 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.

ship 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 the validity of the multiples approach using publicly listed firms, which have the advantage of having both their value and the revenues readily available. However, this typically entails a small sample size. To our knowledge, we are the first to empirically document this relationship, including a large number of public and private firms.

We use the above relationship to predict missing revenues for targets in the SDC database.[11] We make use of all the controls in the specification: transaction value, acquired shares, time, geographic, and industry information. Our preferred baseline approach uses a random forest specification with 3-digit industry fixed effects. The results are almost identical when alternative approaches are used, including linear specifications with fixed effects or Lasso.

II.B Validation of Revenue Transfer

Before proceeding to our main analysis, we 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 pre-merger target revenues and the increase in acquirer revenues after buying up the target. 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 rate of revenue calculated during the previous n periods.[12] We then regress the acquirer's excess revenue on (potential) target's pre-merger revenue:

$$A_{t+1} - A_t(1 + \bar{g_n}) = \beta T_t + \varepsilon_{t+1}, \tag{2}$$

where T_t is the target's revenue if there was a merger or acquisition taking place, and 0 otherwise. We are interested in the coefficient β, which by our intuition should be positive

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

[12] We consider only those years without mergers to get a measure for the organic growth rate of the firm.

and close to 1. Table III presents the results. Columns 1-3 show the regression results in levels at different lags of growth rates, whereas columns 4-6 do the same exercise in logs.[13] 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. Since the result in levels might be driven by outliers of large M&A deals, we also test the hypothesis in logs, presented in Columns 4-6. We find that the effect is also present in logs and is quite stable across different lag specifications. These findings confirm our intuition that mergers induce large revenue changes in acquirers, and these changes closely correspond to the target's revenue.

II.C Revenue Growth from Mergers

We next provide information about our calculation of revenue transfers and present relevant summary statistics. Our baseline measure computes the share of firm growth from M&A's. As such, borrowing from the intuition of the "firm as a bundle of units" literature, if A is the pre-merger revenue of the Acquirer, and T is the pre-merger revenue of the Target, then $T/(A+T)$ share in the newly formed joint firm will come from the M&A - the outside growth.[14] Correspondingly, the share of the acquirer in the merged firm is $A/(A+T)$. This provides the relative revenue share in the newly formed firm from outside growth for one merger. In case of several M&A's the relevant share measure is *cumulative*: meaning that if the same firm is involved in another merger afterwards, then the overall share of the firm's revenues due to mergers will be relative shares from both mergers. That is, if Acquirer A goes through 2 mergers, when its revenues are A_1 and A_2 in each merger case, and the target revenues are T_1 and T_2 correspondingly, then the share of the original acquirer in the new firm will be: $\frac{A_1 * A_2}{((A_1+T_1)(A_2+T_2))}$, and the total share of the firm from mergers will be $1 - \frac{A_1 * A_2}{((A_1+T_1)(A_2+T_2))}$.

Table IV presents the summary statistics. It shows the average growth rate of the Compustat firms, which are then split by year where there is a merger and years with none. Not surprisingly, we find that firms in the years of the merger grow much more than their counterparts or even when considering the same (merging) firms in non-merging years: the

[13] For logs, we add 1 to excess acquirer and target revenues to account for 0's in periods with no mergers.

[14] This specification is invariant to the relative timing of the merger, conditional that the Acquirer and Target grow at proportional rates. We find similar results using an alternative specification where target revenue contributes to the Acquirer's excess revenue growth.

average growth rate of the firms with mergers is 4p.p. higher relative to the growth rate in non-merging firms. Further, we find that target revenues contribute 13 p.p. of the growth rate over the overall firms. This means, that there might be additional growth of the firm that are not accounted for by target revenues.[15]

In terms of which mergers are the Compustat firms involved in, we document that 41% of the mergers, in value-weighted terms, are horizontal mergers defined by being in the same 4-digit industry. This share grows and constitutes 53% for the same set of firms in the 3-digit category and 66% in the 2-digit category. Further, as we mentioned above, 29% of total M&A revenue shares come from predicted revenues, while the rest are directly reported in the SDC.

III. Facts About the Role of Mergers for Market Power

Having documented all mergers and acquisitions in which Compustat firms have been involved, and measuring the revenue transfer that takes place during the M&A, we explore how much does accounting for mergers and acquisitions through revenue transfer can help explain the rise in market power. We first start by documenting the contribution of mergers to the increase in concentration, whose changes are entirely driven by the relative revenue changes of firms in the industry, especially those at the top. Then, we move to markups analyzing first the market share reallocation happening through the revenue transfers, and then causally identifying the direct effect on acquirers' and competitors' markups.

Fact I: Mergers Explain All of the Rise in Concentration

Concentration has been rising in the United States over the last decades (Grullon et al., 2019; Autor et al., 2020b; Covarrubias et al., 2020). Figure III plots the average industry concentration in the United States from 1980 to present. It shows a rise in concentration for publicly listed firms since the 1980s as in Grullon et al. (2019). Figure IIIa focuses on the evolution of the HHI index calculated at the 3-digit industry level and aggregated to the overall US economy, using revenue weights to ensure that smaller or declining industries have less impact on the overall measure of concentration across the economy. Similarly,

[15] This could potentially come from synergies, where the Acquirer's own core revenue grows as a result of the merger.

Figure IIIb shows the evolution of the combined market share of the 4 largest firms within an industry, confirming the extreme relevance of a few *superstar* firms (Autor et al., 2020b).

While many papers have documented the increase in concentration, and the rise of "superstar firms" in many industries (Autor et al., 2020b), it is less clear how much potential drivers, such as M&A or change in technology, have contributed to it. We investigate the contribution of M&A activities by measuring the extent of firm revenue changes due to M&A. We thus construct a counterfactual revenue of the acquiring firm that it would have had absent the revenue transfers from the acquisition. More specifically, using our terminology described above, we take the pre-merger revenues of the acquirer and the revenue transfer and consider both entities growing at the same firm growth rate in the future. For example, suppose acquirer A of size \$30mln in revenues acquires a target T, with revenues of \$10mln. Thus, as we defined above the revenue transfer constitutes $10/(10+30) = 25\%$ of the mergerd firm's overall revenues. If there are no any other future mergers, then the revenue growth of the acquirer from the merger will be 25% in all subsequent year. If there are future mergers, then we calculate the cumulative sum of the mergers, by combining all the revenue transfers.[16] We thus calculate how much revenue transfer has taken place for each acquirer.[17] We then measure how much would the industry concentration have been if the merged entities split as acquirer's own revenues and the cumulative revenue transfer of the acquirers.[18] Ex ante it is not clear which way the direction will go: if larger firms are more likely to merge, then in the counterfactual scenario with no mergers, the concentration will be lower. However, if medium and smaller size firms are more likely to merge, in part because they are less likely to be subject to antitrust scrutiny, then after the mergers, the firm distribution in an industry will be less unequal and the concentration ratio with mergers will be lower.

We calculate concentration measures for the entire industry and then use relevant indus-

[16] This approach may also potentially *undercount* the total effect mergers if an acquirer later becomes a target. For example, if B acquires C, and the B is later acquired by A, then the share of the firm growth in the economy afterwards will be B/(A+B) and thus, the relative contribution of acquiring C will no longer be counted.

[17] In alternative specification we measure the share of the firm revenue transfer by measuring how much revenue transfer has happened from the relative growth of the firm. The results are robust with approach. This second method shuts down target firm growth between merger announcement and effective dates.

[18] Even though the aggregate revenue transfers may arise from multiple mergers, for simplicity, we keep them all as one entity. Also, we keep this entity in the same industry as the acquirer, even though firms might merge or acquire firms outside of their industry. The results are robust to considering only the horizontal mergers. We also take this entity as a standalone company, meaning that if prior to merger the Target was in Compustat, it will remain as a standalone firm. But if it was not, then it will be added to our set of firms. This allows us to keep the industry size the same in counterfactual calculations.

try weights to compute the aggregate concentration ratios for the US economy. Figure III shows the observed concentration ratio along with the counterfactuals. Both concentration measures are much lower than the overall economy-wide measures, and the recent rise in concentration completely disappears. Interestingly, Figure IIIb shows that the largest firms in the economy would grow much less without being able to acquire other firms, to the point that they would actually shrink as a result of the creative destruction process. Figure XI-IIa and Figure XIIIb in the Appendix compute the same counterfacturals considering only revenues from horizontal mergers, finding that also in that case the rise in concentration disappears.

