The Macroeconomic Effects of Mergers and Acquisitions in the United States

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Abstract

I study the macroeconomic impact of merger waves in the United States since 1980 and document these have generated substantial economic losses. Using firm-level event studies, I provide new evidence that merger announcements generate positive abnormal returns for acquirers and their competitors, but not the targets' competitors, patterns inconsistent with industry signaling channels and instead suggesting anticompetitive effects. I aggregate the estimated abnormal returns to construct a novel proxy for merger activity and show consolidation waves predict persistent declines in GDP and labor productivity alongside rising prices. To rationalize these findings, I develop a firm dynamics model with an auction-based market for mergers and variable markups that successfully replicates merger matching patterns, firm sales concentration, and the markup distribution. The model reveals mergers lead to large welfare losses through worsened allocative efficiency from higher markups and reduced firm entry.

JEL Classification: G34, L11, E23, D42, G14, C32, L40

Keywords: mergers and acquisitions, market power, markups, productivity, firm dynamics

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1 Introduction

From 1980 to the turn of the century, the annual share of American publicly listed companies that were either acquired by or merged with a competitor rose from 3% to a peak of 10%. This coincided with significant increases in markups and market concentration (De Loecker et al., 2020; Autor et al., 2020). Whether mergers generate economy-wide gains through capital reallocation (Jovanovic and Rousseau, 2002) and complementarities (Rhodes-Kropf and Robinson, 2008) or impose losses by reducing competition (Farrell and Shapiro, 1990) remains an open question. Resolving it has first-order implications for aggregate welfare since the annual average value of merger transactions in the United States has exceeded $2 trillion in the decade through 2024[1].

In this paper, I show that corporate consolidation waves have reduced aggregate output and welfare in the U.S. since 1980. Three complementary approaches support this conclusion. I assemble an extensive dataset of over 23,000 merger transactions and conduct firm-level event studies (Campbell et al., 1997) around merger announcements. The evidence shows that positive abnormal returns to rivals of merging firms stem from reduced competition, not industry health or takeover signaling channels (Eckbo, 1983; Stillman, 1983; Fee and Thomas, 2004). Second, I construct a novel proxy for aggregate merger activity from estimated firm-level abnormal returns. Using reduced-form local projection (Jordà, 2005), I estimate that merger waves induce persistent declines in economic activity, falling labor productivity, and rising prices. Third, I calibrate a firm dynamics model (Hopenhayn, 1992) with an auction-based market for corporate control and variable markups that rationalizes these empirical findings through worsened allocative efficiency and reduced firm entry.

The empirical analysis leverages a very large database of 23,620 merger and acquisition deals involving U.S. publicly listed firms from 1977 to 2024. I match the dataset with balance sheet and stock return data from Compustat and CRSP. Additionally, I match over 25,000 merging firms from 1988 onwards to their principal product market competitor using the Embeddings-Based text-based network industry classification (Hoberg and Phillips, 2016, 2025). I estimate firm-level TFPR and markups for acquirers and targets in over 13,000 merger deals with data on both merging parties following Ackerberg et al. (2015) and De Loecker et al. (2020).

The empirical evidence shows that mergers concentrate market power among firms already charging the highest markups. Acquirers have markups 4.9 percentage points higher than industry medians, and are larger than both their targets and competitors. Critically, I document strong positive sorting along both the productivity and markup distributions: pro-

[1] Data obtained from the Institute for Mergers, Acquisitions, and Alliances.

ductive acquirers with high markups target similarly productive, high-markup firms. These patterns are consistent with recent European evidence from Guadalupe et al. (2024), who document similar sorting using 2,819 deals during 2008-2018. The evidence I provide supports both Q-theory predictions (Jovanovic and Rousseau, 2002) that larger acquirers with higher valuations target smaller firms, and assortative matching explanations (Rhodes-Kropf and Robinson, 2008) emphasizing complementarities.

Using an event study analysis of stock return responses (Campbell et al., 1997) to merger announcements, I provide firm-level evidence of anticompetitive effects from mergers. I study responses separately for the competitors of acquirers and targets, revealing significant asymmetries: acquirers' competitors earn positive returns following a merger announcement, while the targets' competitors experience negligible effects. This is inconsistent with theories explaining positive rival responses as signaling industry health or increased takeover probability (Eckbo, 1983; Song and Walkling, 2000), which would instead also predict positive returns for the targets' competitors. However, the evidence is consistent with theories stressing that mergers concentrate market power and enable the surviving acquirers' competitors to raise prices. I confirm this hypothesis by separately examining competitors subsequently acquired against those remaining independent around the merger announcement date. The targets' competitors later acquired earn zero returns, while acquirers' competitors eventually acquired earn negative returns, thus validating my interpretation of rivals' responses.

I aggregate the estimated abnormal stock returns to construct a novel proxy for economy-wide merger activity. The proxy measures both variation in deal intensity and value creation. It captures a combination of pro-competitive (productivity synergies) and anticompetitive channels (market power gains) through which mergers affect economic outcomes. At the same time, it is derived from daily abnormal stock returns purged from market-wide movements, ensuring it is not contaminated by other sources of macroeconomic fluctuations. Using local projection methods (Jordà, 2005), I find that consolidation waves predict statistically significant and persistent declines of up to 0.8% for GDP and consumption and over 3% for investment at horizons extending up to five years. Labor productivity falls over the entire forecast horizon while prices moderately rise.

I rationalize the empirical findings described above and quantify the aggregate welfare effects of mergers by developing a firm dynamics model (Hopenhayn, 1992) with an auction-based market for corporate control. Firms face time-varying idiosyncratic productivity shocks and operate in monopolistically competitive markets with Kimball (1995) demand. Acquirers compete for targets through second-price sealed-bid auctions, with target-specific arrival rates endogenously determining the number of competing bidders and merger premia. I calibrate the model to match nine data moments capturing firm concentration, both the level and dispersion of markups, and relevant features of the merger market. The model tightly replicates the firm-level evidence on matching patterns and division of gains between acquirers and targets. Furthermore, it successfully matches the distribution of markups and sales concentration patterns observed in the data.

To understand the channels through which mergers operate, I use the model to solve for a counterfactual economy with a merger ban in place. I find that mergers lead to substantial welfare losses exceeding 15% in consumption-equivalent terms. First, mergers worsen allocative efficiency by raising aggregate markups by 16 percentage points. When firms merge, they exploit productivity synergies not by expanding output but by charging higher markups. This induces competitors to raise their own markups through strategic complementarities, worsening misallocation by diverting labor toward less productive firms. Second, a ban on mergers increases firm entry by 3.7%. Mergers reduce the value of entry by creating superstar firms that crowd out smaller firms, thereby improving the productivity distribution while simultaneously reducing the number of varieties available to households. These results contrast sharply with those obtained by David (2020), who estimates that mergers contribute 14% to steady-state output in a perfectly competitive setting with no market power.

Related Literature. An extensive literature examines the matching patterns in merger transactions. The neoclassical Q-theory (Jovanovic and Rousseau, 2002) predicts "high-buy-low" patterns whereby firms commanding high valuations acquire undervalued targets; other studies largely support these predictions (Servaes, 1991; Maksimovic and Phillips, 2001; Yang, 2008; David, 2020). Alternative theories emphasize instead complementarities between firm assets and predict assortative "like-buy-like" transactions (Rhodes-Kropf and Robinson, 2008), for which recent empirical findings provide extensive evidence (Hoberg and Phillips, 2010; Bena and Li, 2014; Fresard et al., 2020; Guadalupe et al., 2024). I contribute to this literature by assembling a comprehensive dataset of 23,620 U.S. merger transactions combined with estimated firm-level markups and productivity for acquirers and targets involved in 13,000 deals, thus allowing me to directly test these theories. I document that acquirers charge higher markups than both targets and industry medians, and find strong positive assortative matching along both productivity and markup distributions. I show that while sorting on Tobin's Q largely reflects product market differences, positive sorting on markups and productivity occurs both between and within industries.

A large empirical literature attempts to measure value creation from mergers and its distribution across various stakeholders. Early work established that targets earn substantial positive abnormal returns while acquirer returns are much smaller (Jensen and Ruback, 1983; Andrade et al., 2001). Several studies document positive spillovers to competitors (Fee and Thomas, 2004; Shahrur, 2005; Klein, 2020; Stiebale and Szucs, 2022), with competing explanations attributing rival responses either to reduced competition enabling price increases or to positive signals about industry conditions and acquisition opportunities. I extend this literature by showing competitor returns accrue exclusively to firms remaining independent rather than those subsequently acquired, ruling out signaling explanations in favor of anti-competitive channels. I confirm this hypothesis by showing future takeovers do not predict abnormal returns for a sample of over 10,000 product market competitors, overturning prior evidence from Song and Walkling (2000) who rely on a much smaller sample of 141 rivals and use standard industry classifications.

This paper belongs to a growing literature studying the aggregate economic effects of merger activity. David (2020) develops a firm dynamics model with search-and-matching in the merger market in a perfectly competitive setting. Cao and Zhu (2024) extend their framework by introducing monopolistic competition and estimate mergers explain a large share of the rise in aggregate markups. Cavenaile et al. (2021) develop a Schumpeterian model of innovation and mergers, and show that stricter antitrust enforcement can lead to large welfare improvements. Fons-Rosen et al. (2024) study the effects of startup acquisitions on growth in a general equilibrium setting. I contribute to this body of research by simultaneously linking concentration, markups, mergers, and macroeconomic outcomes, while using a novel auction-based model of corporate control that replicates salient features of merger transactions. Additionally, I connect the structural results I derive with extensive empirical evidence, including the first reduced-form estimates of the aggregate effects of merger waves.

This paper also relates to the literature documenting rising markups (De Loecker et al., 2020; Attalay et al., 2025; Dopper et al., 2025), increasing market concentration (Autor et al., 2020; Kwon et al., 2024; Ganapati, 2021), and allocative efficiency (Baqaee and Farhi, 2020; Hsieh and Klenow, 2009; Peters, 2020; Edmond et al., 2023). My analysis identifies mergers as a unifying explanation connecting these phenomena, showing they spur both higher concentration and markups while substantially worsening resource misallocation.

The rest of the paper is organized as follows. Section 2 describes the data, presents stylized facts on merger patterns, and provides firm-level estimates of merger effects. Section 3 constructs the aggregate merger proxy and estimates the dynamic effects of merger activity on macroeconomic outcomes. Section 4 develops the firm dynamics model, while Section 5 discusses the calibration, model fit, and counterfactual analysis. Finally, Section 6 concludes.

2 Microeconomic Evidence

In this section, I document two sets of empirical facts regarding M&A activity in the United States. First, I characterize firms involved in mergers relative to each other and to industry peers. Second, I present event study estimates of firm-level stock market responses to merger announcements, measuring value creation and its distribution between acquirers, targets, and their respective product market competitors.

2.1 Data

I collect data on mergers and acquisitions from LSEG SDC Platinum (SDC). SDC includes data on U.S. firms involved in M&A transactions from 1977 onwards, and covers the universe of deals after 1992. SDC includes data on both private and public transactions valued at $1 million or more. It provides details on both the parties involved in transactions (including corporate ownership), and on characteristics relating to the transaction, such as the purchase price, the stake involved, or the type of consideration offered. From this database, I extract all completed deals announced between 1977 and 2024.

To ensure the sample reflects meaningful changes in corporate ownership and control, I apply a list of preprocessing filters common in the M&A literature. First, I drop deals for which the acquirer and the target share the same ultimate parent since these capture internal reorganizations. Second, I only retain deals for which the acquirer purchases a stake equivalent to at least half of the target's common stock and brings the acquirer's total ownership stake above 90%. Third, I exclude transactions for which data on both acquirer and target characteristics are not available.

I merge the resulting sample with the CRSP/Compustat Merged Database to obtain stock returns, balance sheet, and income statement data. Matches across the two datasets rely on CUSIPs of firms directly involved in M&A transactions. When this approach fails, I attempt matching using the CUSIPs of the immediate or ultimate parents of the transacting firms. For any remaining unmatched firms, I perform name-based matching using cosine similarity on standardized company names, followed by manual verification to ensure data integrity. The final sample includes 23,620 M&A deals: for comparison, David (2020) retains approximately 5,800 deals with joint acquirer-target data while Rhodes-Kropf and Robinson (2008) examine 3,400 transactions.

In a final step, I construct a unique set of competitors for each firm involved in a merger using the Embeddings-Based Text Network Industry Classification (TNIC) database developed by Hoberg and Phillips (2016, 2025). TNIC uses textual analysis of firm product descriptions contained in mandatory SEC 10-K filings to pair each firm with a distinct set of competitors. TNIC covers all Compustat firms from 1988 through 2023 with a link to a 10-K form on the SEC EDGAR website. I also define competitors using the standard NAICS industry classifications.

2.2 Stylized Facts on Acquirers and Targets

In this section, I document systematic patterns in the characteristics of acquirers relative to their respective targets, and of merging parties relative to their industry peers. These stylized facts directly inform two main theories of merger motives which I now discuss. The neoclassical Q-theory of mergers (Jovanovic and Rousseau, 2002) proposes that firms with a high Tobin's Q ratio will seek to acquire undervalued targets with low Q ratios to expand rather than purchase more expensive new assets on the open market. Thus, the theory views merger waves as a response to reallocative opportunities[2]. In contrast, assortative matching theories (Rhodes-Kropf and Robinson, 2008) emphasize complementarities between firms' assets as the underlying driver of merger gains.

Empirically, I examine whether target firms are systematically drawn from the left tail of the firm distribution, as would be predicted by a pure Q-theory of mergers, or whether merging parties exhibit positive assortative matching, i.e. acquirers and targets share similar characteristics. To answer these questions, I leverage the extensive sample described in the previous sub-section. I compare firms along several dimensions capturing productivity, profitability, size, innovation intensity, and market valuation. For merging parties with available Compustat data, I estimate TFPR using the 2-step estimator of Ackerberg et al. (2015); I use the same estimator combined with the firm cost-minimization approach of De Loecker and Warzynski (2012) to estimate markups, see Appendix A for additional details.

In Table 1, I compare the characteristics of acquirers, targets, and their industry peers. The first column reports median deviations between acquirer and target characteristics. Columns 2-5 compare merging parties with their industry peers using either NAICS 3-digit industry classifications or TNIC competitors. All firm characteristics are measured in the fiscal year prior to the announcement. P-values below each estimate test whether the median deviations are significantly different from zero using the Wilcoxon signed-rank test.

Across all characteristics examined, acquirers exceed targets. Acquirers charge markups 2.3 percentage points higher than targets and command valuations, as measured by Tobin's Q, 5.5 percentage points larger. Size deviations are larger still: sales, operating income, and R&D expenditure are over 30% higher for acquirers. The difference is most pronounced when comparing market capitalization, which is higher by 0.64 logarithmic points (88.9%) for acquirers.

