Markups and Business Dynamism across Industries

Brian C. Albrecht* and Ryan A. Decker†

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Evidence of rising market power in the U.S. economy has received widespread attention in macroeconomics literature. Recent research has linked trends in measured market power to other secular trends in the U.S., including multi-decade trends of declining rates of job reallocation and business entry (or "business dynamism"). Intuitively, firms with more market power are less responsive to shocks, and industries characterized by market power may have (or create) significant barriers to entry. Both forces predict a negative correlation between market power and business dynamism. However, industry-level data shows zero, or often a positive, correlation between markups and business dynamism; industries that experienced larger increases in markups had smaller decreases in dynamism on average. Those few industries that saw both large increases in markups and large declines in dynamism do not account for a significant share of the aggregate trends in markups and dynamism. Our results suggest that market power does not explain the decline in dynamism.

JEL-Classification: L11, D24, D40, J30, K20

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*International Center for Law & Economics. Email: mail@briancalbrecht.com.

†Federal Reserve Board. Email: ryan.a.decker@frb.gov. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.

1 Introduction

In recent decades, common measures of "business dynamism"—such as new business entry rates and gross job or worker flows—have seen significant declines in the U.S. (Figure 1, right panel).[1] Over a similar time frame, there is evidence that an important measure of market power—the average markup—has risen significantly (left panel; De Loecker, Eeckhout, and Unger 2020). A natural question raised by policymakers and researchers is whether these patterns are related. The theoretical connection between these two phenomena is straightforward: market power makes firms less responsive to shocks, which dampens job reallocation and deters entry. However, little direct empirical work on the connection between dynamism and markups exists, with De Loecker, Eeckhout, and Mongey (2021) being an important exception.

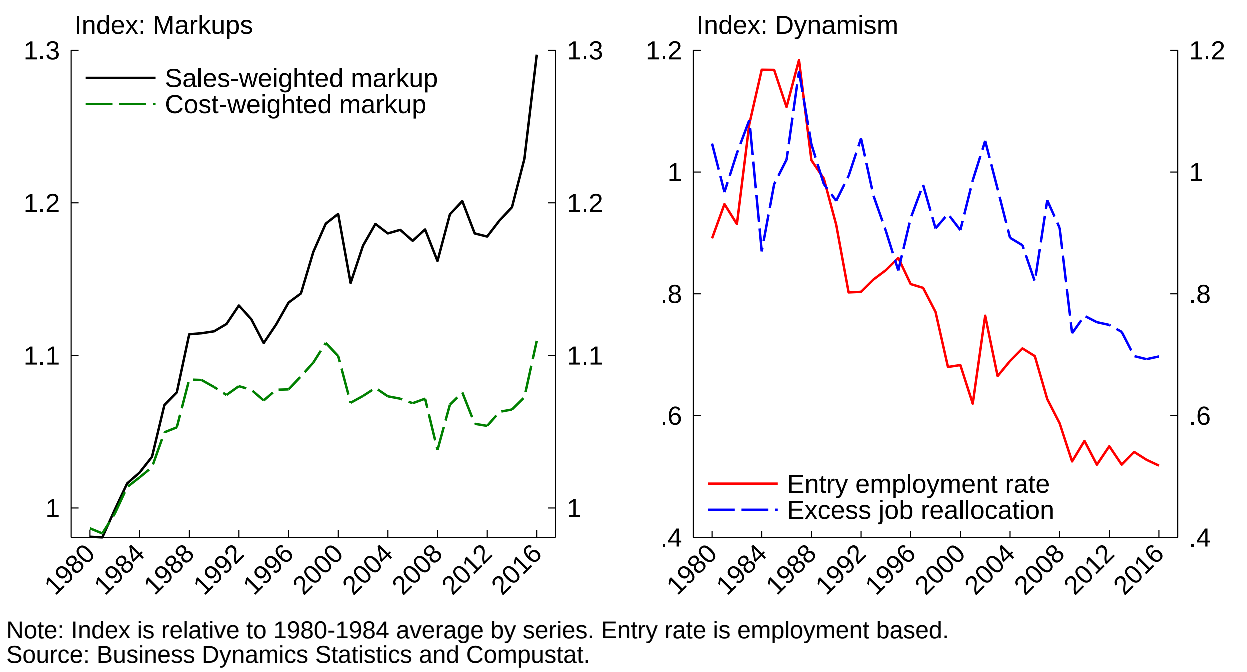
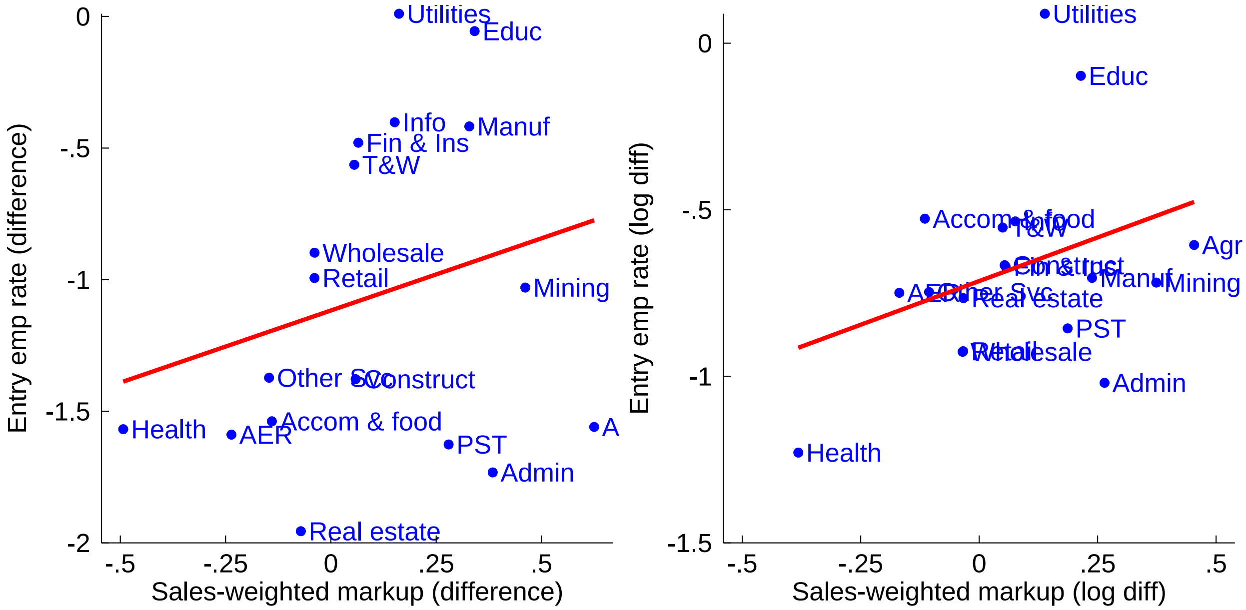