While the concentration ratios with Compustat firms provide valuable insight, these represent publicly traded firms, which tend to be larger. For the overall concentration in the US economy, using Census data, which includes public and private establishments, might be more appropriate. We recalculate C4 concentration ratios, using the total value of each industry, as provided by Census in 5 year intervals, starting from 1992. We then take the 4 largest firms in each respective industry as coming from Compustat.[19] Figure IV presents the results with the Census figures. We find increasing concentration ratios from the 1990's on, in line with prior literature (Autor et al., 2020b). This increase in concentration is greatly diminished, but does not completely disappear, when accounting for merger revenues. With the Census specification, the mergers explain roughly 60% of the overall rise in concentration. Overall, using both Compustat and Census measures of industry concentration, we find significant effect of mergers on the rise in concentration.

Fact II: Large and Higher Markup Firms Are More Likely To Acquire

The previous fact documents that on average the revenue transfers are large and they are more likely to be undertaken by larger firms. We next seek to identify how does the acquisition practice correlate with the markup of the firm. Understanding the relationship between markups and the acquisition will help shed light on the dynamics of market power. We test whether higher markup firms are more likely to engage in M&A activities as acquirers in the

[19]This assumes that the largest firms in each industry are publicly traded.

following specification:

$$\mathbb{1}[\text{A}]_{ist} = \beta_0 + \beta_1 x_{ist-1} + \phi_{ist} + \varepsilon_{ist} \tag{3}$$

with $\mathbb{1}[\text{A}]_{ist}$ being a dummy that takes value 1 if firm *i* in sector *s* engages in a merger as an acquirer at time *t*. x_{ist-1} is firm's lagged markup and finally, Φ_{ist} is the set of fixed effects, which, depending on the specification, include either sector time-varying (defined as 2 digit industry-by-time) and firm specific fixed effects.

Table V presents the results of our analysis. The first column demonstrates that within a sector, firms with higher markups are more likely to engage in M&A as acquirers. The coefficient estimate suggests that a 10% increase in a firm's markup increases the likelihood of it being an acquirer by 13%. This is a substantial effect, considering that approximately 14% of all possible firm-year combinations in Compustat involve M&A activity. In column 2, we focus on within-firm analysis and find that the effect not only remains significant but also increases in magnitude.

This effect may be driven by higher markup firms being larger in size. Prior literature, such as Autor et al. (2020b), has documented a positive correlation between markup and size using Census data, a finding we also confirm for Compustat firms (Figure X). When we test an alternative specification with firm size replacing markup, we find that size is a significant predictor of being an acquirer. Columns 3 shows that a 10% increase in firm size translates to roughly a 3.5% increase in the likelihood of merging. This effect diminishes but remains significant when including firm fixed effects, as shown in Column 4.

To determine whether the effects are driven by firm size or markups, we conduct a "horse race" with both variables. Columns 5 and 6 present these results, indicating that despite the high correlation between the two variables, both coefficients remain statistically significant and similar in magnitude to those in prior columns. These findings demonstrate that higher markup firms are more likely to merge and acquire, independent of their size.

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

So far we have established that there is a large number of mergers taking place and that high-markup firms are more likely to acquire other firms. These facts, taken together, imply

that M&A could potentially raise overall markups, as high-markup firms grow through mergers and acquisitions, thus increasing 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 examine the decomposition effect as specified by De Loecker et al. (2020) (DLEU, hereafter). 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 net entrants:

$$\begin{aligned}\mu_t - \mu_{t-1} = &\underbrace{\sum_{i \in C} s_{it-1}(\mu_{it} - \mu_{it-1})}_{\text{within}} + \underbrace{\sum_{i \in C} \tilde{\mu}_{it-1}(s_{it} - s_{it-1}) + \sum_{i \in C}(s_{it} - s_{it-1})(\mu_{it} - \mu_{it-1})}_{\text{reallocation}} \\ &\underbrace{+ \sum_{i \in E} s_{it}\tilde{\mu}_{it} - \sum_{i \in X} s_{it-1}\tilde{\mu}_{it-1}}_{\text{net entry}}\end{aligned} \tag{4}$$

where μ_t is sales-weighted aggregate markup in time t, μ_{it} is firm i markup in time t, and s_{it} denotes sales in time t. C represents the groups of firms active in $t-1$ and t, E constitutes the set of entrants in time t, and X are the exiters in $t-1$. Finally, $\tilde{\mu}_{it} = \mu_{it} - \mu_t$ and $\tilde{\mu}_{it-1} = \mu_{it-1} - \mu_{t-1}$ which are rescaling parameters (Haltiwanger, 1997).

We follow DLEU in using 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 V shows that the reallocation term alone accounts for more than two-thirds of the change in the weighted markup, replicating DLEU's results. We then perform an exercise similar to the one for the rise in concentration to measure the contribution of mergers to aggregate markup growth. Specifically, we calculate the share of revenue growth that is due to incorporating target sales in each year as:

$$\text{Merger Growth Share}_t = \frac{\text{Target Sales}_{t-1}}{\Delta\text{Acquirer Revenue}_t} \tag{5}$$

Then we construct a counterfactual setting all other terms to zero and leaving only the merger growth component in the reallocation term, thus measuring how much of the aggregate markup is driven by firm growth only through mergers. Figure V 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 the overall contribution. The modest effect of the contribution of the merger is partly driven by the small number of mergers that take place during this period (Figure I). As the overall number 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.

In addition to measuring the effect on the reallocation, we can also calculate how much of the overall increase in the markups is explained by the merger effect. We again find that the merger effect explains a small share of the overall effect of the rising markup, about 10-15% in the 1990s. However, as both the number and size of merger activities increase, their effect on the overall rise in markups also increases, explaining close to 35-38% of the total effect.[20]

Next, we analyze what share of the overall effect is driven by horizontal mergers. We take mergers and acquisitions to be horizontal if the acquirer and the target are in the same 3-digit industry sector.[21] In an alternative specification, we also consider the impact of mergers if the target and the acquirer are in the same 2-digit industry sector. Figure VI presents the results for horizontal mergers, showing that they explain 60-70% of the overall effect of mergers. In Figure XIV 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.

Fact IV: Target Firms Have Low Markups

The decomposition formula shows that mergers and acquisitions can affect the overall aggregate markups in two ways. First, they increase acquirer revenues and impact aggregate

[20] Table X reports the yearly observations underlying Figure V.

[21] While 3-digit sectors might be a broad definition for horizontal mergers, this is the finest level available for target firms in the SDC database.

markup through the reallocation effect. Second, they can also affect aggregate markup through the exit effect as the target firms leave the economy. So far, we have focused on the effect of M&A through the reallocation effect alone. However, to measure the full impact of mergers and acquisitions, we also need to take into account the effect of the exit of the targets. Specifically, the change in aggregate markup due to a merger between acquirer *A* and target *T* through the lens of Equation (4) is given by the difference between acquirer's and target's markup weighted by target sales, capturing the essence of our revenue transfer approach. For the subset of acquisitions for which the target is also in Compustat, we relate our measured markup effect to the overall effect by accounting for target exit. Figure VII shows the ratio of our estimate to the true estimate for the cumulative sum of mergers, starting with the total mergers up to 1990 and extending further. The graph shows that our estimated merger effect on markups is between 40 and 50% of the total effect, consistent with targets having lower markups on average. To confirm, we run the following specification:

$$\mathbb{1}[\mathrm{T}]_{ist} = \beta_0 + \beta_1 x_{ist-1} + \Phi_{ist} + \varepsilon_{ist}$$

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*, x_{ist-1} is the markup of firm *i* at time *t*-1, and Φ_{ist}, similar to the specification in Fact II, is the set of fixed effects that includes sector time-varying and firm fixed effects.

Table VI 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 implies that, if anything, we are *undercounting* the full effect of mergers on markups. If we were to extend the results of Figure VII to *all* targets we would find that the M&A activities could explain up to 80% of the increase in the markup.

Fact V: Firm Markups Increase After Mergers

Facts I-IV focused on the reallocation effect, showing the impact of mergers on the rise in concentration and markups is significant. We next focus on the effect of the mergers on the acquirer markups directly, in line with prior literature (Blonigen and Pierce, 2016; Chen,

2019; Cao and Zhu, 2022; Arnold et al., 2022). Further, by measuring the revenue transfer during M&A we can also distinguish between large and small mergers. We examine whether the merger increases the firm's own markup using the following specification:

$$\mu_{ist} = \beta_0 + \beta_1 X_{ist} + \Phi_{ist} + \varepsilon_{ist} \tag{6}$$

with μ_{ist} being firm *i*'s markup at time *t* in sector *s* and Φ_{ist} includes sector time-varying or firm fixed effects. X_{ist} is the merger treatment, which we take as either a dummy, equal to 1 if firm *i* engages in a merger as an acquirer in time *t*, or a continuous treatment measuring the share increase in revenues coming from mergers. Further, our continuous treatment allows for a potential instrument by utilizing merger waves across many industries (Cowgill et al., 2023). We propose to instrument the continuous treatment of revenue share increase with revenue share increases of other mergers in that year, in a leave one-out approach, where we exclude not just own firm, but the *entire industry* of the firm. Thus, our instrument is driven by the relative magnitude of mergers in other industries.