The fact that acquirers exceed targets across all dimensions examined supports the "high-

[2]Several studies have confirmed such predictions. For instance, Servaes (1991) shows that joint stock returns are larger when targets have low Q and bidders have high Q. Maksimovic and Phillips (2001), analyzing plant-level ownership changes, find that productivity gains from transactions are higher when more efficient firms acquire less efficient assets.

buy-low" prediction made by the Q-theory of mergers. The magnitudes reported in Table 1 align with previous findings. For instance, using a sample of 4,300 completed deals over the period 1973-1998, Andrade et al. (2001) document that over two-thirds of acquirers' Q exceeded their target's. I find a comparable figure of 60% in my sample.

As shown in Columns 2-3, acquirers also substantially exceed industry medians. Using TNIC competitors as the comparison group, acquirers charge markups 4.9 percentage points higher than their median competitors, and command valuations 5.6 percentage points higher as measured by Tobin's Q. Acquirers are marginally more productive with TFPR 0.5% higher than for the median competitor. Additionally, acquirers are also substantially larger than their median competitors, with differences in market capitalization, sales, operating income, and R&D expenditure ranging from 1.28 to 1.80 logarithmic points, i.e. acquirers are 2.5 to 5 times larger than their competitors depending on the metric used. Finally, acquirers are also older by 4 years than their median competitors. The patterns highlighted above are consistent regardless of the industry classification used. Together, these facts imply that acquirers are drawn from the upper right tail of firm distributions.

In contrast, targets are closer to industry medians. Columns 4-5 show that targets exhibit similar productivity, markups, and Tobin's Q as their competitors. For size-based measures, targets considerably exceed industry medians, but by smaller margins than their acquirers; the logarithmic deviations imply targets are 2 to 4.2 times larger than their competitors. Again, the results are robust to using NAICS 3-digit industry classifications instead.

In summary, acquirers systematically exceed both their targets and industry benchmarks, consistent with Q-theory predictions. However, the share of deals for which acquirers exceed targets ranges from 50-60% across characteristics. This suggests that while acquirers tend to be larger and charge higher markups on average, there is substantial heterogeneity in matching patterns. To evaluate whether firms pair themselves with similar counterparts, I now turn to assortative matching regressions.

Table 2 reports regression coefficients from two specifications measuring assortative matching in mergers. Panel A presents results from a baseline specification regressing acquirer characteristics onto target characteristics and controlling for year fixed effects. Panel B presents results from an industry-demeaned specification where both acquirer and target characteristics are demeaned by their respective TNIC competitor-year means. This specification tests for relative assortative matching within industries, i.e. whether acquirers ranking higher among their competitors purchase targets which also exceed their own competitors. Heteroskedasticity-robust standard errors are reported in parentheses. Values of $\hat{\beta}$ significantly above zero indicate positive assortative matching.

The results reveal strong positive assortative matching among acquirers and targets.

Table 1: Comparison of the Characteristics of Acquirers, Targets, and their Competitors

	Acquirer vs Target	**Acquirer vs Industry**		**Target vs Industry**	
		NAICS 3-digit	TNIC	NAICS 3-digit	TNIC
Panel A: Median Arithmetic Deviations					
Markup (percentage points)	0.024	0.041	0.048	0.008	0.003
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=13,146	N=16,683	N=12,455	N=16,801	N=12,758
Tobin's Q (percentage points)	0.055	0.031	0.056	−0.015	−0.001
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=13,290	N=16,710	N=12,631	N=16,986	N=12,894
Firm Age (years)	0	5	4	6	4
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=13,721	N=17,073	N=12,646	N=17,196	N=12,915
Panel B: Median Logarithmic Deviations					
TFPR	0.002	0.004	0.005	0.000	0.001
	p=0.02	p=0.00	p=0.00	p=0.00	p=0.10
	N=13,146	N=16,683	N=12,455	N=16,801	N=12,758
Market Value	0.636	2.266	1.664	1.893	1.190
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=13,311	N=16,727	N=12,637	N=17,009	N=12,899
Sales	0.306	2.088	1.373	1.990	1.187
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=13,721	N=17,073	N=12,646	N=17,196	N=12,915
Operating Profits	0.357	2.697	1.805	2.656	1.653
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=11,586	N=15,652	N=11,714	N=14,982	N=11,286
R&D Expenditure	0.274	2.068	1.284	1.898	1.093
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=5,363	N=7,750	N=5,674	N=8,279	N=6,032

Notes: This table compares characteristics of acquirers, targets, and their industry peers. Column 1 shows median differences between acquirers and targets. Columns 2-5 show median deviations from industry medians, defined by NAICS 3-digit classification and TNIC competitors. Panel A reports arithmetic deviations (percentage points for Markup and Tobin's Q, years for Firm Age). Panel B reports logarithmic deviations. Market Value, Sales, Operating Profits, and R&D Expenditure are deflated using the GDP deflator. Statistical significance is tested using the Wilcoxon signed-rank test. The number of observations is shown below each estimate. All firm characteristics are measured in the fiscal year prior to the announcement. The sample covers M&A deals announced during the period 1977-2024; for TNIC comparisons, the sample starts in 1988. See Appendix A for details on TFPR and markup estimation.

An increase of 1 percentage point in the markup of the target is associated with a rise of 0.5 points for the acquirers. Magnitudes are similar for productivity and Tobin's Q. Size-based metrics also indicate positive sorting, though coefficients are smaller in economic magnitude: a $1 increase in the sales, profits, or market valuation of targets is approximately associated with a $0.07 increase for the acquirer. All coefficients are statistically significant at the 99% confidence level. In summary, acquirers pair themselves with targets exhibiting similar productivity levels, charging comparable markups, and commanding the same type of valuations. Larger and older acquirers also tend to match with larger and older targets.

Table 2: Assortative Matching in Mergers

	TFPR	Markup	Tobin's Q	Mkt. Value	Sales	Op. Profits	R&D Exp.	Age
Panel A: Absolute Assortative Matching between Merging Parties								
Sorting $\hat{\beta}$	0.451	0.499	0.425	0.071	0.069	0.068	0.092	0.162
	(0.020)	(0.033)	(0.055)	(0.014)	(0.011)	(0.012)	(0.023)	(0.009)
N	13,146	13,146	13,290	13,311	13,721	13,619	5,891	13,721
Panel B: Relative Assortative Matching between Merging Parties within Industries (TNIC Competitors)								
Sorting $\hat{\beta}$	0.202	0.207	0.287	0.035	0.035	0.045	0.007	0.064
	(0.027)	(0.036)	(0.172)	(0.019)	(0.010)	(0.014)	(0.023)	(0.012)
N	8,634	8,634	8,807	8,816	8,834	8,779	3,689	8,834

Notes: This table reports regression coefficients measuring assortative matching in mergers. Panel A reports results from the following specification: $x^{acq}_{i,t} = \alpha_t + \beta x^{tar}_{j,t} + \varepsilon_{ijt}$, where $x^{acq}_{i,t}$ and $x^{tar}_{j,t}$ denote acquirer and target characteristics, and α_t represents year fixed effects. Panel B reports results from the industry-demeaned specification: $(x^{acq}_{i,t} - \bar{x}_{i,t}) = \beta \cdot (x^{tar}_{j,t} - \bar{x}_{j,t}) + \varepsilon_{ijt}$, where both acquirer and target characteristics are demeaned by their respective TNIC competitor-year means $\bar{x}_{i,t}$ and $\bar{x}_{j,t}$. White (1980) standard errors reported in parentheses. All firm characteristics are measured in the fiscal year prior to the announcement. The sample covers M&A deals announced during the period 1977-2024; for the TNIC specification in Panel B, the sample starts in 1988. See Appendix A for details on TFPR and markup estimation.

Panel B of Table 2 shows that positive assortative matching persists when controlling for industry composition. Acquirers that are more productive and charge higher markups than their competitors also target firms ranking higher among their own peers along these dimensions. There is modest but statistically significant positive sorting across sales, profits, and firm age, with coefficients ranging from 0.035 to 0.064. On the other hand, the coefficient on Tobin's Q is no longer statistically significant at the 95% level. Comparing coefficients across specifications, approximately half of the sorting observed in Panel A reflects cross-industry matching, while the remainder reflects matching on relative firm quality within industries.

These findings align with recent empirical evidence on complementarity-driven mergers. Hoberg and Phillips (2010) show that firms acquiring targets with similar product descriptions (as measured through a text-based analysis of 10-K filings) experience higher profitability post-merger. Similarly, Bena and Li (2014) provide evidence that overlap between acquirers' and targets' patent portfolios positively correlates with matching probabilities.

Furthermore, they show that prior technological linkages between acquirers and targets result in more patents post-merger, thus confirming that innovation-driven synergies underlie acquisitions. Using data on European deals, Guadalupe et al. (2024) find that productive acquirers match with similarly productive targets. Rhodes-Kropf and Robinson (2008) document "like-buys-like" patterns in mergers, showing that firms commanding high valuations, as measured by Tobin's Q, match with similarly valued targets. However, my analysis suggests that valuation sorting primarily reflects differences in the industries in which acquirers and targets operate.

Taken together, the evidence presented in this section provides support for both Q-theory and assortative matching in mergers, and these may not necessarily be mutually exclusive as highlighted by David (2020). This reconciliation of reallocation- and complementarity-driven matching has direct implications for modeling mergers. Any quantitative model must generate the following features: (i) productivity and size differentials favoring acquirers; (ii) merging parties exceed their competitors, but acquirers more so than targets; (iii) positive assortative matching between acquirers and targets along both the productivity and markup distributions.

2.3 Firm-Level Estimates of the Effects of M&A Activity

In this section, I estimate stock market responses to merger announcements to measure value creation and its distribution across acquirers, targets, and competitors.

To measure abnormal stock returns following merger announcements, I rely on the event study methodology described by Campbell et al. (1997). Event studies that exploit time-series variation only are well-suited for the study of merger announcements. Alternative econometric approaches relying on cross-sectional variation, e.g. differences-in-differences, face fundamental challenges in this setting. First, parallel trends assumptions will not hold given the pervasive differences between merging parties and their competitors which were discussed in the previous section. Second, it would be difficult to construct valid control groups for large acquirers without having to extrapolate from smaller firms since most large companies routinely engage in the market for corporate control. Finally, the stable unit treatment value assumption (SUTVA) is generally violated since merger announcements induce spillover effects on competitors as I document below.

For each merger event k involving acquirer i and target j, I estimate a factor model for normal returns over an estimation window extending from 273 to 21 trading days before the announcement date:

$$r_{i,t} - r_t^f = \alpha_{i,k} + \sum_f \beta_{i,k}^f F_t^f + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return on firm i's stock, r_t^f is the risk-free rate, and F_t^f denote the risk factors. I use the five factors proposed by Fama and French (2015): market excess return, size, value, profitability, and investment. I estimate Equation (1) separately for each event-firm pair.

Abnormal returns over the event window are computed as the difference between actual returns and the counterfactual returns under the estimated model described by Equation (1):

$$\widehat{AR}_{i,k,t_{i,k}+h} = r_{i,t_{i,k}+h} - \left(\hat{\alpha}_{i,k} + \sum_f \hat{\beta}^f_{i,k} F^f_{t_{i,k}+h}\right) \tag{2}$$

where h indexes days relative to the announcement date $t_{i,k}$. To assess the total impact of merger announcements, I compute cumulative abnormal returns (CAR) by aggregating abnormal returns over event windows $[t_1, t_2]$, and, for inference, I compute cross-sectional averages of cumulative abnormal returns (CAAR) across all merger events:

$$\widehat{CAR}_{i,k}[t_1, t_2] = \sum_{h=t_1}^{t_2} \widehat{AR}_{i,k,t_{i,k}+h} \qquad \text{and} \qquad \widehat{CAAR}[t_1, t_2] = \frac{1}{N}\sum_{k=1}^{N} \widehat{CAR}_{i,k}[t_1, t_2] \tag{3}$$

where N denotes the number of merger events in the sample. I assess the statistical significance of CAAR using the nonparametric GRANK-T test statistic proposed by Kolari and Pynnönen (2011), which is robust to event-induced changes in variances and cross-sectional correlations in abnormal returns. In unreported results, I verify that the results discussed below are robust to using other test statistics.

For each merging party, I identify its primary competitor as the firm with the highest TNIC similarity score in the year of the merger announcement[3]. This yields one competitor for each acquirer and target with available TNIC data.

Table 3 presents CAAR for acquirers, targets, and their respective primary competitors across event windows ranging from two days before through five days after merger announcements. Considering all merging parties together, the CAAR is 2.92% over the $[-2, 0]$ window surrounding the announcement, rising to and stabilizing at 3.6% over longer horizons. All estimates are statistically significant at the 99% confidence level. Over the entire sample, investors therefore view mergers as value-creating, though there is substantial heterogeneity across merger deals. Notably, 63.2% of targets register positive CAR over the $[-2, 5]$ window, while only slightly above half of acquirers do.

In fact, disaggregating results by party type reveals large asymmetries in the distribution of merger gains. The CAAR of targets increase by 5.6% over the $[-2, 0]$ window and rise

[3] I exclude the other party to the merger when defining competitors.

Table 3: Event Study Results: Cumulative Abnormal Returns around M&A Announcements

Event Window	**All Merging Parties**	**Merging Parties**		**TNIC Competitors**	
		Acquirers	Targets	Acquirers	Targets
$[-2, -1]$	0.46%	0.08%	0.83%	0.06%	−0.02%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,819	N=18,711	N=19,108	N=15,666	N=12,098
$[-2, 0]$	2.92%	0.18%	5.60%	0.38%	−0.02%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,819	N=18,711	N=19,108	N=15,666	N=12,098
$[-2, 1]$	3.66%	0.35%	6.91%	0.43%	0.06%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,782	N=18,711	N=19,071	N=15,666	N=12,097
$[-2, 2]$	3.66%	0.36%	6.91%	0.38%	−0.03%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,769	N=18,710	N=19,059	N=15,665	N=12,093
$[-2, 3]$	3.62%	0.33%	6.85%	0.37%	−0.03%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,759	N=18,707	N=19,052	N=15,664	N=12,091
$[-2, 4]$	3.61%	0.32%	6.85%	0.31%	0.01%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,756	N=18,707	N=19,049	N=15,662	N=12,091
$[-2, 5]$	3.58%	0.28%	6.83%	0.24%	0.00%
	p=0.00	p=0.00	p=0.00	p=0.00	p=0.00
	N=37,750	N=18,707	N=19,043	N=15,662	N=12,089

Notes: This table reports cumulative average abnormal returns (CAARs) around M&A announcement dates for all merging parties (acquirers and targets combined), acquirers separately, targets separately, and their product market competitors. Event windows are specified in trading days relative to the announcement date (day 0). Abnormal returns are estimated using a five-factor Fama-French model (see Equations (1)–(2)) over a 252-day estimation window ending 21 days before the announcement. For each merging party, competitors are identified as the firm with the highest TNIC similarity score in the merger announcement year following Hoberg and Phillips (2016, 2025). Statistical significance is assessed using the GRANK-T test statistic (Kolari and Pynnönen, 2011). p-values from the GRANK-T test are reported below each CAAR estimate, followed by the number of observations. The sample covers M&A deals announced during the period 1977-2024; for competitors, the sample starts in 1988.

to close to 7% at longer horizons. The estimated effects are very persistent and remain statistically significant at the 99% confidence level beyond a trading week following the announcement. In contrast, the CAAR of acquirers are much smaller and less persistent: 0.18% over the window $[-2, 0]$, peaking at 0.36% on day +2, and slowly declining afterwards. These results corroborate longstanding findings in the empirical corporate finance literature that targets capture most of the surplus from transactions (Jensen and Ruback, 1983).