Table VII 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. Specifically, the merger increases the acquirer's markup by about .02, a very sizable effect, and in line with contemporaneous work in Stiebale and Szücs (2022). 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 bigger mergers have a larger impact. We find that this is indeed 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. An increase in the merger share of one percent would increase the markup by 0.15%. Finally, column 3 presents the IV specification. We instrument the merger share of 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 take place during the same

period across many industries. In creating our instrument, we again exclude not only own firm, but the entire industry of that firm.[22] We confirm that strength of our instrument in the first stage, and Column 3 shows that the OLS result in column 2 continues to hold with the IV specification.

Fact VI: Merger Effect on Competitors' Markup

Given that mergers increase the firm's markup, we next explore if they also affect competitors' markups within the same industry sector. We compute the sector weighted average markup, excluding the merging firm(s) and calculate its changes following a M&A event using this specification:

$$\mu_{st}^{-M} = \beta_0 + \beta_1 X_{st} + \phi_s + \phi_t + \varepsilon_{st} \tag{7}$$

with μ_{st}^{-M} being the sales-weighted markup in sector *s* at time *t*, excluding firms engaging in mergers. ϕ_s and ϕ_t are sector- and time-fixed effects, respectively. X_{st} is the merger treatment, and in the first specification 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, 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 in that year. Table VIII 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 competitors' markups. The effect holds both when we look at the mergers as event studies and also as shares of acquirer revenues. The coefficients indicate that a M&A event in the sector increases competitors' weighted markups by 2%, indicating a worsening of overall competition in that sector. Similarly, a one-standard deviation increase in merger share leads to an increase in sales-weighted competitors' markup of 0.015. This Fact, combined with Fact 2 shows that as other firms' markups in the industry increase, they are more likely to be engaged in M&A, further increasing overall sector-wide markups.

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

IV. Robustness and Discussion

IV.A Assumptions Underlying the Merger Effect

Critical to our analysis is calculating the revenue share that takes place during an 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. These will further increase joint revenues, and if there are significant merger synergies, our estimates provide, if anything, a lower bound of the overall merger effect. Additionally, we assume that there are no cost-cutting activities that may follow acquisitions. However, SDC also reports divestments, and the results are robust to account for them. We also assume that the entire revenue of the merging firm is realized in the year the merger is completed.[23] While this may hold for most mergers, larger mergers may take several years to be fully internalized. The results are robust to considering longer time periods for 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. The results are robust to considering longer time horizon of revenue transfers such as three or five years.

IV.B Selection into Missing

Figure VIII breaks down the overall contribution of mergers in Fact 3 based on reported and 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. However, also,

[23] We take this at the effective date of the merger.

their revenue contribution to the acquiring firm is also likely to be small. As a robustness, we rerun the analysis where we exclude predicted sales for mergers with transaction value less than $100 million, finding consistent results. 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 these transactions may then differ greatly 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 in several ways. First, we plot the kernel densities of (log) transaction value for both targets with reported and missing sales in Figure IX. As expected, the distribution of transaction values with known revenues is 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 the imputed revenues for the largest transactions. Table IX 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.[24] Column 5 in Table IX shows the revenues figures that we obtain and Column 6 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) acquisitions of WhatsApp, where close to $19.5 billion price paid 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

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

industry, with established revenues. This means that the predicted revenues combine both current and 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 also 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 was reported to have $26 billion in revenues, comprising roughly half of Meta's total revenues.[25] Instagram, if it were a standalone company, was valued at more than $100 billion in 2018 based on the revenues it generated.[26] 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 is 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 synergies, where the revenues of the core business for Facebook would be increased by the predicted revenues. This would apply to acquisitions such as WhatsApp, where no future revenues were generated from the acquisition 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. However, we do not think 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

[25] https://www.yahoo.com/entertainment/instagram-now-makes-more-half-140500679.html. These figures are most likely estimates, as Meta does not split the total revenues across its different platforms.

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

to avoid reporting, and thus attract 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 transactions, the acquiring firms will spend a significant amount to acquire a well-established company or a very promising young startup, just to shut it down.[27] Though potentially shutting down potential competitors might have long-term consequences and impact on markups in a longer horizon.[28]

IV.C Revenue Figures

The other concern for our analysis is the accuracy of the revenue figures reported 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 the targets, revenue figures are also available in Compustat.[29] We compare the revenue reported by the SDC with those in Compustat.[30] 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 II for detailed definitions of revenues in each of the datasets.) As our baseline, we compare SDC revenue figures with Compustat revenues that correspond to the fiscal year prior to the merger announcement, that is, the latest available fiscal year revenues when the deal was announced. Since the SDC figures are constantly updated, as a robustness we also consider a window of $+/-2$ years. Figure XV 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 that using the SDC revenues provides a lower bound for the overall merger effect.

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

[28] While very important, it is challenging to try to quantify these effects.

[29] These also include share buybacks.

[30] 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.

As a robustness, we also impute revenue figures using Compustat revenues. We do it in 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 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 log-linear relation between value and revenue also holds when restricted to Compustat firms only (Figure XVI). Figure XVII then presents the robustness results under both specifications for Fact III). We find that the total merger effect, if anything, is larger, reaching as high as 70% of the 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.

V. Conclusion

There has been an 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. Several hypotheses have been presented, 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 transferred 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.

Using Compustat data, our findings provide crucial insights into M&A effects on ag-

gregate markups and market dynamics among publicly listed firms. Future research could further enrich these findings by applying our methods to granular data, offering a broader perspective on the effects across the entire firm distribution.

The findings of this paper also have significant policy implications. The significant effect of M&A activities on market power suggests that regulators and policymakers need to closely scrutinize the broader revenue implications of such activities. Traditional analyses focusing solely on direct effects may underestimate the true economic impact of mergers.

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APPENDIX

A. 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, and it just requires firms to use a flexible input and to minimize static 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. For each period, firms minimize the contemporaneous cost of production for a given target level of output to produce, $\bar{Q}_{it}$. Hence, the Lagrangian of the static cost minimization problem 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 the flexible input and r_{it} 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. Taking the first order derivative with respect to V yields:

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

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:

$$\frac{P_{it}}{\lambda_{it}} = \theta_{it}^{v}\frac{P_{it}Q_{it}}{P_{it}^{V}V_{it}}$$

The markup therefore 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 of De Loecker et al. (2020). These elasticities are estimated using the production approach initially proposed by Olley and Pakes (1996), with

the Ackerberg et al. (2015) correction and additional controls for imperfections in the output and input markets. De Loecker et al. (2020) impose the assumption that firms produce according to a Cobb-Douglas production function with time-varying elasticities common across 2-digit industries.

B. MERGING/MATCHING

We first match acquiring firms in the SDC dataset to firms in Compustat, using the CUSIP number as our primary matching identifier, as is usually done in the literature (e.g. in Cowgill et al., 2023). For unmatched firms, about 10% of the total, we expand our matching algorithm to also include exact name matches, matches via ticker symbols, and commonality of search engine results.[31] For all matches that are not done via CUSIP or exact name matches, we manually check the results to account for false positives. Table XI provides the matching results by the different methods.

B.A Additional Details on Matching

The first method includes merging with the CUSIP number. The Compustat data include the 9-digit CUSIP of the companies, whereas the SDC Platinum includes only 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 – the actual company, the immediate parent, and the ultimate parent. In case of multiple matches, the priority is given first to the actual, then to the immediate, then to the ultimate (the actual number of such matches is not frequent).

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. 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

[31] The latter has been shown to perform well in identifying different name variants and spellings of the same company (Autor et al., 2020a)

match new CUSIP numbers with old CUSIP using the CRSP linking tables.

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

We also match using the URL method of Autor et al. (2020a). The approach utilizes the search engine algorithm to match different versions of companies. They use this approach to account for abbreviations or misspellings and find that it works remarkably well. For example, on the basis of 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 criterion of having an overlap of at least 4 matches from the first 10 search results on Bing.

Finally, we match by ticker symbol. In the SDC data, the ticker symbols are again given as three types - actual company, Immediate Parent, and Ultimate Parent. However, the tickers can refer to any of the worldwide exchanges, wherever the company is traded. In Compustat, the ticker symbols are primarily for US-based exchanges. After matching by the ticker symbol, we then ensure that the matched companies are indeed the same by checking their other identifiers, such as the headquarter location or the industry sector.