Beyond the vastly extended sample size, a contribution of my analysis relative to the prior literature is to measure competitive spillovers using product market descriptions rather than standard industry classification schemes. Column 4 of Table 3 shows that competitors of acquiring firms experience statistically significant positive abnormal returns comparable to those of the acquirers: 0.38% over $[-2, 0]$, reaching a maximum of 0.43% by day +1, and slowly declining afterwards. Conversely, the abnormal returns of the targets' competitors are mostly 0 and not economically meaningful.

The asymmetric responses of acquirers' and targets' competitors provide evidence for the anticompetitive effects of mergers. Prior research cautions that positive rival returns are not, in isolation, sufficient to establish anticompetitive effects (Eckbo, 1983; Stillman, 1983; Fee and Thomas, 2004; Shahrur, 2005). Alternative explanations, such as industry health signaling or increased takeover probability (”in-play”) for rival firms, predict that the targets' competitors, as the most likely next acquisition candidates, should experience positive abnormal returns. Song and Walkling (2000), using a sample of 141 rival portfolios over 1982-1991, find supporting evidence: rivals who subsequently become targets record higher returns following merger announcements. However, using a sample of over 27,000 rivals with firm-specific industry definitions, I reject this hypothesis. The targets' competitors earn near-zero returns while the acquirers' competitors earn positive abnormal returns comparable to the bidding firm. These findings are inconsistent with industry signaling or in-play channels, but instead suggest consolidation reduces competitive pressure for acquirers' rivals (Farrell and Shapiro, 1990).

To further investigate the anticompetitive channels of mergers, I examine the cross-sectional relationships between abnormal returns and firm characteristics. For each merger event k occurring in year t, involving firm i (either acquirer, target, or competitor) operating in NAICS 3-digit industry j, I estimate regressions of the form:

$$\widehat{CAR}_{i,k}^{j,t}[t_1, t_2] = \beta X_{i,k}^{j,t-1} + \gamma_t + \delta_j + \epsilon_{i,k} \tag{4}$$

where $X_{i,k}^{j,t-1}$ denotes a firm characteristic measured in the fiscal year prior to the merger announcement, γ_t are year fixed effects, and δ_j are NAICS-3 industry fixed effects.[4] Standard errors are clustered by year. I report results over the event window $[-2, 5]$, but results are robust to using other windows.

Table 4 presents the results: Panel A examines how ex-ante firm characteristics predict abnormal returns for merging parties. First, I confirm previous findings in the literature that abnormal returns correlate negatively with firm size for both acquirers and targets. However, targets charging higher markups are able to extract larger premiums, with a 10% increase

[4] Note that one cannot use TNIC industry fixed effects since TNIC competitor definitions are firm-year specific.

in markups associated with a statistically significant 1.7 basis point higher CAR. Second, I find that acquirers earn higher abnormal returns if they operate in concentrated product markets. This supports the idea that part of the merger benefits accruing to acquirers derive from anticipated higher market power.

Table 4: Cross-Sectional Determinants of Cumulative Abnormal Returns

Variable	**Merging Parties**		**TNIC Competitors**	
	Acquirers	Targets	Acquirers	Targets
Panel A: Ex-ante Effects of Firm Characteristics				
Log(TNIC Industry Concentration (HHI))	0.0031	0.0024		
	(0.0011)	(0.0030)		
	N=11,765	N=12,122		
Log(Markup)	−0.0088	0.0168		
	(0.0023)	(0.0042)		
	N=14,300	N=14,438		
Log(Real Sales)	−0.0036	−0.0197		
	(0.0005)	(0.0010)		
	N=14,492	N=14,633		
Panel B: Ex-post Effects of Takeovers				
Acquired Within 6 Months			−0.0071	−0.0003
			(0.0026)	(0.0017)
			N=12,234	N=9,245
Acquired Within 12 Months			−0.0071	−0.0022
			(0.0020)	(0.0018)
			N=12,234	N=9,245
Acquired Within 24 Months			−0.0105	−0.0014
			(0.0024)	(0.0023)
			N=12,234	N=9,245

Notes: This table reports results from univariate cross-sectional regressions of CARs over the $[-2, 5]$ event window on firm characteristics and future acquisition outcomes. Panel A examines the relationship between CARs and ex-ante firm characteristics for merging parties. Panel B tests whether competitors eventually acquired in subsequent periods earned different returns at the initial merger announcement. All regressions include year and NAICS-3 industry fixed effects. Standard errors clustered by year are reported in parentheses below coefficient estimates. Number of observations reported below standard errors. The sample covers M&A deals announced during the period 1977-2024; for the TNIC specifications in Panel B, the sample starts in 1988. See Appendix A for details on markup estimation.

In panel B, I provide evidence against the industry signaling and in-play hypotheses by examining whether competitors subsequently acquired earned different returns than those remaining independent around the merger announcement. For the targets' competitors, results for all three specifications are not significant and have the wrong sign, thus contradicting the idea that their returns reflect future takeover expectations[5]. More importantly, the acquirers' competitors later targeted in a merger within 24 months experience returns 1.05 percentage points lower than those remaining independent. Together with the estimate that the acquirers' competitors earn CAAR of 0.24% over the $[-2, 5]$ event window, these results imply that the acquirers' competitors eventually acquired earn negative abnormal returns over the event window.

These findings are difficult to reconcile with the view that mergers convey information about industry health. Under this hypothesis, the acquirers' competitors would earn non-negative abnormal returns regardless of whether they were subsequently targeted in a merger. Instead, I find that the positive spillovers documented in Table 3 accrue primarily to the acquirers' competitors remaining independent and benefiting from reduced competitive pressure, rather than to competitors subsequently acquired. In summary, the firm-level evidence supports the hypothesis that merger gains entail a substantial component linked to expectations of increased market power.

3 Macroeconometric Evidence

This section establishes stylized facts on the trend and cyclical properties of M&A activity. I then estimate the dynamic effects of merger activity on macroeconomic variables using local projections (Jordà, 2005).

3.1 Aggregate Trends and Cyclicality in M&A Activity

I derive an annual measure of aggregate M&A activity from the merged SDC-Compustat sample. Specifically, I define the acquisition rate as the percentage of Compustat firms targeted in completed merger deals each year. This measure accounts for both trends in the number of M&A transactions and the evolving size of the publicly listed firm population over time. Figure 1 plots this acquisition rate alongside the aggregate markup, computed as the harmonic average of sales-weighted firm-level markups.

Figure 1 reveals strong comovements between M&A activity and markups during the merger waves that occurred over the 1980s and 1990s. In the early 1980s, the acquisition rate is approximately 3% while firms charge markups of 10-15% on average. By the turn of the century, the acquisition rate peaks at close to 10% before slowly declining following the dot-com crash. Similarly, the aggregate markup rises to 30% over that period and

[5]Using a smaller sample of 1,751 mergers, an older version of the TNIC database by Hoberg and Phillips (2016), and focusing exclusively on the competitors of targets, Klein (2020) also fails to find evidence that the abnormal returns of target competitors capture anticipations of future takeovers.

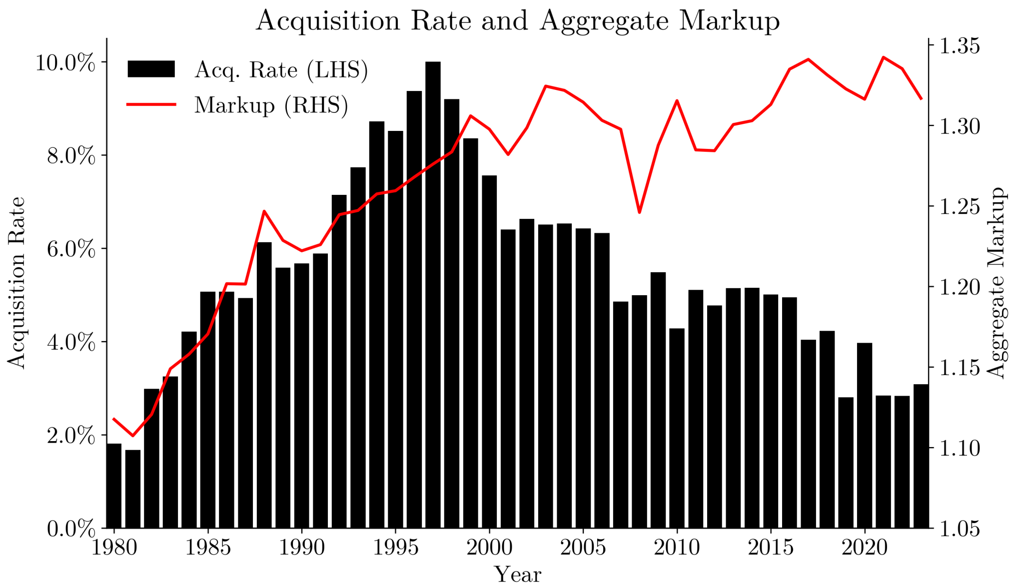


Figure 1: M&A Acquisition Rate and Aggregate Markup

Notes: Figure plots the annual M&A acquisition rate (left axis, black bars) and the aggregate markup (right axis, red line) over 1980-2023. The acquisition rate is defined as the percentage of Compustat firms targeted in merger transactions each year. The aggregate markup is computed as the harmonic sales-weighted average of firm-level markups; see Appendix A for details on markup estimation.

remains broadly stable thereafter. Using instead the raw count of transactions from either the matched SDC-Compustat sample or from SDC directly, I document similar patterns; see Appendix Figure B.1.

Beyond secular trends, M&A activity exhibits countercyclical leading and procyclical lagging behaviors: merger waves precede economic slowdowns by 2-3 years, while corporate consolidations intensify following periods of strong economic growth. Table 5 reports cross-correlations between the cyclical components of real GDP and M&A activity at leads and lags ranging from $k = -3$ to $k = 3$ years. The cyclical components are extracted using the Hodrick-Prescott filter with smoothing parameter $\lambda = 6.25$ for annual data (Ravn and Uhlig, 2002). All three measures display negative correlations with GDP at leads and contemporaneously ($k = -3$ to $k = 0$). This pattern reverses at lags: merger activity exhibits strong positive correlation with GDP at $k = 1$, ranging from 0.39 to 0.50. At longer lags, correlations remain positive but decline in magnitude.

3.2 Reduced-Form Estimates of the Aggregate Effects of M&A

To estimate the aggregate dynamic effects of M&A activity, I derive a quarterly measure of merger intensity by aggregating the CARs estimated in Section 2.3. Specifically, let $\mathcal{M}_t$

Table 5: Cyclical Properties of M&A Activity

M&A Measure	**Correlation(Real GDP$_t$, M&A Activity$_{t-k}$)**						
	$k=-3$	$k=-2$	$k=-1$	$k=0$	$k=1$	$k=2$	$k=3$
Acquisition Rate	-0.24	-0.25	-0.02	-0.22	0.48	0.26	0.17
Deal Count (Matched)	-0.12	-0.17	-0.29	-0.24	0.50	0.48	0.19
Deal Count (All SDC)	-0.25	-0.29	-0.07	-0.17	0.39	0.30	0.23

Notes: Table reports cross-correlations between the cyclical component of real GDP at time t and the cyclical component of M&A activity at time $t-k$. Negative k indicates M&A leads GDP; positive k indicates M&A lags GDP. Cyclical components extracted using the Hodrick-Prescott filter with $\lambda = 6.25$ for annual data (Ravn and Uhlig, 2002). The acquisition rate is defined as the percentage of Compustat firms targeted in merger transactions each year. Deal count (matched) only includes SDC transactions matched with Compustat. Deal count (all SDC) includes all completed deals satisfying the filters described in Section 2.1. The sample covers the period 1980-2024.

denote the set of completed mergers announced in quarter t. Let $w_{i,k,t}$ represent the pre-announcement market capitalization of firm i in merger event k and quarter t as a share of total U.S. stock market capitalization (obtained from CRSP). I aggregate CARs for acquirers and targets within each quarter using a value-weighted sum with weights given by $w_{i,k,t}$:

$$z_t^{t_1,t_2} = \sum_{k\in\mathcal{M}_t} \sum_{i\in\{k\}} w_{i,k,t} \cdot \widehat{CAR}_{i,k}[t_1,t_2] \tag{5}$$

where the inner sum is over all firms i (both acquirer and target) involved in merger event k. In the benchmark specification, I use the event window $[-2,1]$ to cumulate abnormal returns. The proxy $z_t^{t_1,t_2}$ captures both the volume of merger activity and the market's assessment of value creation through the number of deals and abnormal returns respectively.

By construction, the proxy $z_t^{t_1,t_2}$ is uncorrelated with macroeconomic shocks which do not stem from merger activity. First, abnormal returns are computed using daily financial data in short windows around merger announcements, thus reducing the possibility that these might be contaminated by confounding events. Second, the event study model (1) explicitly controls for the predictable cross-sectional components of stock returns, including market-wide movements.

However, insofar as mergers operate through multiple economic channels, the proxy $z_t^{t_1,t_2}$ does not identify a single structural shock. Instead, it captures a composite of: (i) productivity effects, through efficiency gains resulting from synergies and reallocation; and (ii) supply-side market power effects, through higher concentration and price setting power. The reduced-form estimates presented below therefore reflect the net impact of these competing forces.

Figure 2 plots the resulting standardized series with NBER recessions shaded in gray.

To facilitate interpretation, I show a 4-quarter moving average of the proxy. The measure exhibits substantial variations over time, with pronounced peaks of one standard deviation and greater in the mid 1980s, late 1990s, and mid 2010s. Sharp declines occur prior to the dotcom crash and following the 2008 financial crisis. The series' fluctuations are markedly different from the aggregate trends in M&A activity shown in Figure 1, thereby highlighting that value creation through mergers varies considerably over time.