Table XI provides summarizes the total 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).

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TABLES

TABLE I
Summary Statistics

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

Notes: The table presents the summary statistics for the main variables – Sales and Cost of Goods Sold – used to measure markups for Compustat firms from 1980 to 2016. All variables are expressed in thousands of Dollars deflated using the GDP deflator with base year 2010.

TABLE II
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

Notes: The table reports the coefficient estimates of the target (log) sales regressed on the (log) transaction values. The regression controls include sequentially year fixed effects, sector fixed effects at the 2-digit, 3-digit, and 4-digit level for both the acquirer and target firm, as well as the location of the acquirer and the target. Standard errors are clustered at the acquirer level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE III
Validation of Methodology

	Levels			Logs		
	(1)	(2)	(3)	(4)	(5)	(6)
Target Sales	0.59	0.94	1.03	1.01	1.01	1.00
Lags	2	3	4	2	3	4
N	104,731	82,506	66,015	48,012	37,127	29,061

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 previous 2, 3, or 4 periods. The first three columns report coefficients from a regression in levels, and the last three in logs.

TABLE IV
Growth Rates

Growth	(1) All	(2) Non-Acquiror	(3) Acquiror	(4) M&A Year	(5) Non M&A Year	(6) M&A Share
Mean	0.07	0.04	0.08	0.18	0.06	0.13
Median	0.05	0.03	0.06	0.13	0.04	0.08

Notes: This table shows average and median growth rates of firms in Compustat over the period from 1980 to 2016. The first column exhibits values for the whole sample, the second for firms that never acquired another firm, the third for firms that acquired at least another firm over the time period, the fourth column only for the year in which the merger actually takes place, and the final column the revenue transfer measured as target revenues divided by acquiror revenues.

TABLE V
Mergers and Acquirer Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Markup	0.013	0.015			0.018	0.014
	(0.003)	(0.004)			(0.003)	(0.003)
log(Sales)			0.035	0.021	0.036	0.021
			(0.002)	(0.005)	(0.002)	(0.004)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Sector x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
R2	0.04	0.28	0.08	0.28	0.09	0.28
N	184,410	184,410	184,410	184,410	184,410	184,410

Notes: The table reports the coefficient estimates of the acquirer dummy regressed on markups and (log) sales. The regression controls for sector-by-year fixed effects, and firm fixed effects. Standard errors are clustered at the industry level.

TABLE VI
Target dummy on markup

	(1)	(2)	(3)	(4)	(5)
Markup	-0.002	0.011	-0.004	-0.007	-0.0004
	(0.014)	(0.014)	(0.018)	(0.017)	(0.0002)
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

Notes: The table reports the coefficient estimates 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 industry level.

TABLE VII
Merger Effect on Own Markups

	(1)	(2)	(3)
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
First Stage F-Stat			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.

TABLE VIII
Merger Effect on Other Firms in the Sector

	(1)	(2)
Merger	0.019	
	(0.011)	
MergerShare		0.514
		(0.158)
Constant	Yes	Yes
Sector x year FE	Yes	Yes
4d Industry 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.

TABLE IX
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
Coty Inc	Procter & Gamble Co, Beauty Business	2016	14,917	11,477	5,151
Molson Coors Brewing Co	Miller Brewing Co	2016	12,000	7,726	5,109
General Electric Co	Alstrom SA, Energy Business	2015	10,700	15,984	3,273
DuPont	Conoco Inc	1981	9,520	18,800	3,820
Valor Communications	Alltel Holding Corp	2006	9,096	2,420	3,236
Lockheed Martin Corp	Sikorsky Aircraft Corp	2015	9,000	4,380	3,766

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

Appendix Tables

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 X
Merger Effect by Year

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 XI
Matching by Criterion

FIGURES

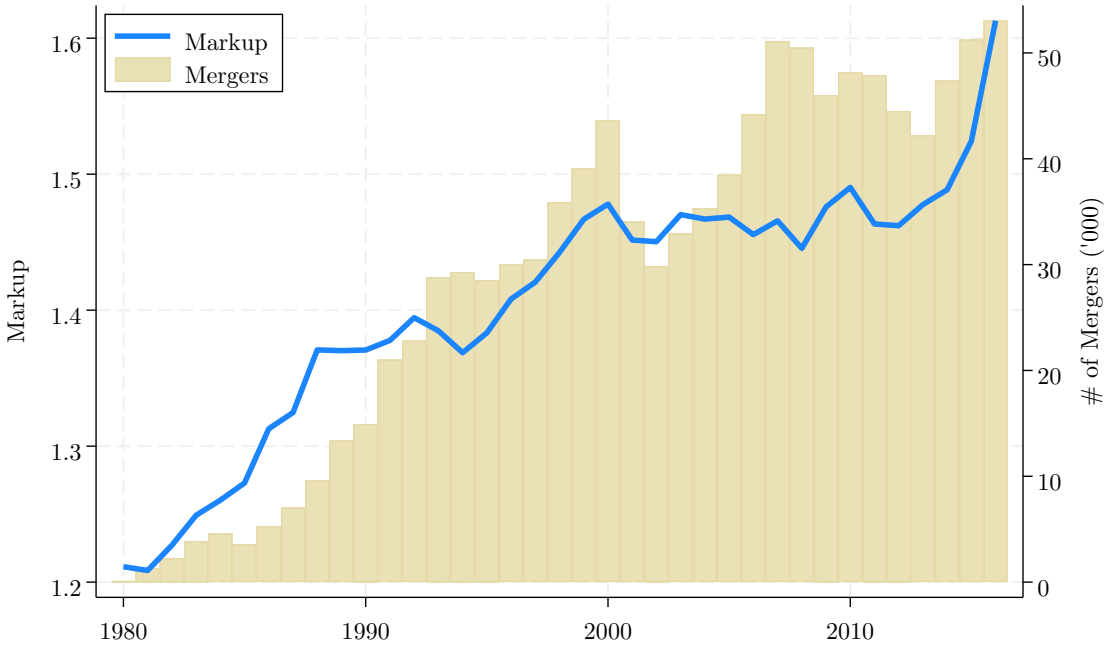


FIGURE I
Aggregate Markup and Mergers

Notes: The graph shows the evolution of aggregate sales-weighted markup in the United States, sourced by De Loecker et al. (2020), and the total number of mergers and acquisitions reported by the SDC.

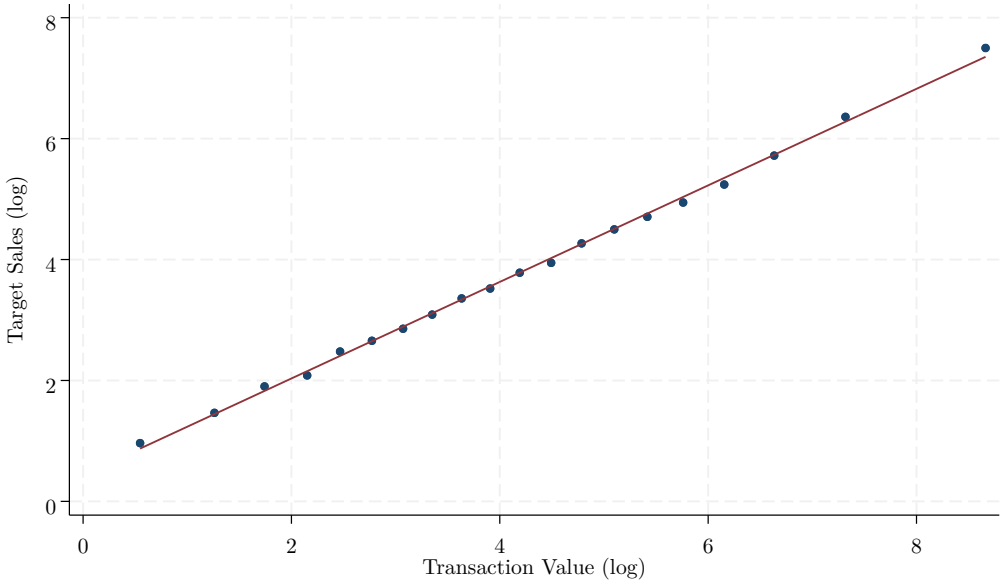
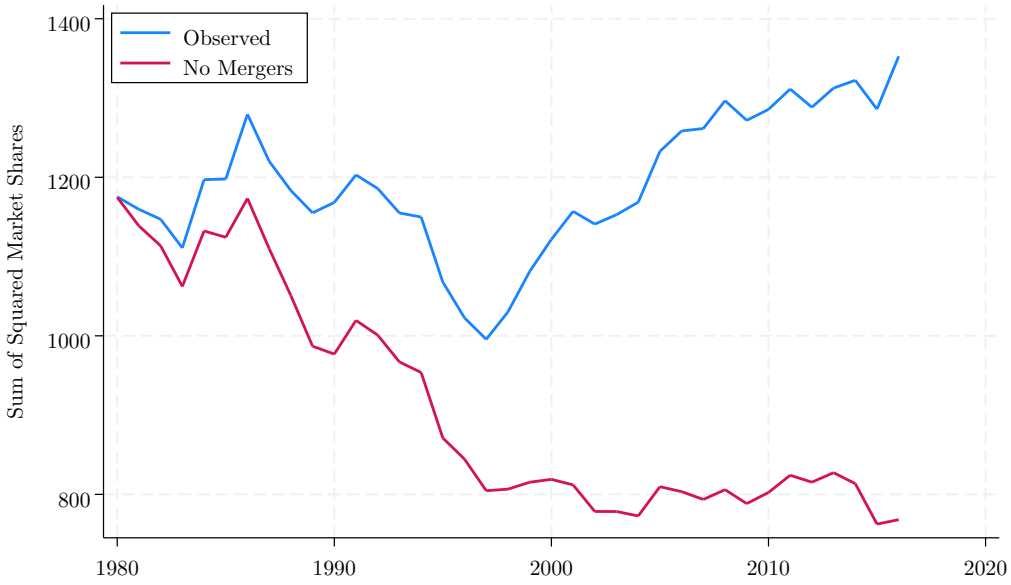
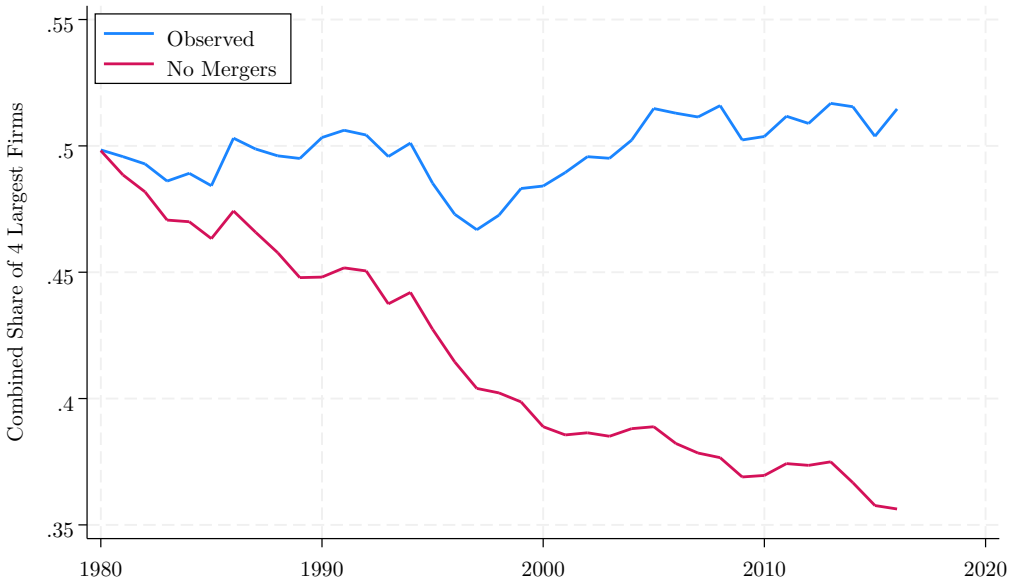


FIGURE II
A Log-linear Relation

Notes: Binscatter of log target sales on log transaction value.



(A)
HHI Index



(B)
C4 Index

FIGURE III
Concentration and Mergers

Notes: The figure shows concentration measures for the economy. The top panel displays the HHI index, the sum of the squared market shares, in blue, and its counterfactual value with no mergers in red. The bottom panel displays the C4 index, the sum of market shares of the four largest firms, in blue, and its counterfactual value with no mergers in red. Counterfactuals are constructed by splitting acquirers from targets and keeping the same size ratio over time. Each indicator is computed for the 3-digit industry and then aggregated using total sales as weights.

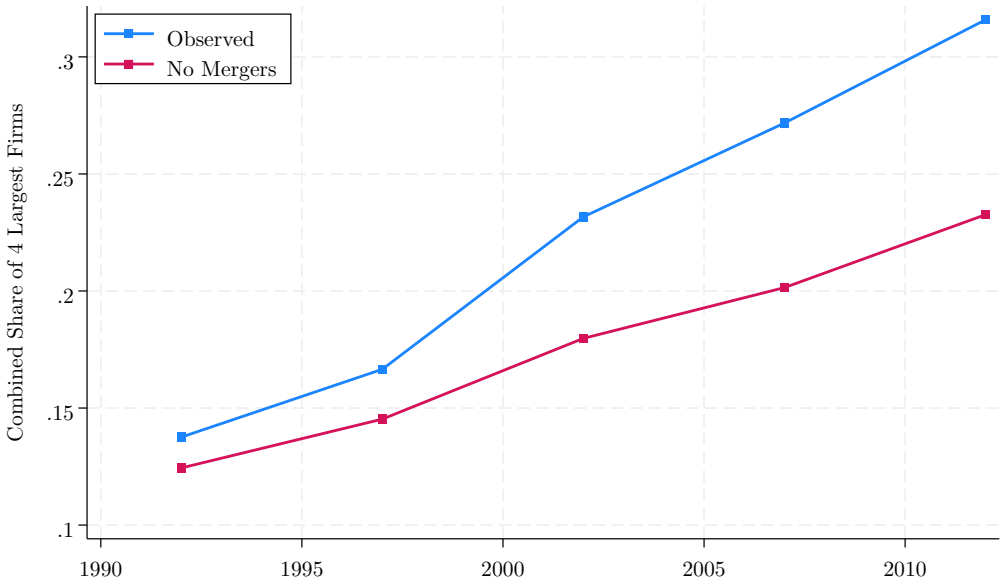


FIGURE IV
Concentration Index in the Census

Notes: The figure shows the C4 index, the sum of the squared market shares, using census weights. The blue lines represents the observed indicator using census revenues as industry size and assuming that the largerst four firms are publicly listed. The red line illustrates a counterfactural scenario with no mergers. Each indicator is computed for the 3-digit industry and then aggregated using total sales as weights.

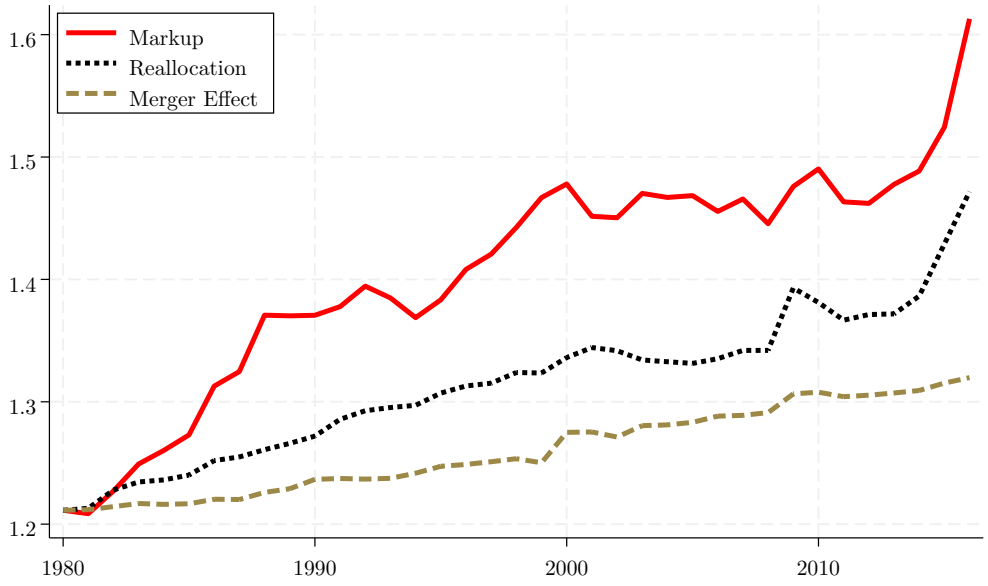


FIGURE V
The Importance of Mergers for Aggregate Markups

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 4). 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.