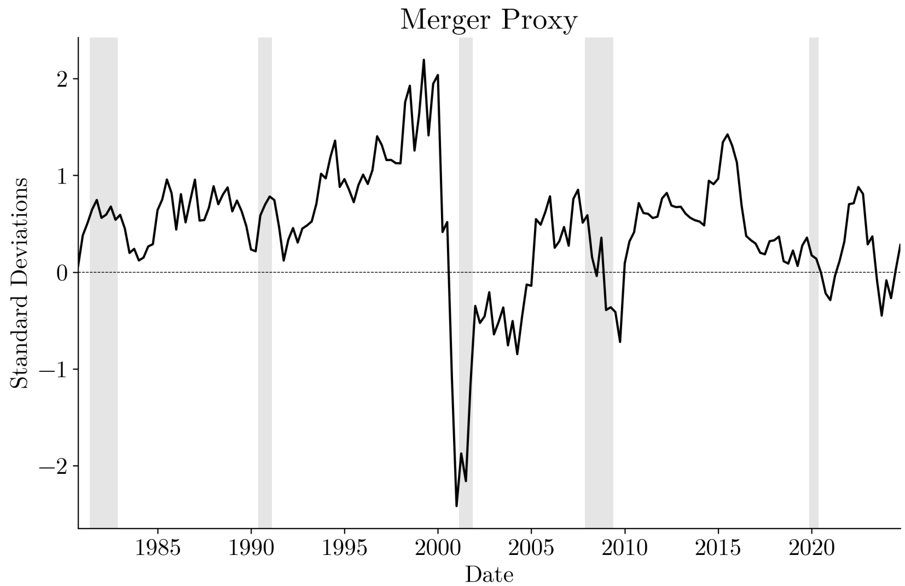


Figure 2: Aggregate M&A Activity Proxy

Notes: Figure plots a 4-quarter moving average of the quarterly aggregate M&A activity measure $z_t^{-2,1}$ described by Equation (5), normalized to have zero mean and unit variance. Gray shaded regions indicate NBER recessions. Sample covers the period 1980Q1-2024Q4.

For each macroeconomic outcome Y_t, I estimate the following bias-corrected local projections (Herbst and Johannsen, 2024):

$$\frac{1}{4}\sum_{j=0}^{3} Y_{t+h-j} = \alpha^h + \beta^h z_t^{-2,1} + \sum_{j=1}^{4} \gamma_j^h Y_{t-j} + \sum_{j=1}^{4} \delta_j^h z_{t-j}^{-2,1} + \sum_{j=1}^{4} \boldsymbol{\theta}_j^h \mathbf{Z}_{t-j} + \epsilon_{t+h} \tag{6}$$

for horizons $h = 0, \ldots, 20$ quarters. The specification includes a rich set of controls with four lags of the outcome variable, the proxy, and all other variables considered on the left-hand side $\mathbf{Z}$ (variables used are described below). The coefficients β_h trace out the impulse response of Y to a one standard deviation increase in $z_t^{-2,1}$. The left-hand side is a 4-quarter backward moving average of the outcome variable. Since the specification includes four lags of the dependent variable as controls, this is equivalent to taking moving averages of the impulse response coefficients, thereby smoothing out quarterly noise. Finally, Li, Plagborg-

Møller, and Wolf (2024) show that bias-corrected local projections exhibit the least bias among popular macroeconometric estimators for impulse-responses.

I consider the following nine macroeconomic outcomes: real GDP, real consumption, real investment, the CPI inflation rate, the Federal funds rate, labor productivity, real hourly compensation, real corporate profits, and the real S&P 500 stock price index. All the time series were obtained from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis. All variables enter in logarithms except for the federal funds rate, which enters in levels, and CPI inflation, which is computed as the logarithmic difference of the CPI index. Labor productivity is measured as output per hour. Both labor productivity and real hourly compensation are for the nonfarm business sector and are provided by the U.S. Bureau of Labor Statistics. Corporate profits are measured as after-tax profits with inventory valuation and capital consumption adjustments. Both corporate profits and stock prices are deflated by the GDP deflator. The sample spans 1980Q1-2024Q4, yielding 180 observations.

Figure 3 presents impulse responses to a one standard deviation shock in merger activity along with 90% Newey and West (1987) confidence bands. Overall, M&A shocks cause persistent declines in economic activity. Real GDP remains flat for a year before persistently declining, reaching a trough of -0.8% after four years. Similarly, real consumption starts to fall after four quarters and remains persistently below trend through the end of the forecast horizon. Real investment reacts more quickly and strongly, gradually contracting over the entire forecast horizon and attaining a maximum decline of -3% after 4 years. All three variables exhibit very similar patterns, and their responses are statistically significant at the 90% confidence level after two years and at the 95% level after three years.

On the other hand, real corporate profits trace out a hump-shaped trajectory, remaining flat for four quarters before bottoming out at -2% after two years and reverting to trend thereafter. The trough is statistically significant at the 95% confidence level. In part, the delayed responses in macroeconomic aggregates may reflect the fact that the proxy is constructed using the earliest merger announcement date. The actual synergies, price-setting power, and spillovers resulting from these transactions, which may only be completed several weeks or months following the announcement, could therefore take multiple quarters to materialize.

On the monetary side, inflation moderately increases over the forecast horizon despite the persistent contraction in economic activity. The response is less precisely estimated, but remains statistically significant at the 90% level during the second year when it reaches its maximum. Interest rates react consistently with the observed increase in inflation, and the response is statistically significant beyond the 90% level: rates rise by almost 40 basis points in the year and a half following the shock before reverting to trend.

Crucially for understanding the channels through which mergers affect macroeconomic outcomes, labor productivity immediately falls on impact, declining to -0.3% after a year. The response is significant at the 90% level over the entire forecast horizon and is very persistent. Real hourly earnings contract by similar magnitudes, but the response is only significant at the 90% level for two quarters one year following the shock and at horizons greater than three and a half years. Finally, real equity valuations remain initially flat for six quarters before falling by up to 4% after 4 years, but the standard errors are large.

I verify the robustness of the results across a wide range of specifications. First, I consider alternative event windows for cumulating abnormal returns, using windows ranging from $[-2, 1]$ through $[-2, 10]$. Second, I weigh CARs by the inverse of their forecast standard errors[6], thus giving more weight to units for which the counterfactual model is estimated with higher accuracy. Third, I include either two or six lags of the dependent variables and the proxy. Fourth, I include either a linear or a quadratic trend. Fifth, I consider local projections estimated without the bias correction. Sixth, I estimate the model without smoothing the left-hand side variable. Seventh, I verify that statistical significance is broadly preserved when using White (1980) standard errors instead as suggested by Montiel Olea and Plagborg-Møller (2021). Across all specifications, the main patterns remain qualitatively unchanged.

Overall, the impulse response estimates rule out procompetitive effects as the dominant channel through which corporate consolidations affect macroeconomic outcomes. If mergers primarily operated through productivity synergies from capital reallocation or complementarities, then labor productivity and measures of economic activity should rise unambiguously following consolidation waves. Instead, these variables decline very persistently over the entire forecast horizon. Concurrently, I observe a mild increase in price levels despite declines in economic activity. This stagflationary configuration suggests market power effects dominate productivity synergies at the aggregate level.

The macroeconometric evidence is also consistent with the micro-level findings presented in Section 2.3. While mergers generate private value for both acquirers and targets, the event study results highlight that expectations of higher profits mostly operate through the possibility of increased market power. At the aggregate level, the estimates presented above suggest such firm-level distortions compound into substantial economy-wide costs. As highlighted by Baqaee and Farhi (2020), rising markup dispersion reduces aggregate productivity by reallocating resources toward less efficient firms.

[6] Forecast standard errors account for both the residual variance unexplained by the event study factor model and the fact that CARs over the event window are computed using estimated regression coefficients.

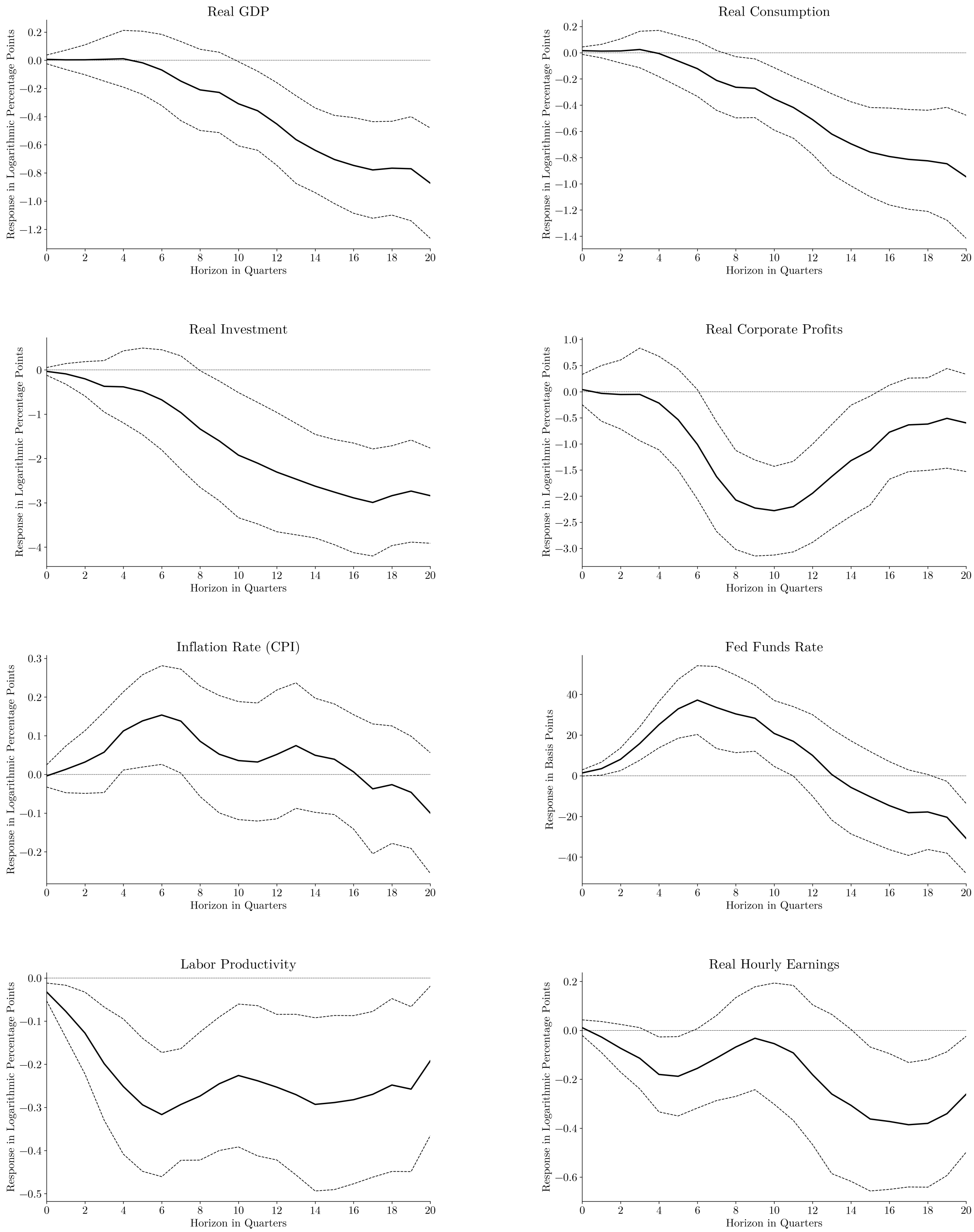


Figure 3: Impulse Responses to M&A Shock (continued on next page)

Notes: Impulse responses to a one standard deviation shock in aggregate M&A activity. Solid lines depict point estimates from bias-corrected local projections, see Equation (6); dashed lines show Newey and West (1987) 90% confidence intervals. Vertical axis measures logarithmic percentage points for all variables except the Federal funds rate, for which responses are in basis points. Sample spans 1980Q1-2024Q4.

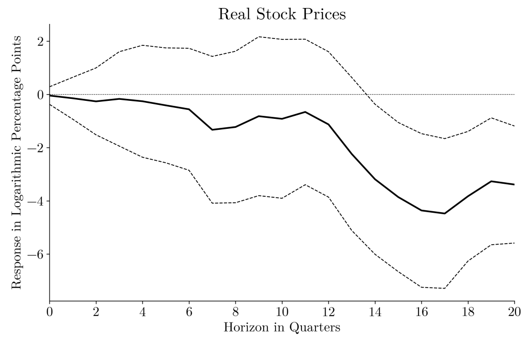


Figure 3: Impulse Responses to M&A Shock (continued)

4 Firm Dynamics Model

To rationalize the empirical findings obtained in the previous sections, I develop a quantitative general equilibrium model with the following core elements: (1) firm dynamics with heterogeneous productivity, entry, and exit; (2) a market for corporate control where acquirers compete for targets in auctions; and (3) variable markups. I begin by describing households, then firms, the M&A market structure, and finally the equilibrium.

4.1 Households

The economy is populated by a unit mass of identical infinitely-lived households. There is no aggregate uncertainty and time is discrete. The representative household maximizes its lifetime discounted utility given by:

$$\max_{\{C_t, L_t, K_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left[\log(C_t) - \psi \frac{L_t^{1+\nu}}{1+\nu} \right] \tag{7}$$

subject to the sequence of budget constraints:

$$C_t + K_{t+1} = W_t L_t + (R_t + 1 - \delta) K_t + \Pi_t \tag{8}$$

where $\beta \in (0,1)$ is the discount factor, $\psi > 0$ governs disutility of labor, $\nu > 0$ denotes the inverse Frisch elasticity of labor supply, and $\delta \in (0,1)$ the capital depreciation rate. C_t denotes final good consumption, K_t the capital stock, W_t the wage, R_t the rental rate of capital, and Π_t represents profits from firm ownership net of entry costs (described below). Capital evolves according to:

$$K_{t+1} = (1-\delta) K_t + I_t \tag{9}$$

where I_t denotes investment. The final good serves as the numeraire.

The household's capital choice is characterized by the Euler equation:

$$\frac{1}{C_t} = \beta \left[\frac{1}{C_{t+1}} (R_{t+1} + 1 - \delta) \right] \tag{10}$$

and labor supply satisfies the intratemporal condition:

$$\psi L_t^{\nu} = \frac{W_t}{C_t} \tag{11}$$

4.2 Final Good Production

Consumption, investment, and intermediates M_t are in units of the final good Y_t:

$$Y_t = C_t + I_t + M_t \tag{12}$$

The final good is produced by competitive firms that aggregate a continuum of differentiated varieties $\{y_{i,t}\}_{i \in \mathcal{Y}_t}$, where $\mathcal{Y}_t$ denotes the set of variety producers with measure N_t, using a Kimball (1995) aggregator:

$$\int_{i \in \mathcal{Y}_t} \Upsilon \left(\frac{y_{i,t}}{Y_t} \right) di = 1 \tag{13}$$

with $\Upsilon(\cdot)$ satisfying $\Upsilon'(x) > 0$, $\Upsilon''(x) < 0$, and $\Upsilon(1) = 1$. The cost minimization problem faced by final good producers yields the demand curve:

$$\frac{y_{i,t}}{Y_t} = (\Upsilon')^{-1}(p_{i,t} D_t) \tag{14}$$

where $p_{i,t}$ is the price charged by variety producer i and D_t the aggregate demand index defined by:

$$D_t = \int_{i \in \mathcal{Y}_t} \Upsilon' \left(\frac{y_{i,t}}{Y_t} \right) \frac{y_{i,t}}{Y_t} di \tag{15}$$

I adopt the following functional form for the Kimball aggregator (Klenow and Willis, 2016):

$$\Upsilon(x) = 1 + (\bar{\theta} - 1) \exp\left(\frac{1}{\varepsilon} \right) \varepsilon^{(\bar{\theta}/\varepsilon) - 1} \left[\Gamma \left(\frac{\bar{\theta}}{\varepsilon}; \frac{1}{\varepsilon} \right) - \Gamma \left(\frac{\bar{\theta}}{\varepsilon}; \frac{x^{\varepsilon/\bar{\theta}}}{\varepsilon} \right) \right] \tag{16}$$

where $\bar{\theta} > 1$ is the constant elasticity of substitution in the limiting Dixit and Stiglitz (1977) case when $\varepsilon = 0$, $\varepsilon \geq 0$ governs the curvature of demand, and $\Gamma(a; x)$ denotes the incomplete upper gamma function. This specification nests CES demand as a special case when $\Upsilon(x) = x^{(\bar{\theta}-1)/\bar{\theta}}$, but otherwise allows for variable demand elasticities as a function of firm relative size. Specifically, $\sigma_{i,t}$ is the demand elasticity faced by variety producer i:

$$\sigma_{i,t}(x_{i,t}) = -\frac{\Upsilon''(x_{i,t})x_{i,t}}{\Upsilon'(x_{i,t})} = \bar{\theta}x_{i,t}^{-\varepsilon/\bar{\theta}} \tag{17}$$

where $x_{i,t} = y_{i,t}/Y_t$ is firm i's relative output. Larger firms face less elastic demand whenever $\varepsilon > 0$, allowing them to charge higher markups. The superelasticity $\varepsilon_{i,t}$ is in turn given by:

$$\varepsilon_{i,t}(x_{i,t}) = 1 - \frac{\Upsilon'(x_{i,t})}{x_{i,t}\Upsilon''(x_{i,t})} - \frac{\Upsilon'(x_{i,t})\Upsilon'''(x_{i,t})}{\Upsilon''(x_{i,t})^2} = \varepsilon x_{i,t}^{-\varepsilon/\bar{\theta}} \tag{18}$$

The superelasticity measures how rapidly the demand elasticity declines with firm size.

4.3 Variety Production

At the end of each period, potential entrants may pay a fixed cost κ in labor units to enter and draw their initial productivity from the stationary distribution $\mu(z)$ of incumbent firms. At time t, variety producer i is characterized by its productivity $z_{i,t}$, which evolves according to:

$$\log(z_{i,t+1}) = \rho\log(z_{i,t}) + \varepsilon_{i,t+1} \tag{19}$$

where $\rho \in [0, 1)$ is the persistence parameter and $\varepsilon_{i,t+1} \sim N(0, \sigma_z^2)$ is an i.i.d. productivity shock. Firms discount future profits using the household's stochastic discount factor $\beta C_t/C_{t+1}$ and survive to the next period with probability $(1 - \varphi)$, where $\varphi \in (0, 1)$ is the exogenous exit rate.

Within every period, firms statically produce gross output $y_{i,t}$ using the following technology:

$$y_{i,t} = z_{i,t}v_{i,t}^{\phi}m_{i,t}^{1-\phi}, \quad v_{i,t} = k_{i,t}^{\alpha}l_{i,t}^{1-\alpha} \tag{20}$$

where $\phi \in (0, 1)$ is the value-added share and $\alpha \in (0, 1)$ is capital's share in value added. $v_{i,t}$ denotes value-added, $m_{i,t}$ intermediates, $k_{i,t}$ capital, and $l_{i,t}$ labor.

The firm minimizes the total cost of producing gross output given factor prices (W_t, R_t) and its idiosyncratic productivity $z_{i,t}$. In the first stage, conditional on $v_{i,t}$, cost minimization yields the following factor demands for capital and labor:

$$R_tk_{i,t} = \alpha\Omega_tv_{i,t} \tag{21}$$

$$W_tl_{i,t} = (1 - \alpha)\Omega_tv_{i,t} \tag{22}$$

where the value-added price index Ω_t is defined as:

$$\Omega_t = \left(\frac{R_t}{\alpha}\right)^{\alpha} \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha} \tag{23}$$

In the second stage, conditional on $y_{i,t}$, cost minimization yields the following factor demands for value-added and intermediates:

$$\Omega_t v_{i,t} = \phi\, MC_{i,t} y_{i,t} \tag{24}$$

$$m_{i,t} = (1-\phi)\, MC_{i,t} y_{i,t} \tag{25}$$

where the firm's marginal cost is defined as:

$$MC_{i,t} = \frac{\Omega_t^{\phi}}{z_{i,t}} \tag{26}$$

Taking the aggregate scalars $D_t^* = \Omega_t^{\phi} D_t$, Y_t, and N_t as given, variety producer i chooses its markup $\mu_{i,t} \geq 1$ to maximize variable profits:

$$\pi_{i,t} = (\mu_{i,t} - 1) MC_{i,t} y_{i,t} \tag{27}$$

subject to the demand curve Equation (14) with $p_{i,t} = \mu_{i,t} MC_{i,t}$. The first-order condition yields the standard Lerner formula for the optimal markup:

$$\mu_{i,t} = \frac{\sigma_{i,t}}{\sigma_{i,t} - 1} \tag{28}$$

where $\sigma_{i,t}$ is the demand elasticity defined in Equation (17). Combining Equation (28) with Equation (17) implicitly determines the firm's relative output $x_{i,t}$ and hence $y_{i,t}$ as a function of $z_{i,t}$ and aggregates (D_t^*, Y_t, N_t).

4.4 The Market for Corporate Control

Each period, constant shares p^{acq} and p^{tgt} of variety producers are randomly selected as potential acquirers and targets respectively to participate in the market for corporate control. For each potential target j with productivity $z_{j,t}$, bidders compete in a second-price sealed-bid auction to acquire the target.

4.4.1 Merger Synergies

When acquirer i with productivity $z_{i,t}$ merges with target j with productivity $z_{j,t}$, the merged entity's new productivity level is determined by the following synergy function:

$$z_{m,t} = Ae^{\omega_{i,j}} z_{i,t}^{\gamma_a} z_{j,t}^{\gamma_b} \tag{29}$$

where $A > 0$ is a scale parameter, $\gamma_a, \gamma_b \in (0,1)$ govern the relative contributions of acquirer and target productivities respectively, and $\omega_{i,j,t} \sim N(0, \sigma_\omega^2)$ is an i.i.d. idiosyncratic synergy shock with cdf $F(\cdot)$.

The synergy function (29) is simple yet flexible enough to capture both the theories of capital reallocation and complementarities laid out in Section 2.2. As shown by David (2020), the shape parameters γ_a and γ_b determine the size of acquirers relative to targets and the extent of sorting among merging parties. For $\gamma_a > \gamma_b$, acquirers are larger than targets, a pattern predicted by the Q-theory of mergers. One obtains positive assortative matching among acquirers and targets with sufficient complementarities, i.e. $\gamma_a + \gamma_b > 1$, and curvature in the synergy function, i.e. $\gamma_a < 1, \gamma_b < 1$. The scale parameter A affects the level of synergies unlocked by mergers without affecting matching patterns. Finally, the synergy shock $\omega_{i,j,t}$ introduces match-specific heterogeneity in surpluses, generating a smooth distribution of merger surpluses across potential pairs (i,j).

4.4.2 Auction Setup

A merger is economically viable if the surplus generated is positive, i.e. the value of the merged entity exceeds the sum of standalone values. Define the surplus as:

$$\mathcal{S}_{i,j,t}(\omega_{i,j,t}) = V(z_{m,t}(\omega_{i,j,t})) - V(z_{i,t}) - V(z_{j,t}) \tag{30}$$

with $z_{m,t}$ determined by Equation (29) and where $V(z_{i,t})$ represents the value of a firm with idiosyncratic productivity $z_{i,t}$ (defined below). To ease notation, I omit the dependence of $V(\cdot)$ on aggregate scalars (D_t^*, Y_t, N_t) and the distribution of firms over productivity states $\mu_t(z)$. A pair (i,j) is viable with probability:

$$\chi_{i,j,t} = \Pr(\mathcal{S}_{i,j,t}(\omega_{i,j,t}) > 0) = 1 - F(\bar{\omega}_{i,j,t}) \tag{31}$$

where $\bar{\omega}_{i,j,t}$ is the threshold synergy shock level satisfying $\mathcal{S}_{i,j,t}(\bar{\omega}_{i,j,t}) = 0$.

Define the set $\mathcal{T}_{i,t}$ of viable targets for acquirer i with productivity $z_{i,t}$ and the set $\mathcal{A}_{j,t}$

of viable acquirers for target j with productivity $z_{j,t}$ as:

$$\mathcal{T}_{i,t} = \left\{ z_{j,t} : \int \mathcal{S}_{i,j,t}(\omega) dF(\omega) > 0 \right\}, \quad \mathcal{A}_{j,t} = \left\{ z_{i,t} : \int \mathcal{S}_{i,j,t}(\omega) dF(\omega) > 0 \right\} \tag{32}$$

The first set determines which auctions acquirer i can be assigned to, while the second defines the productivity types of acquirers that can randomly arrive at the auction initiated by target j.

For each target j, the number of participating bidders follows a Poisson distribution $N_{j,t} \sim \text{Poisson}(\lambda_{j,t})$ with cdf $G_{j,t}(\cdot)$ and arrival rate $\lambda_{j,t}$:

$$\lambda_{j,t} = \frac{p^{acq}}{p^{tgt}} \cdot \frac{M_{j,t}^{acq}}{\bar{M}_t^{acq}} \tag{33}$$

where the mass of viable acquirers for target j with productivity $z_{j,t}$ is:

$$M_{j,t}^{acq} = \int_{z_{i,t} \in \mathcal{A}_{j,t}} \chi_{i,j,t} d\mu_t(z_{i,t}) \tag{34}$$

and the average mass of viable acquirers across all targets is:

$$\bar{M}_t^{acq} = \int \left[\int_{z_{i,t} \in \mathcal{A}_{j,t}} \chi_{i,j,t} d\mu_t(z_{i,t}) \right] d\mu_t(z_{j,t}) \tag{35}$$

The ratio p^{acq}/p^{tgt} corresponds to the average arrival rate if all targets were equally attractive. The second term $M_{j,t}^{acq}/\bar{M}_t^{acq}$ captures the relative attractiveness of target j, scaling the arrival rate depending on the mass of viable acquirers for target j.

4.4.3 Auction Outcome

In a second-price sealed-bid auction, the dominant strategy is to bid one's true valuation. Therefore, each acquirer i participating in an auction initiated by target j bids:

$$b_{i,j,t} = V(z_{m,t}) - V(z_{i,t}) \tag{36}$$

where $z_{m,t}$ is determined by Equation (29). Let $\mathcal{N}_{j,t} = \{(z_{k,t}, \omega_{k,j,t})_{k=1}^{N_{j,t}} : z_{k,t} \in \mathcal{A}_{j,t}\}$ denote the set of acquirers arriving at target's j's auction with their respective synergy shocks, and let $\mathcal{N}_{j,t}^{-i} = \{(z_{k,t}, \omega_{k,j,t}) : z_{k,t} \in \mathcal{A}_{j,t}\}_{k \neq i, k=1}^{N_{j,t}-1}$ be the set of bidders competing with acquirer i. The auction winner i^* is the bidder with the highest valuation:

$$i^* = \arg\max_{i \in \mathcal{N}_{j,t}} b_{i,j,t} \tag{37}$$

The auction price equals the second-highest bid conditional on the target's reservation value:

$$P_{i^*,j,t} = \max\left\{ \max_{i \in \mathcal{N}_{j,t}^{-i^*}} \{b_{i,j,t}\}, V(z_{j,t}) \right\} \tag{38}$$

and subject to the incentive compatibility constraint:

$$b_{i^*,j,t} \geq P_{i^*,j,t} \tag{39}$$

This ensures the highest bidder can afford the auction price and therefore receives a non-negative share of the surplus. In turn, Equation (38) guarantees that the target receives at least its standalone value. The auction is unsuccessful if either no acquirers arrive ($\mathcal{N}_{j,t} = \varnothing$) or if the winning bid fails to satisfy the incentive compatibility constraint (39). In this case, no merger occurs and all firms continue operating independently.

The auction price $P_{i^*,j,t}$ determines the distribution of the surplus across acquirer i^* and target j. Specifically, the acquirer's gain is given by:

$$\mathcal{S}^{acq}_{i^*,j,t} = V(z_{m,t}) - V(z_{i^*,t}) - P_{i^*,j,t} \tag{40}$$

and the target's gain is:

$$\mathcal{S}^{tgt}_{i^*,j} = P_{i^*,j} - V(z_j) \tag{41}$$

By construction, $\mathcal{S}^{acq}_{i^*,j,t} + \mathcal{S}^{tgt}_{i^*,j,t} = \mathcal{S}_{i^*,j,t}$. The merger premium is defined as the target's gain relative to its standalone value:

$$\text{Premium}_{j,t} = \frac{\mathcal{S}^{tgt}_{i^*,j}}{V(z_j)} = \frac{P_{i^*,j}}{V(z_j)} - 1 \tag{42}$$

As the number of bidders participating in an auction increases, the second-highest bid approaches the winner's bid, causing $P_{i^*,j,t} \to b_{i^*,j,t} = V(z_{m,t}) - V(z_{i^*,t})$, which implies $\mathcal{S}^{acq}_{i^*,j,t} \to 0$ and $\mathcal{S}^{tgt}_{i^*,j,t} \to \mathcal{S}_{i^*,j,t}$. This mechanism generates heterogeneity in merger premia across pairs (i^*, j) as a function of the target's arrival rate $\lambda_{j,t}$. In simulations, I find that a handful of bidders are sufficient to generate premia matching the empirical evidence. Additionally, this auction structure generates the pattern documented in Section 2.3: targets capture the majority of the merger surplus but both parties gain. I can now describe the option value of entering the M&A market and the firm's Bellman equation.