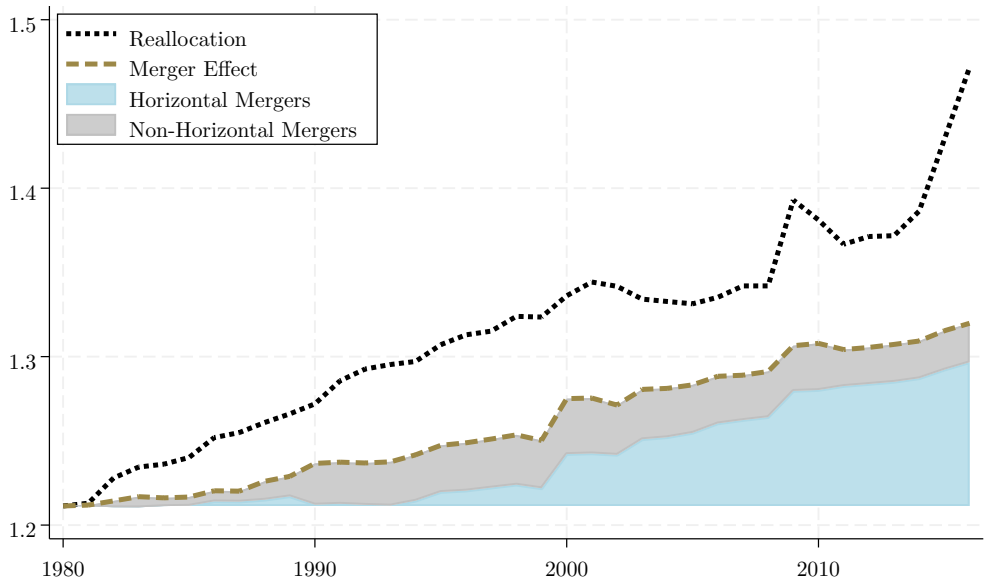


FIGURE VI
The Importance of Horizontal Mergers (3d-industry)

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 4). 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.

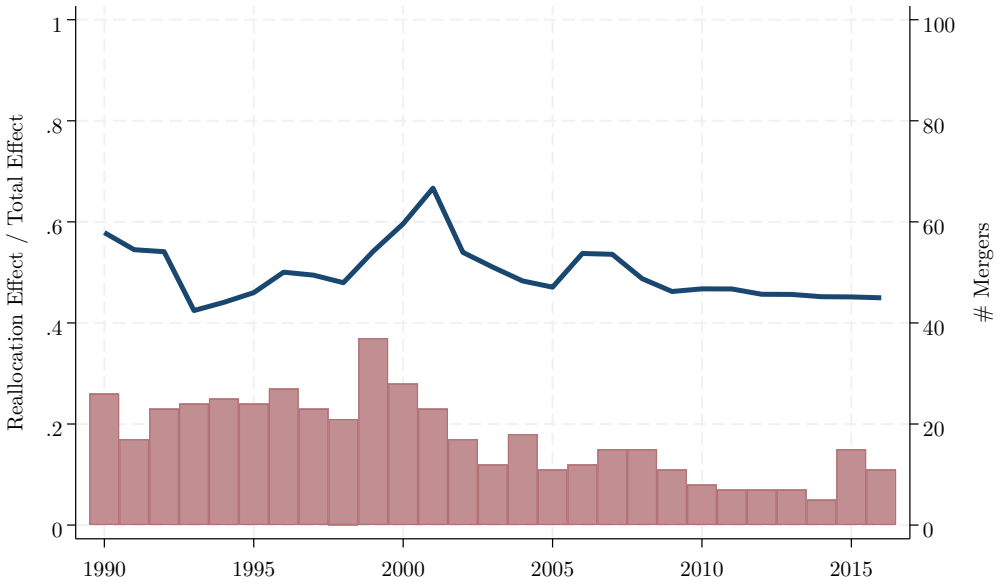


FIGURE VII
Total Merger Effect for Compustat Targets

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.

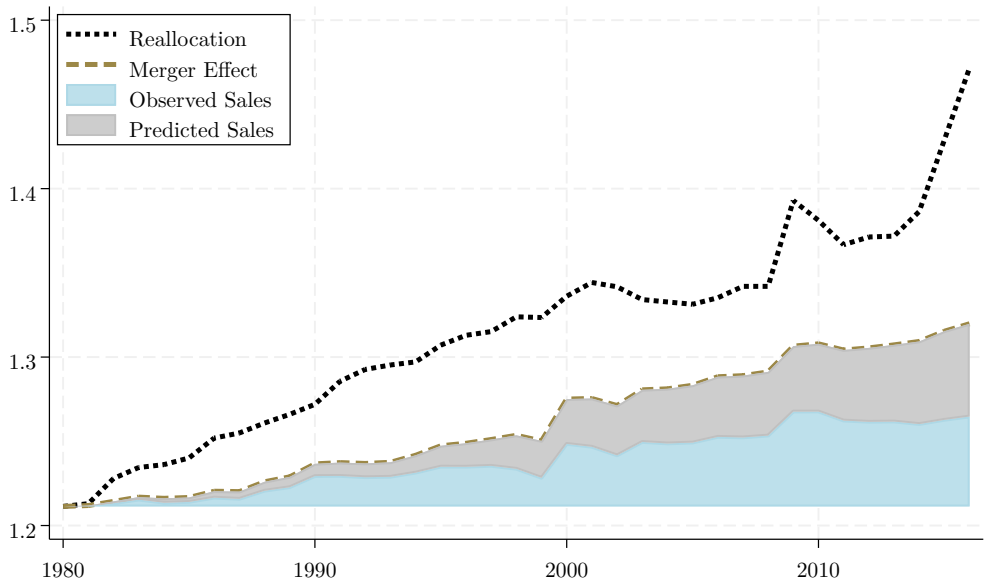


FIGURE VIII
The Importance of Predicting Sales

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 4). 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 II.

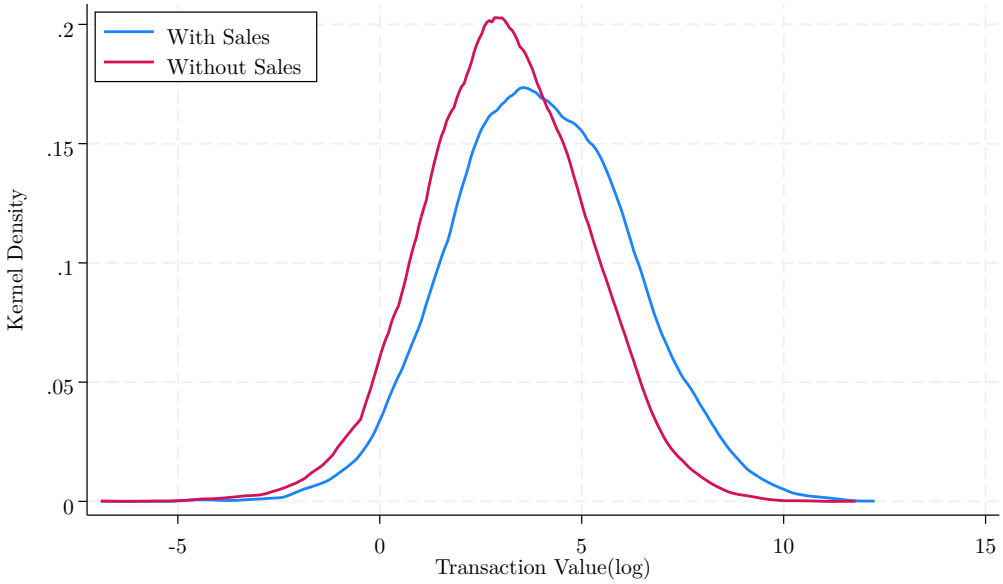


FIGURE IX
Kernel Densities

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

APPENDIX FIGURES

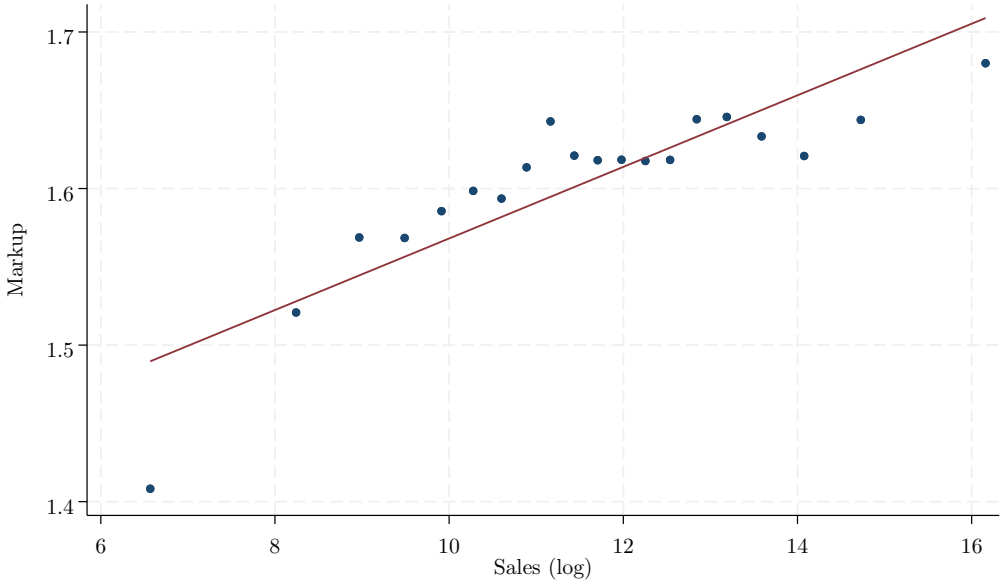


FIGURE X
Markups vs logsale

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

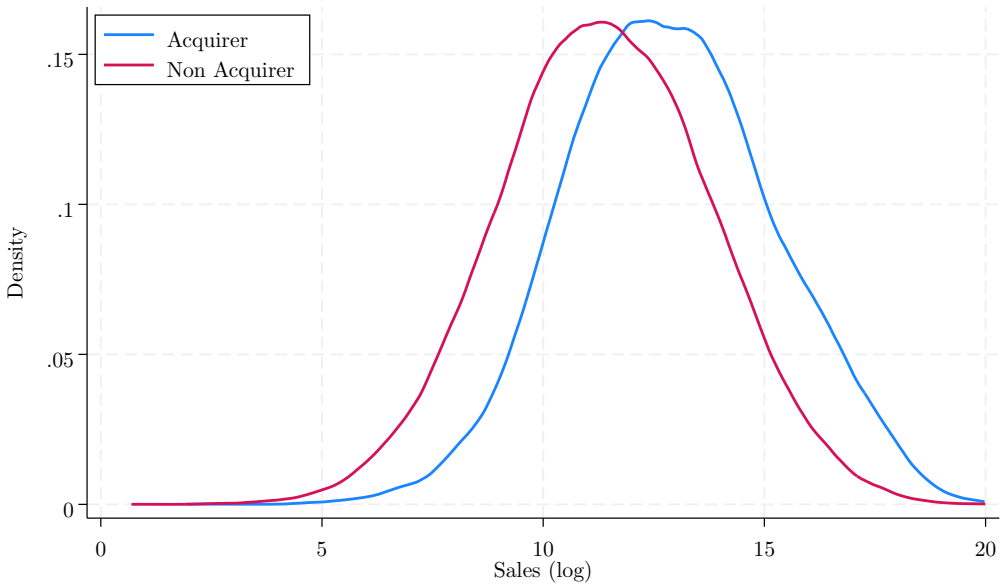


FIGURE XI
Comparing sales before merger

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

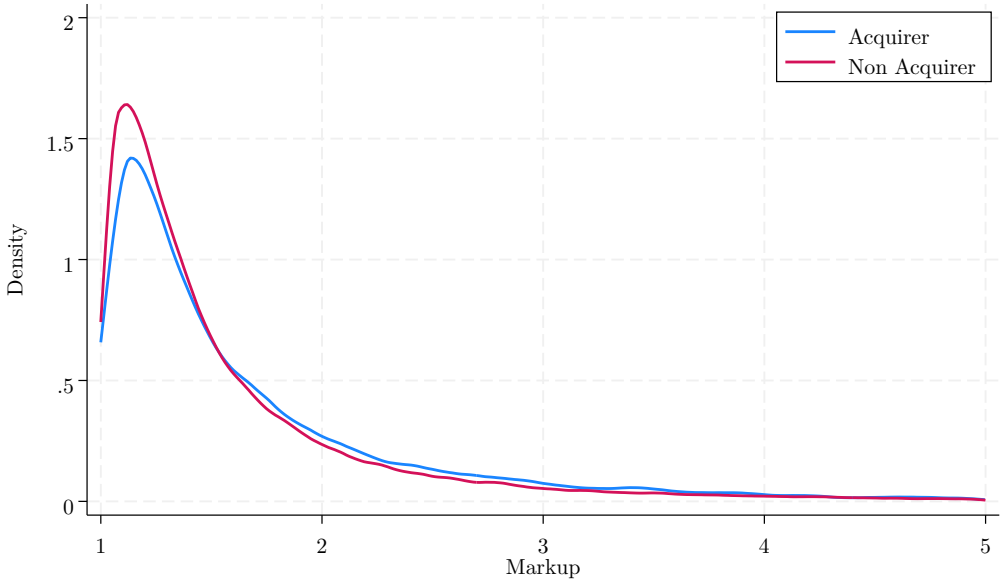
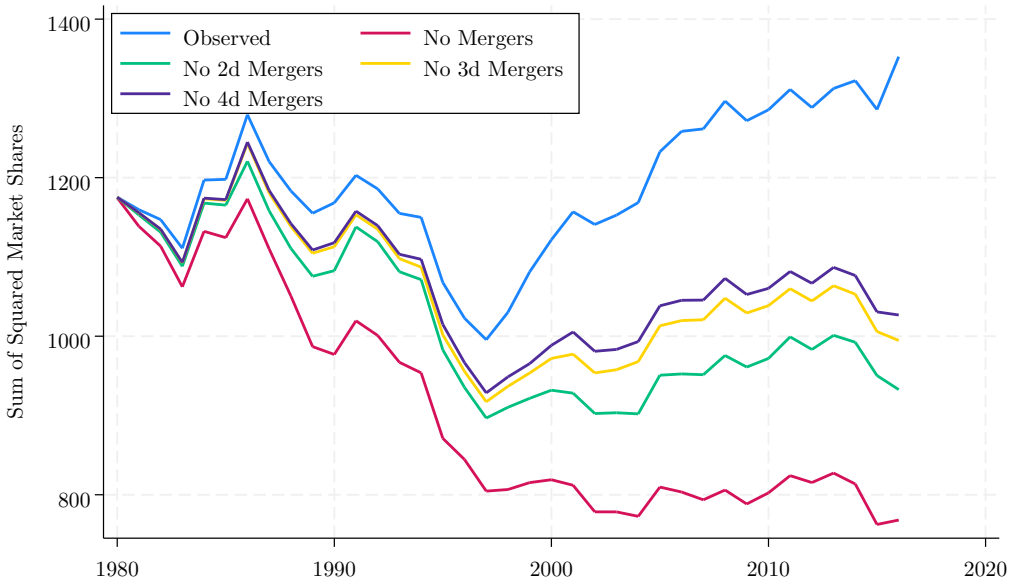
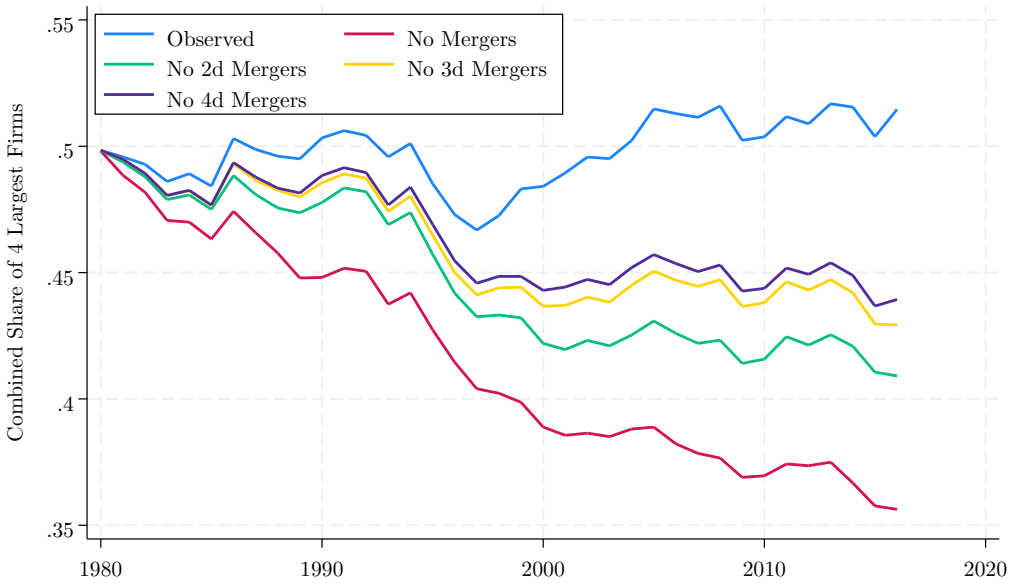


FIGURE XII
Comparing markup before merger

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



(A)
HHI Index



(B)
C4 Index

FIGURE XIII
Concentration and Horizontal Mergers

Notes: The figure shows concentration measures for the economy. The top panel displays the HHI index, the sum of the squared market shares, and its counterfactuals with no mergers, with no mergers between firms in the same 2-digit, 3d-digit, and 4-digit industry. The bottom panel displays the C4 index, the sum of market shares of the four largest firms, and its counterfactuals with no mergers, with no mergers between firms in the same 2-digit, 3d-digit, and 4-digit industry. Counterfactuals are constructed by splitting acquirers from targets and keeping the same size ratio over time. Each indicator is computed for the 3-digit industry and then aggregated using total sales as weights.