4.5 Recursive Problem of Variety Producers

The value of an incumbent variety producer i with productivity $z_{i,t}$ satisfies the following Bellman equation:

$$
\begin{aligned}
V(z_{i,t}) = \quad & \underbrace{\pi^*(z_{i,t})}_{\text{Maximized static profit}} \\
& \underbrace{+ p^{acq} \int_{z_{j,t} \in \mathcal{T}_{i,t}} \left[\sum_{N_{j,t}=1}^{\infty} \frac{e^{-\lambda_{j,t}} \lambda_{j,t}^{N_{j,t}}}{N_{j,t}!} \int_{\omega_{i,j,t}} \int_{\mathcal{N}_{j,t}^{-i}} \mathcal{S}_{i,j,t}^{acq} \cdot \mathbf{1}_{\{i \text{ wins auction}\}} \, d\Psi_{j,t}(\mathcal{N}_{j,t}^{-i}) \, dF(\omega_{i,j,t}) \right] g_{j,t}(z_{j,t}) \, dz_{j,t}}_{\text{Expected gain as an acquirer}} \\
& \underbrace{+ p^{tgt} \left[\sum_{N_{i,t}=0}^{\infty} \frac{e^{-\lambda_{i,t}} \lambda_{i,t}^{N_{i,t}}}{N_{i,t}!} \int_{\mathcal{N}_{i,t}} \mathcal{S}_{i,j,t}^{tgt} \cdot \mathbf{1}_{\{\text{auction success}\}} \, d\Psi_{i,t}(\mathcal{N}_{i,t}) \right]}_{\text{Expected gain as a target}} \\
& \underbrace{+ \beta \frac{C_t}{C_{t+1}} (1-\varphi) \int_{z_{i,t+1}} V(z_{i,t+1}) \, P(dz_{i,t+1} | z_{i,t})}_{\text{Continuation value}}
\end{aligned}
\tag{43}
$$

The indicator functions are defined as:

$$
\mathbf{1}_{\{i \text{ wins auction}\}} = \mathbf{1} \left\{ b_{i,j,t} \geq \max \left\{ \max_{k \in \mathcal{N}_{j,t}^{-i}} \{b_{k,j,t}\}, V(z_{j,t}) \right\} \right\} \tag{44}
$$

$$
\mathbf{1}_{\{\text{auction success}\}} = \mathbf{1} \left\{ \left(\max_{k \in \mathcal{N}_{i,t}} \{b_{k,i,t}\} \right) \geq P_{k^*,i,t} \right\} \tag{45}
$$

and the joint distribution of competing bidders' characteristics is given by:

$$
\Psi_{j,t}(\mathcal{N}_{j,t}^{-i}) = \prod_{k \in \mathcal{N}_{j,t}^{-i}} g_{j,t}(z_{k,t}) \, dF(\omega_{k,j,t}) \tag{46}
$$

where the density of acquirer productivity conditional on viability with target j is:

$$
g_{j,t}(z_{k,t}) = \mu(z_{k,t}) \left[\int_{z_{i,t} \in \mathcal{A}_{j,t}} d\mu(z_{i,t}) \right]^{-1} \tag{47}
$$

The first component, $\pi^*(z_{i,t})$, denotes the maximized static profit:

$$
\pi^*(z_{i,t}) = \max_{\mu_{i,t} \geq 1} \quad p_{i,t} y_{i,t} - W_t l_{i,t} - R_t k_{i,t} - m_{i,t} \tag{48}
$$

subject to the demand curve defined in Equation (14) and aggregate scalars (D_t^*, Y_t, N_t).

The second component captures expected gains from acquiring other firms. With probability p^{acq}, firm i is selected as a potential acquirer. Conditional on selection, the firm evaluates all viable targets $z_{j,t} \in \mathcal{T}_{i,t}$. For each viable target j, the number of competing bidders $N_{j,t}$ follows a Poisson distribution with arrival rate $\lambda_{j,t}$. Firm i draws a synergy shock $\omega_{i,j,t} \sim F(\cdot)$ that determines the productivity of the merged entity. The indicator function $\mathbf{1}_{\{i \text{ wins auction}\}}$ equals one if firm i's bid exceeds both the second-highest bid and the target's reservation value. When i wins, it captures surplus $\mathcal{S}_{i,j,t}^{acq} = V(z_m) - V(z_{i,t}) - P_{i,j,t}$. The innermost integral over $\mathcal{N}_{j,t}^{-i}$ averages over all possible configurations of viable competing bidders' productivities and synergy shocks, weighted by their joint distribution $\Psi_{j,t}(\mathcal{N}_{j,t}^{-i})$.

The third component captures expected gains from being acquired. With probability p^{tgt}, firm i is selected as a potential target and conducts an auction. The number of arriving bidders $N_{i,t}$ is Poisson-distributed with arrival rate $\lambda_{i,t}$. The indicator function $\mathbf{1}_{\{\text{auction success}\}}$ equals one if the winning bid exceeds the auction price. When the auction succeeds, firm i captures surplus $\mathcal{S}_{i,j,t}^{tgt} = P_{i^*,j,t} - V(z_{i,t})$. The integral over $\mathcal{N}_{i,t}$ averages over all possible configurations of viable bidders, weighted by their joint distribution $\Psi_{j,t}(\mathcal{N}_{i,t})$.

The fourth component is the continuation value for firms remaining independent (neither acquiring nor acquired). These firms discount future profits using the household's stochastic discount factor $\beta C_t / C_{t+1}$ and survive to the next period with probability $(1 - \varphi)$. Their productivity evolves stochastically according to the transition kernel $P(dz_{i,t+1} | z_{i,t})$ induced by the AR(1) process in Equation (19). Firms that successfully merge exit the distribution at their current productivity level in period t and enter period $t+1$ as a new entity with productivity $z_{m,t}$; their continuation value is captured through the merged firm's value $V(z_{m,t})$ embedded in the surplus calculations.

4.6 Aggregation

Aggregation of the firm-level outcomes described in the previous sub-sections is standard and follows David (2020) and Edmond et al. (2023). Aggregate capital, labor, and intermediates are obtained by integrating over all variety producers $i \in \mathcal{Y}_t$. Aggregate markups are defined as a sales-weighted harmonic average of firm-level markups:

$$\bar{\mu}_t = \left[\int_{i \in \mathcal{Y}_t} \frac{1}{\mu_{i,t}} \frac{p_{i,t} y_{i,t}}{Y_t} di \right]^{-1} \tag{49}$$

where $p_{i,t} y_{i,t}$ is firm i's nominal sales revenue, and the weights are given by the firms' revenue share in aggregate gross output. Similarly, aggregate gross output productivity is the output-weighted harmonic mean of firm-level productivities:

$$\bar{Z}_t = \left[\int_{i \in \mathcal{Y}_t} \frac{y_{i,t}/Y_t}{z_{i,t}} di \right]^{-1} \tag{50}$$

with $\bar{\mu}_t = \bar{Z}_t / \Omega_t^{\phi}$, i.e. aggregate markups are defined as the economy-wide wedge between gross output TFP and the aggregate component of marginal costs. In turn, value-added aggregate productivity measures how efficiently the economy uses labor and capital inputs and is given by:

$$\bar{Z}_t^{VA} = \bar{Z}_t^{1/\phi} \left[\frac{1-\phi}{\bar{\mu}_t} \right]^{(1-\phi)/\phi} \left[1 - \frac{1-\phi}{\bar{\mu}_t} \right] \tag{51}$$

Markups induce distortions through the inefficient use of materials, which vanish when setting $\bar{\mu}_t = 1$ in Equation (51), and through lower gross output TFP due to misallocation. This completes the presentation of the model and I now turn to the definition of the equilibrium I consider.

4.7 Stationary Recursive Competitive Equilibrium

Within each period, events unfold in the following sequence. Incumbent firm i begins the period with productivity z_i and produces. The M&A market then opens: firms are randomly selected as potential acquirers and targets, viable matches conduct auctions in which acquirers compete for targets, and successful mergers create new entities with productivity z_m. Acquirers and targets involved in successful mergers exit the distribution at their pre-merger productivities and enter the next period with productivity z_m. Surviving non-merged firms exit exogenously at rate φ and then experience stochastic productivity transitions according to $P(dz_i'|z_i)$. Finally, new entrants arrive at rate M^e, drawing their initial productivity from the stationary distribution $\mu(z)$ to replace the mass of exiting firms.

In a stationary recursive competitive equilibrium, the distribution of firm productivities $\mu(z)$ satisfies the following invariance condition:

$$\begin{aligned}
&\underbrace{p^{acq}p^{tgt}\int_{z_i}\int_{z_j}\int_{\omega_{i,j}} \mathbf{1}\{z = z_m(z_i, z_j, \omega_{i,j})\}\cdot \chi^{merger}(z_i, z_j, \omega_{i,j})\, dF(\omega_{i,j})\, d\mu(z_j)\, d\mu(z_i)}_{\text{Merged firms entering at } z} \\
&+ \underbrace{\int_{z'\neq z} P(z|z')\left[1 - p^{acq}\chi^{acq}(z') - p^{tgt}\chi^{tgt}(z')\right] d\mu(z')}_{\text{Non-merged firms transitioning into } z} + \underbrace{M^e\,\mu(z)}_{\text{Entry}} \\
&= \underbrace{p^{acq}\chi^{acq}(z)\,\mu(z)}_{\text{Exit as acquirer}} + \underbrace{p^{tgt}\chi^{tgt}(z)\,\mu(z)}_{\text{Exit as target}} \\
&+ \underbrace{\left[1 - p^{acq}\chi^{acq}(z) - p^{tgt}\chi^{tgt}(z)\right]\int_{z'\neq z} P(z'|z)\,\mu(z)\, dz'}_{\text{Non-merged firms transitioning out of } z} + \underbrace{\varphi\,\mu(z)}_{\text{Exogenous exit}}
\end{aligned} \tag{52}$$

where M^e denotes the mass of entrants. In equilibrium, M^e needs to satisfy the following free-entry condition ensuring that the expected value of entry equals the entry cost (paid in labor units):

$$\int V(z)\, d\mu(z) = \kappa W \tag{53}$$

The probability that a merger between acquirer i and target j with synergy shock $\omega_{i,j}$ is successful, conditional on both being selected, is given by:

$$\chi^{merger}(z_i, z_j, \omega_{i,j}) = \sum_{N_j=1}^{\infty} \frac{e^{-\lambda_j}\lambda_j^{N_j}}{N_j!} \int_{\mathcal{N}_j^{-i}} \mathbf{1}_{\{i \text{ wins auction}\}}\, d\Psi_j(\mathcal{N}_j^{-i}) \tag{54}$$

The probability that target i with productivity z_i successfully gets acquired is defined as:

$$\chi^{tgt}(z_i) = \sum_{N_i=0}^{\infty} \frac{e^{-\lambda_i} \lambda_i^{N_i}}{N_i!} \int_{\mathcal{N}_i} \mathbf{1}_{\{\text{auction success}\}} \, d\Psi_i(\mathcal{N}_i) \tag{55}$$

The probability that acquirer i with productivity z_i successfully exits as an acquirer is:

$$\chi^{acq}(z_i) = \int_{z_j \in \mathcal{T}_i} \left[\sum_{N_j=1}^{\infty} \frac{e^{-\lambda_j} \lambda_j^{N_j}}{N_j!} \int_{\omega_{i,j}} \int_{\mathcal{N}_j^{-i}} \mathbf{1}_{\{i \text{ wins auction}\}} \, d\Psi_j(\mathcal{N}_j^{-i}) \, dF(\omega_{i,j}) \right] g_j(z_j) \, dz_j \tag{56}$$

Expressions (54)-(56) mirror the merger components of the Bellman Equation (43), but integrate only over the indicator functions rather than the surplus terms to yield the probabilities of successful M&A outcomes.

The left-hand side of the invariance condition (52) captures inflows into productivity state z: (i) merging entities with new productivity $z_m = z$; (ii) non-merging firms whose productivity transitioned into state z stochastically; (iii) and new entrants. The right-hand side describes outflows: (a) firms that exit through the merger market either as successful acquirers or targets; (b) non-merging firms whose productivity transitioned out of state z; and (c) exogenous exits.

For this economy, a stationary recursive competitive equilibrium consists of (i) an allocation $\{y_i, k_i, l_i, m_i\}_{i \in \mathcal{Y}}$ and prices $\{p_i\}_{i \in \mathcal{Y}}$ for all variety producers; (ii) aggregate quantities $\{Y, C, M, L, K\}$; (iii) factor prices $\{W, R\}$; (iv) a stationary distribution $\mu(z)$ of firms over productivity states; (v) a value function $V(z)$; and (vi) acceptance sets $\{\mathcal{T}(z), \mathcal{A}(z)\}$ such that (a) consumers and firms optimize; (b) the stationary distribution $\mu(z)$ satisfies the invariance condition (52) and the mass of entrants M^e is consistent with free-entry (53); and finally (c) the aggregate resource constraint (12) holds and markets for inputs used by variety producers clear:

$$\int_{i \in \mathcal{Y}} l_i \, d\mu(z_i) + M\kappa = L \tag{57}$$

$$\int_{i \in \mathcal{Y}} k_i \, d\mu(z_i) = K \tag{58}$$

$$\int_{i \in \mathcal{Y}} m_i \, d\mu(z_i) = M \tag{59}$$

In the next section, I calibrate the model described above and solve for the stationary recursive competitive equilibrium.

5 Quantitative Analysis

5.1 Model Estimation and Fit

The model includes 18 parameters which need to be determined: (β, ν, δ, φ, ϕ, α, σ_ω^2, ψ, κ, ρ, σ_z, $\bar{\theta}$, ε, p^{tgt}, p^{acq}, A, γ_a, γ_b). I assume a period lasts one year. I fix seven parameters to standard values from the literature. The discount factor $\beta = 0.96$, implying an annual real interest rate of 4%. The inverse Frisch elasticity of labor supply is set to 1 and the capital depreciation rate to 6%. I set the exogenous exit rate to 4% to match the exit rate of publicly listed firms not due to mergers. The value-added share $\phi = 0.55$ and capital share $\alpha = 1/3$ are set to match U.S. national accounts data. I fix the variance of the synergy shock σ_ω^2 to 0.05; this generates smooth acceptance sets $\mathcal{T}_i$ and $\mathcal{A}_t$ over productivity states while letting the remaining merger parameters determine matching patterns. Finally, the labor disutility ψ and entry cost κ parameters are backed out to normalize $Y = N = 1$ in the benchmark economy.

The remaining nine parameters are estimated by matching economy-wide and merger-related moments. The Kimball parameters $\bar{\theta}$ and ε directly govern the level of markups and their dispersion. I target the aggregate markup (computed as a sales-weighted harmonic average) in 2023, which I estimate to be 1.32, and the 90th percentile of the cost-weighted markup distribution[7], which was 1.82 that year; see Appendix A for further details on the estimation methodology. In my sample, I obtain a sales-weighted arithmetic average markup of 1.66 in 2018, a value in line with those reported in the literature. For instance, using household panel data with both prices and quantities, Attalay et al. (2025) estimate revenue-weighted markups of 1.52 in 2018 while Dopper et al. (2025) report median markups exceeding 1.6.

The productivity persistence ρ and innovation variance σ_z shape the stationary distribution of firms, which together with the Kimball parameters, define labor demand by firms and sales concentration. Therefore, I match the labor share of output provided by the U.S. Bureau of Labor Statistics for 2023 (60.4%) and the top 5% firm sale share in Census microdata of 57.2% reported by Edmond et al. (2023).

The parameters (p^{tgt}, p^{acq}, A, γ_a, γ_b) jointly govern M&A activity, synergies, and matching patterns. Specifically, the target selection probability p^{tgt} controls the acquisition rate. In turn, the acquirer selection probability p^{acq} affects the number of bidders competing in auctions, which determines the premia extracted by targets. The synergy scale parameter A governs the average surplus created by mergers, while the synergy weights γ_a and γ_b

[7]Sales-weighted harmonic averages of markups are equivalent to cost-weighted arithmetic averages in this class of models, see Edmond et al. (2023).

Table 6: Calibration and Estimation

A. Assigned Parameters		**B. Estimated Parameters**	
Description	Value	Description	Value
Discount factor, β	0.96	Productivity persistence, ρ	0.83
Inverse Frisch elasticity, ν	1.00	Productivity std. dev., σ_z	0.15
Depreciation rate, δ	6%	Demand elasticity, $\bar{\theta}$	9.34
Firm exit rate, φ	4%	Demand curvature, ε	3.52
Value-added share, ϕ	55%	Target selection rate, p^{tgt}	4.8%
Capital share, α	33%	Acquirer selection rate, p^{acq}	21%
Synergy shock variance, σ_ω^2	0.05	Synergy scale, A	1.17
		Acquirer synergy weight, γ_a	0.92
		Target synergy weight, γ_b	0.42

C. Moments Used for Estimation

Moment	Model	Data
Labor share of GDP	59.6%	60.4%
Top 5% firm sales share	57.1%	57.2%
Aggregate markup	1.37	1.32
90th percentile of cost-weighted markups	1.82	1.82
M&A acquisition rate	3.06%	3.04%
Average merger premium	46%	46.8%
Average merger surplus	12.3%	13%
Acquirer/target average TFP ratio	1.13	1.14
Acquirer/target TFP correlation	0.42	0.39

Notes: This table describes the estimation of the structural model. Panels A and B respectively show assigned and estimated parameter values. Panel C shows the data moments, along with their model counterparts, used to estimate the parameters listed under panel B. Model moments are computed directly from the stationary distribution. The labor disutility ψ and entry cost κ parameters are backed out to normalize $Y = N = 1$ in the benchmark economy. See text for a description of the calibration strategy.

shape the relative size of acquirers and targets and the degree of assortative matching among merger pairs. I estimate these parameters using five merger-related moments: (i) an M&A acquisition rate of 3.06% in 2023 computed from the matched SDC-Compustat sample; (ii) the average merger premium of 46.8% reported by David (2020); (iii) an average merger surplus of 13% estimated by Bhagat et al. (2005); (iv) the average acquirer-to-target productivity ratio of 1.14 and (v) the unconditional correlation in the productivities of acquirers and targets of 0.39, both of which I estimate in my sample.

As shown in Table 6, the model fits the data moments very tightly. Furthermore, the estimated parameters are consistent with values reported in the literature. The productivity persistence $\rho = 0.83$ and standard deviation $\sigma_z = 0.15$ align with estimates by Foster et al.

(2008) of 0.8 and 0.14 respectively. Though the demand parameter estimates $\bar{\theta} = 9.34$ and $\varepsilon = 3.52$ fall in the upper range of the empirical distributions given by Beck and Lein (2020), they remain well below the values commonly employed in the macroeconomic models they surveyed. The synergy scale parameter $A = 1.17$ sits between the values of 1.05 and 1.21 used by David (2020) and Cavenaile et al. (2021) respectively. Finally, the synergy weights $\gamma_a = 0.92$ and $\gamma_b = 0.42$ closely match those calibrated by David (2020) (0.91 and 0.54 respectively).

Beyond the matched moments, the model correctly captures the distribution of markups and concentration patterns in the data, see Figure 4[8]. This is crucial to quantify the effects of mergers on the economy, since anticompetitive effects arise primarily through higher markups and misallocation of resources as I discuss now.

5.2 Structural Estimates of The Aggregate Effects of M&A

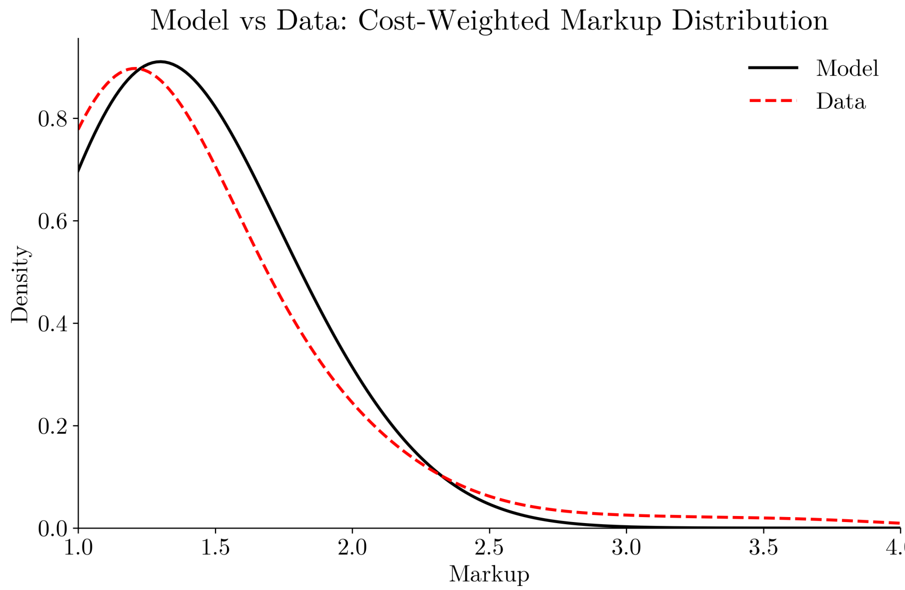
To investigate the effects of mergers through the lens of the model, I consider a counterfactual economy in which a ban on mergers is enacted. I compare aggregates between the benchmark economy and the counterfactual in Table 7.

Banning mergers generates substantial welfare gains, with GDP increasing by 21% and consumption by 15.4%, while labor supply remains stable, thus yielding a static consumption-equivalent welfare gain exceeding 15%. These gains arise because mergers induce anticompetitive effects through two channels that distort resource allocation and reduce firm entry.

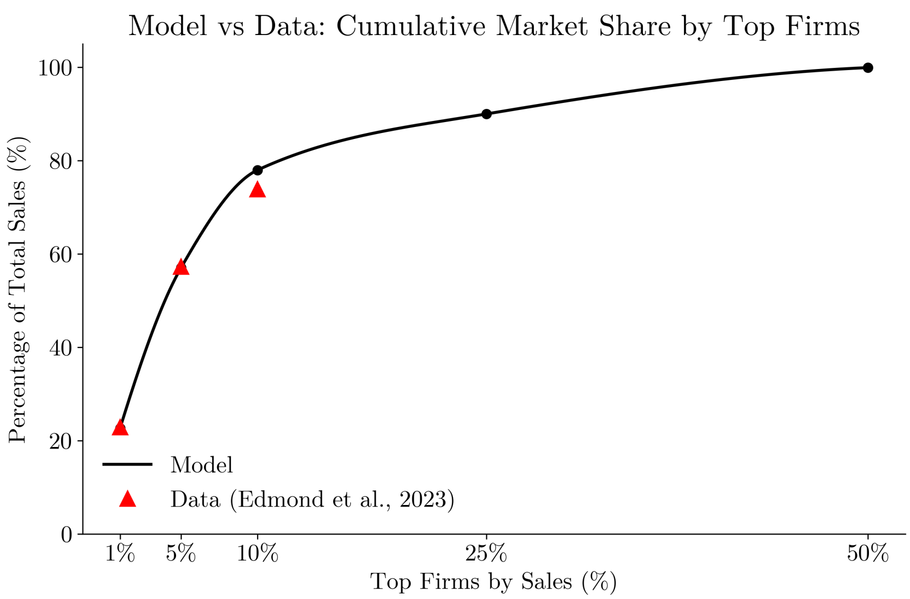
The first channel operates through higher misallocation. When two firms merge, the resulting combined entity becomes more productive due to synergies but also exploits its improved productivity by charging higher markups rather than expanding output. Consequently, the merged firm's production falls below the combined output of its constituent parts, thus reducing aggregate gross output. This contraction sets off general equilibrium effects: as the merged entity restricts output, competing firms mechanically gain market share and therefore raise their own markups, intensifying misallocation across the economy. If misallocation is sufficiently severe, labor is increasingly diverted toward less efficient producers, depressing the real wage.

The second channel works through firm entry and the extensive margin. Mergers create highly productive superstar firms with large market shares charging high markups. The existence of such firms reduces the relative output shares of lower productivity firms, thereby reducing the markups they can charge and therefore the profits they earn. In fact, only firms in the right tail of the firm distribution benefit from the existence of a merger market, with

[8] In the data, markups exhibit a very long right tail and some markups are smaller than 1. I drop markups below 1 and truncate the right tail at three times the aggregate markup.



(a) Cost-Weighted Markup Distribution



(b) Cumulative Market Share by Top Firms

Figure 4: Model Fit: Markup Distribution and Market Concentration

Notes: Panel (a) shows the density of cost-weighted markups in the model (solid black line) compared to the data (dashed red line), see Appendix A for details on markup estimation. Panel (b) displays the cumulative market share held by the top firms by sales in the model (solid black line) against the data from Edmond et al. (2023) (red triangles).

Table 7: Comparative Statics: Aggregate Effects of M&A

Variable	Benchmark Economy	With Merger Ban	Change
Measure of firms	1.00	1.04	+3.7%
GDP	0.55	0.67	+21%
Consumption	0.50	0.57	+15.4%
Real wage	0.85	0.98	+15.3%
Value added TFP	0.27	0.28	+1.2%
Aggregate markup	1.37	1.19	−13.1%
Top 1% firm sales share	22.7%	8%	−14.7 pp
Top 10% firm sales share	78%	46.7%	−31.3 pp
Static consumption-equivalent welfare gain from banning mergers: 15.4%			

Notes: This table compares aggregate outcomes in the benchmark model and a counterfactual with a ban on mergers. Changes for sales shares are reported in percentage points (pp); all other changes are in percent.

all other firms having lower values in the benchmark economy than under the counterfactual. Essentially, mergers induce "superstar crowding-out" effects which are large enough to offset the decline in entry costs from lower real wages. Together, these imply that firm entry is lower under the benchmark economy. In turn, the smaller equilibrium measure of firms negatively impacts aggregate productivity through love-of-variety effects induced by the Kimball aggregator's concavity. Table 7 confirms this channel is at play since banning mergers increases the measure of firms by 3.7% despite higher entry costs.

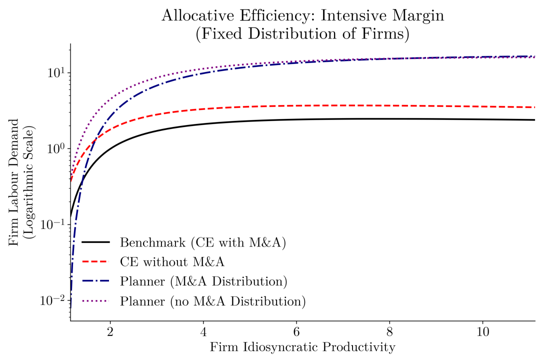
Note that in a perfectly competitive environment, which one obtains as the demand elasticity tends to infinity, mergers[9] would unambiguously increase welfare since synergies would only translate into higher output rather than elevated markups. As shown in Table 7, misallocation is severe enough that value-added TFP is 1.2% higher in the economy with the merger ban in place despite the synergies. These results differ markedly from those reported by David (2020), who estimates M&A contributes 14% to steady-state output but considers a perfectly competitive setting in which mergers cannot have any anticompetitive effects.

To further illustrate the severity of misallocation induced by mergers, Figure 5 compares the allocation of labor across four economies. The first two are the competitive equilibria considered above. The remaining two are economies in which a fictitious planner inherits a fixed distribution of firms drawn from either the benchmark or no-merger competitive equilibria. The planner optimally allocates labor across variety producers, holding firm productivity time-invariant and abstracting from entry or merger decisions[10]. The planner allocations

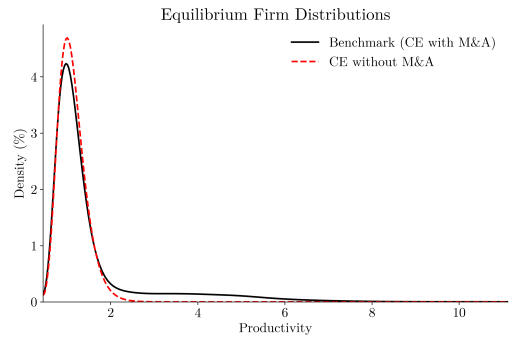
[9] Note that under perfect competition, decreasing returns to scale are necessary to generate positive firm values and merger incentives.

[10] The planner sets all markups to one, which directly defines the relative quantities produced by variety producers of each productivity type.

isolate the intensive-margin distortions arising from market power. Despite mergers creating highly productive superstar firms as shown in panel (b), panel (a) reveals that these firms severely restrict production while low-productivity firms employ excessive labor, thereby more than offsetting improvements in the productivity distribution of firms.



(a) Allocative Efficiency: Intensive Margin



(b) Equilibrium Firm Distributions

Figure 5: Misallocation and Firm Distributions

Notes: Panel (a) shows firm labor demand as a function of idiosyncratic productivity across four allocations: (i) the benchmark economy; (ii) the competitive equilibrium with the merger ban; (iii) the economy in which a planner inherits the distribution of firms from the benchmark economy or (iv) from the counterfactual with the merger ban in place. Panel (b) displays the density of firms over productivity states in the two competitive equilibria.