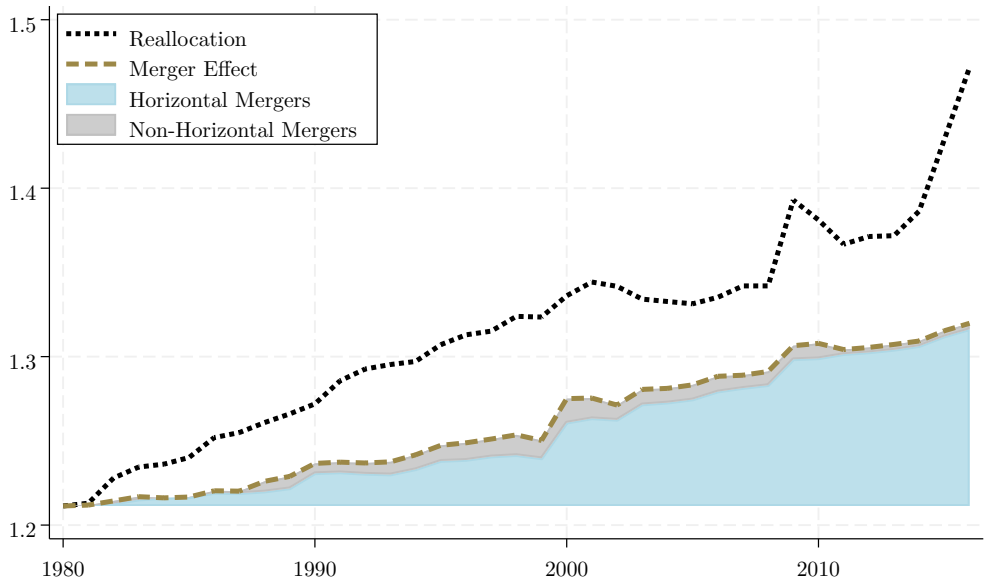


FIGURE XIV
The Importance of 2-digit Industry Mergers

Notes: The reallocation term comes from the decomposition of aggregate markup growth (equation 4). 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.

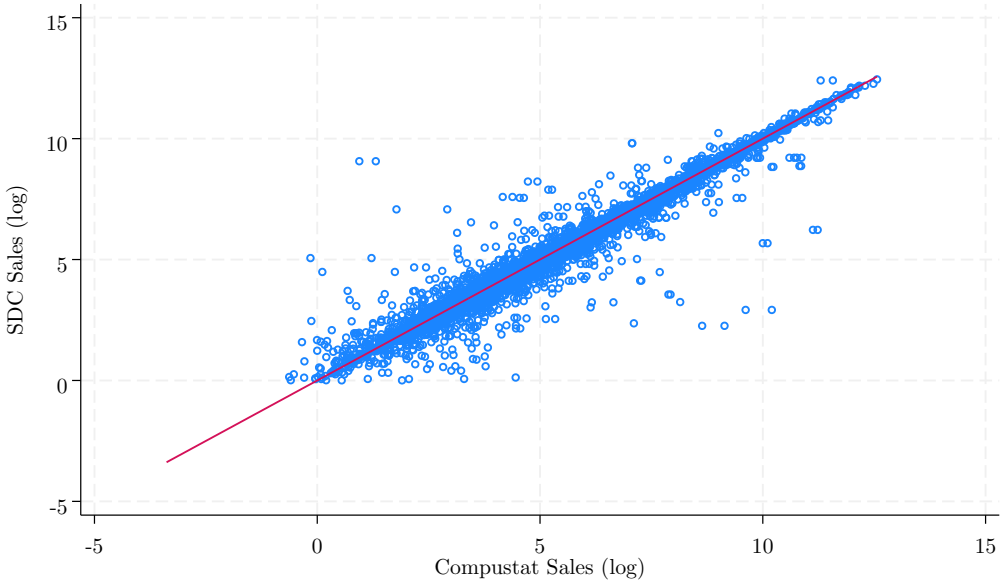


FIGURE XV
Comparing SDC and Compustat Sales

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

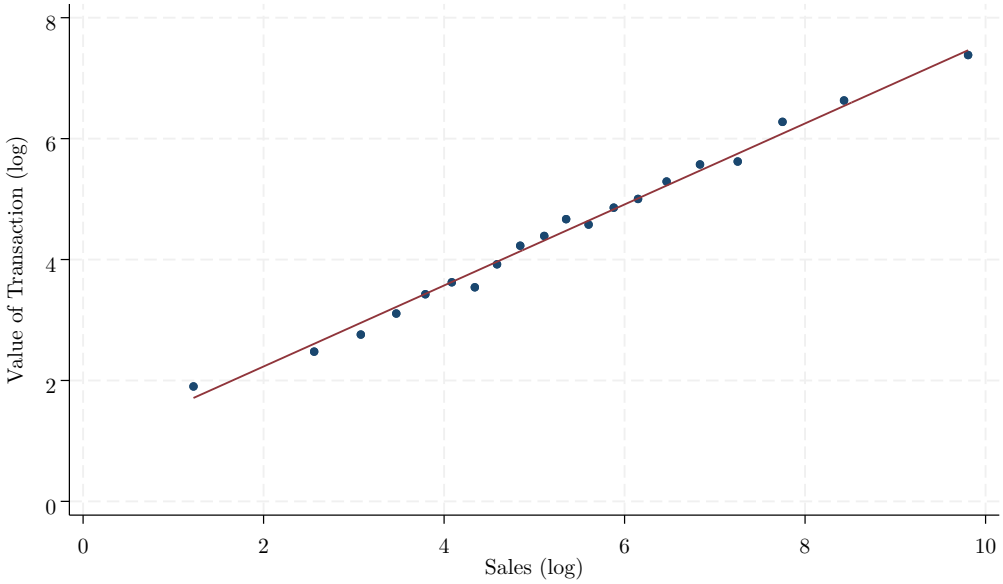


FIGURE XVI
A Log-linear Relation in Compustat

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

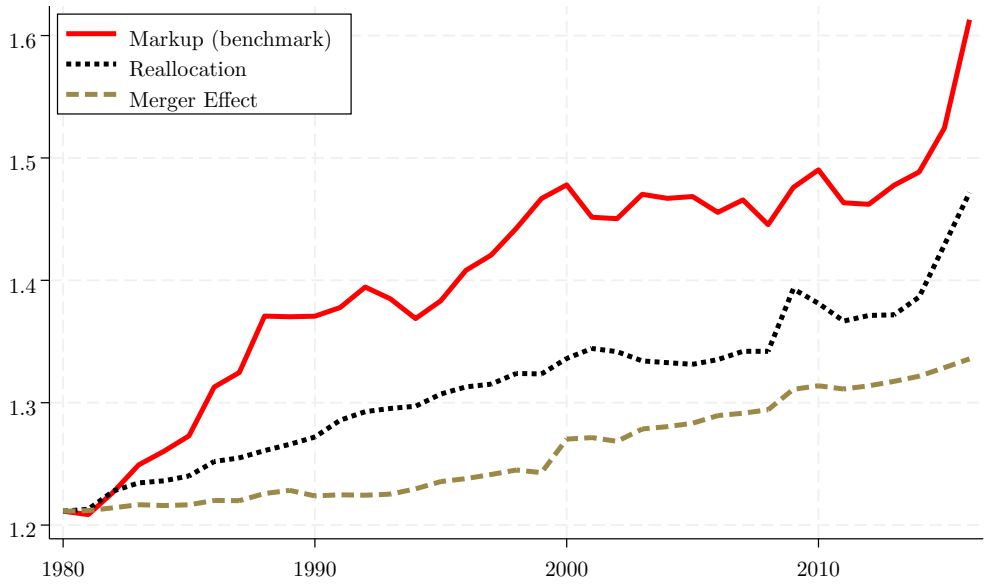


FIGURE XVII
Merger Effect Based on Compustat

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 4). 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.