The model rationalizes the microeconomic and aggregate empirical evidence documented earlier. At the firm-level, mergers generate private gains for acquirers and targets yet simultaneously enable competitors to raise their markups. These predictions align with the positive competitor returns documented in Section 2.3. At the macroeconomic level, misallocation induced by higher markups reduces labor productivity and depresses economic activity, consistent with the estimated impulse-responses for these variables given in Section 3.2.

6 Conclusion

In this paper, I use three complementary approaches to establish that merger waves in the United States since the 1980s have depressed economic activity by worsening misallocation across firms. First, high-markup acquirers target similar firms, thus concentrating market power. I also find that publicly listed merging firms derive higher valuations from anticipations of market power gains rather than efficiency synergies. Second, I construct a novel proxy for aggregate merger activity and show that merger waves predict persistent output declines alongside rising prices, confirming anticompetitive channels dominate. Third, I calibrate a firm dynamics model with auction-based competition for targets and variable markups to rationalize these patterns. In a counterfactual economy implementing a blanket ban on mergers, I find large welfare gains stemming from improvements in allocative efficiency and rising firm entry.

These results carry direct policy implications challenging the standard paradigm for antitrust evaluation of mergers. Since the 1980s, antitrust enforcement has emphasized the consumer welfare standard and short-run price effects in narrowly defined markets. My empirical estimates highlight that antitrust enforcement may have been too lax[11] and allowed many mergers generating private value mostly through increased market power. The structural model emphasizes the importance of accounting for industry-wide implications for allocative efficiency alongside effects on firm entry in concentrated markets with substantial product differentiation.

In line with findings from this paper and related research, the 2023 Merger Guidelines issued by the Federal Trade Commission and Department of Justice have signaled a shift away from the permissive merger enforcement of recent decades. The new guidelines lowered concentration thresholds triggering structural presumptions of illegality[12]. Though non-binding, the guidelines directly influence judicial review and enforcement decisions.

Several extensions merit further investigation. First, the analysis does not distinguish mergers preserving or eliminating target innovation[13]. Second, the model abstracts from collusive behavior that mergers may facilitate through reduced competition, information exchange, or common ownership. Third, while the model establishes that mergers reduce real wages and raise markups, incorporating household heterogeneity would allow one to study the distributional consequences of increased merger activity. I pursue some of these extensions in ongoing work.

[11]See also Cavenaile et al. (2021) and Nocke and Whinston (2022) who reach similar conclusions.

[12]Specifically, mergers are presumed to have anticompetitive effects if they lead to increases in the HHI greater than 100 and raise industry concentration above an HHI of 1800 (against previous 2010 guidance using 200 and 2500 as thresholds respectively).

[13]For instance, Cunningham et al. (2021) document that 5.3% to 7.4% of pharmaceutical acquisitions constitute "killer acquisitions" to preempt competition.

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A Markup Estimation

This appendix describes the procedure for estimating revenue-based productivity and firm-level markups using the control function approach of Ackerberg et al. (2015) combined with the cost-minimization-based markup estimation of De Loecker and Warzynski (2012). I estimate production functions at the NAICS 2-digit level using yearly firm panel data from Compustat. I follow the procedure described in De Loecker et al. (2020) for cleaning the Compustat data.

A.1 Production Function Estimation

Consider a firm i in industry j and year t with gross output technology given by:

$$y_{ijt} = \beta_j^v x_{ijt}^v + \beta_j^f x_{ijt}^f + z_{ijt} + \epsilon_{ijt} \tag{A.1}$$

where lowercase variables denote logs, y denotes sales, x^v are variable inputs (cost of goods sold, COGS), x^f is the fixed input (capital stock), z is revenue-based productivity, and ϵ represents measurement error. Productivity evolves according to a first-order Markov process:

$$z_{ijt} = g(z_{ij,t-1}) + \upsilon_{ijt}, \quad \mathbb{E}_{t-1}[\upsilon_{ijt}] = 0 \tag{A.2}$$

The challenge is that productivity z_{ijt} is observed by the firm but not by the econometrician, but it affects input choices. Therefore, OLS estimates are biased. Instead, I use the control function approach described by Ackerberg et al. (2015). Specifically, assume variable inputs x_{ijt}^v are chosen flexibly each period as a function of the state variables and productivity:

$$x_{ijt}^v = \upsilon_t(x_{ijt}^f, z_{ijt}, s_{ijt}) \tag{A.3}$$

where s_{ijt} denotes the firm's market share, which controls for markup differences across firms as suggested by De Loecker et al. (2020). Under strict monotonicity of $\upsilon_t(\cdot)$ in z, productivity can be expressed as:

$$z_{ijt} = \upsilon_t^{-1}(x_{ijt}^v, x_{ijt}^f, s_{ijt}) \equiv \phi_t(x_{ijt}^v, x_{ijt}^f, s_{ijt}) \tag{A.4}$$

Substituting into Equation (A.1):

$$y_{ijt} = \beta_j^v x_{ijt}^v + \beta_j^f x_{ijt}^f + \phi_t(x_{ijt}^v, x_{ijt}^f, s_{ijt}) + \epsilon_{ijt} \tag{A.5}$$

In the first stage, I follow De Ridder et al. (2025) and approximate $\Phi_t(x_{ijt}^v, x_{ijt}^f, s_{ijt}) \equiv$

$\beta_j^v x_{ijt}^v + \beta_j^f x_{ijt}^f + \phi_t(x_{ijt}^v, x_{ijt}^f, s_{ijt})$ using a third-order polynomial in (x^v, x^f) with parameters θ. I assume market shares s_{ijt} and time fixed effects δ_t entering linearly and additively:

$$y_{ijt} = \Phi_t(x_{ijt}^v, x_{ijt}^f; \theta) + \gamma s_{ijt} + \delta_t + \epsilon_{ijt} \tag{A.6}$$

Estimating Equation (A.6) by OLS yields purged output $\tilde{y}_{ijt} = y_{ijt} - \hat{\Phi}_t(x_{ijt}^v, x_{ijt}^f; \hat{\theta}) - \hat{\gamma} s_{ijt} - \hat{\delta}_t$.

In a second stage, I identify the production function coefficients $\beta_j = (\beta_j^v, \beta_j^f)$ by exploiting timing assumptions. Capital x_{ijt}^f is predetermined (chosen prior to t), and thus uncorrelated with the productivity shock υ_{ijt}. Variable inputs x_{ijt}^v are correlated with lagged variable inputs $x_{ij,t-1}^v$ due to serial correlation in market shares, but $x_{ij,t-1}^v$ is uncorrelated with υ_{ijt}.

I assume z_{ijt} follows an AR(1). I then recover $\hat{\upsilon}_{ijt}$ as the residual of the AR(1) for z_{ijt} estimated via OLS, and I minimize the following moment conditions over $\beta_j = (\beta_j^v, \beta_j^f)$:

$$\beta_j = \arg\min_{\beta_j} \mathbb{E}\left(\hat{\upsilon}_{ijt}(\beta_j) \begin{pmatrix} x_{ij,t-1}^v \\ x_{ijt}^f \end{pmatrix} \right) \tag{A.7}$$

Using the estimated elasticity parameters β_j and purged output $\tilde{y}_{ijt}$, one can recover the estimates for revenue-based productivity $\hat{z}_{ijt}$.

A.2 Markup Calculation

Given production function estimates $\hat{\beta}_j$, I compute markups following De Loecker and Warzynski (2012). The key insight is that markups can be recovered from the ratio of output elasticities to expenditure shares.

For the variable input x^v (COGS), the firm's cost-minimization first-order condition is:

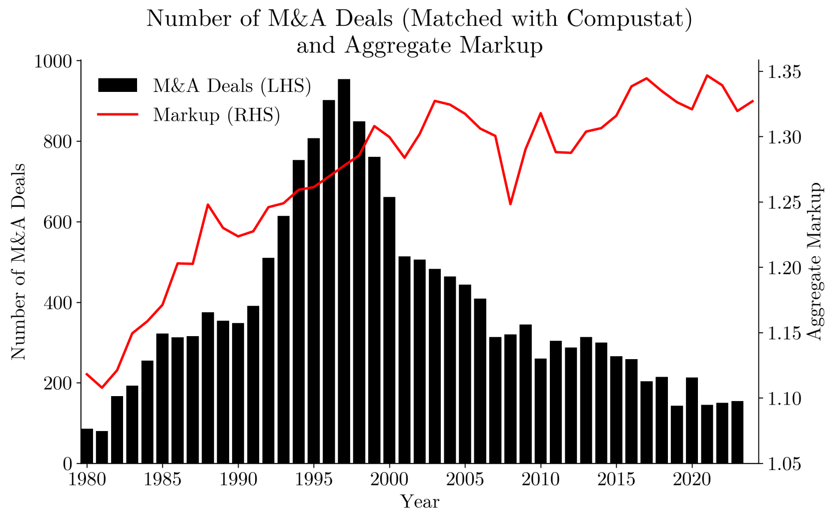
$$\frac{\partial Y_{ijt}}{\partial X_{ijt}^v} = \mu_{ijt} \frac{W_{jt}^v}{P_{ijt}} \tag{A.8}$$

where $Y_{ijt} = \exp(y_{ijt})$ is output, $X_{ijt}^v = \exp(x_{ijt}^v)$ is the variable input, W_{jt}^v is the input price, P_{ijt} is output price, and μ_{ijt} is the markup. Rearranging:

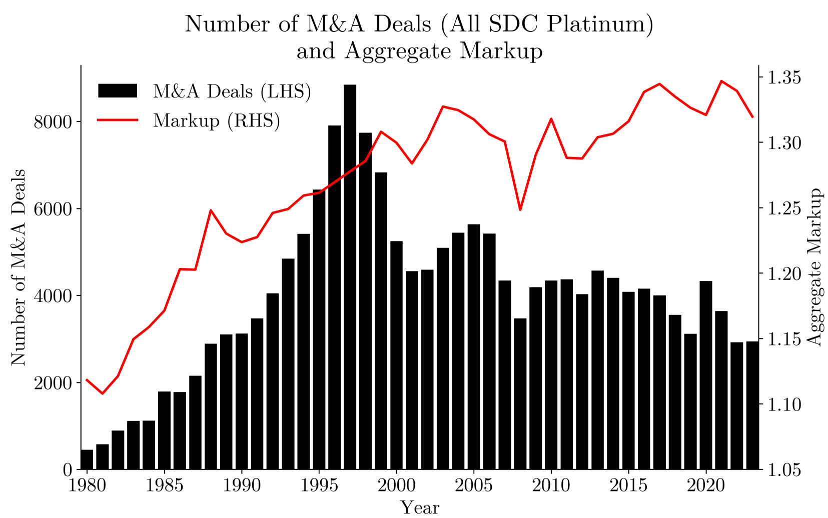
$$\mu_{ijt} = \frac{\partial Y_{ijt}}{\partial X_{ijt}^v} \cdot \frac{P_{ijt}}{W_{jt}^v} = \frac{\partial \log Y_{ijt}}{\partial \log X_{ijt}^v} \cdot \frac{P_{ijt} Y_{ijt}}{W_{jt}^v X_{ijt}^v} = \frac{\theta_{ijt}^v}{\alpha_{ijt}^v} \tag{A.9}$$

where $\theta_{ijt}^v = \partial \log Y_{ijt} / \partial \log X_{ijt}^v = \beta_j^v$ is the output elasticity (which one obtains from the production function estimates) and $\alpha_{ijt}^v = W_{jt}^v X_{ijt}^v / (P_{ijt} Y_{ijt})$ is the variable cost share in sales (observable in Compustat).

B Additional Descriptive Statistics



(a) Matched SDC-Compustat Sample



(b) Full SDC Sample

Figure B.1: M&A Deal Volume and Aggregate Markup

Notes: Figure plots the annual number of M&A deals (left axis, black bars) and the aggregate markup (right axis, red line) over 1980-2023. Panel (a) shows deals from the merged SDC-Compustat sample with available firm characteristics. Panel (b) shows all completed deals from the SDC database. The aggregate markup is computed as the harmonic sales-weighted average of firm-level markups; see Appendix A for details on markup estimation.

C Numerical Solution Method

C.1 Algorithm

I compute the benchmark stationary competitive equilibrium through nested fixed-point iterations over four layers: (i) an outer general equilibrium loop over the aggregate scalar $D^* = \Omega^\phi D$; (ii) a loop over the value function V and the stationary distribution μ; (iii) a loop over the merger component of the Bellman equation; and (iv) an innermost loop iterating the Bellman equation with a fixed merger component. I use 75 productivity grid points.

First, I solve for the aggregate scalar D^* that clears the Kimball aggregator market condition (13) using Brent's method. For the benchmark economy, the remaining aggregate scalars (Y, N) are normalized to 1.[14] Given D^*, I recover the markup charged by each variety producer by numerically solving the static first-order condition to the optimization problem described by Equations (27) and (14) using Brent's method, which requires evaluating the Kimball aggregator (16) and its derivative at each iteration.

Second, for each candidate D^*, I iterate over (V, μ) until both converge. Given μ, I solve for V as described below. Given V, I find the stationary distribution μ by solving the law of motion forward until convergence. I update both V and μ using successive under-relaxation. The loop typically converges in less than 50 iterations.

Third, solving for V given μ requires two nested loops. In the outer loop, I simulate the merger market (described below) to compute the option value of participating in the market for corporate control (the second and third terms in Equation (43)). In the inner loop, I hold this merger component fixed and iterate over the Bellman Equation (43) until convergence. I repeat these nested loops until the merger component converges.

C.2 Auction Simulation

To simulate the merger market, I first compute the acceptance sets described by Equation (32). For each productivity pair (z_i, z_j), this requires solving for the threshold synergy shock $\bar{\omega}$ satisfying Equation (31) to recover the viability probability $\chi_{i,j}$. I use Brent's method to solve this equation.

A major computational challenge is the high-dimensional integral over the set of bidders arriving at an auction. For each viable pair, I employ quasi-Monte Carlo methods with Sobol sequences to simulate auctions. Quasi-Monte Carlo techniques provide superior convergence properties compared to standard Monte Carlo by ensuring uniform coverage of the high-dimensional probability space. This is important given the curse of dimensionality from

[14] In non-benchmark equilibria, one needs to solve for aggregate scalars (D^*, Y, N).

jointly drawing rival counts, productivities, and synergy shocks for each auction.

For each draw, I sample the number of rival bidders from a Poisson distribution with arrival rate described by Equation (33) (bounded from above by 100), draw their productivities from the conditional distribution of potential acquirers (47), draw synergy shocks from $F(\cdot)$, compute each bidder's valuation using (36), and determine the auction winner and price from Equations (37)-(38). I average outcomes across draws to obtain merger probabilities, expected acquirer and target gains, and the distribution of merged firms' productivities. This yields the mass of flows resulting from mergers, which is required to simulate the stationary distribution forward, and the expected value of the merger component for the Bellman equation.