Figure 1: Markups and business dynamism, 1980-2016

1. For examples see Hyatt and Spletzer (2013), Decker et al. (2014), Karahan, Pugsley, and Sahin (2019), Decker et al. (2020), and Akcigit and Ates (2019).

In this paper, we ask whether rising markups can explain declining business dynamism. While the time series evidence suggests a potential connection, our approach is to explore *cross-sectional* evidence, with a focus on patterns of markup growth and dynamism decline across industries. If rising markups and market power are an important driver of recent dynamism patterns, we would expect to see a strong negative correlation between changes in markups and changes in dynamism at the industry level. Additionally, we would expect that industries in which such correlations are strong would account for a large share of the overall decline in dynamism and the overall rise in markups. In fact, we find no significant negative correlation between changes in dynamism and markups at the industry level—and sometimes strong positive correlations; this can be seen at the broad sector level on Figure 2, which plots changes in entry rates against changes in sales-weighted average markups (with log differences in the right panel). Moreover, the few industries in which a negative correlation is evident are too small, taken together, to meaningfully account for even a share of the aggregate trends. In preliminary exercises, we also relate markups and dynamism measures at annual frequency, finding that contemporaneous and lagged markups are typically positively associated with dynamism measures, sometimes statistically significantly so. These results are robust to constructing markups with both sales and cost weights, and the results are broadly consistent for employment-based entry rates, gross job reallocation, and simple firm entry rates. While our evidence is limited to reduced-form correlations, it strongly suggests that rising markups—as commonly measured in the literature on broadly rising market power—are not a major explanatory factor behind declining dynamism. In ongoing work in progress, we will explore the time series relationship of markups and dynamism more formally.

Our empirical approach and inference depend heavily on measurement considerations. For markups, we follow the seminal work of De Loecker, Eeckhout, and Unger



Note: Difference/log difference, 2012-2016 average vs. 1980-1984 average. Entry rate is employment based.
Source: Business Dynamics Statistics and Compustat.

Figure 2: Change in entry rates and markups, broad sectors

(2020), which constructed markup estimates using sales and cost data along with revenue function estimation for the universe of publicly traded firms. Since this markup measure—which we call "DEU markups"'—is available at the firm level in publicly available data, we can construct average markups at the industry level; given data limitations, we focus on the 2-digit and 3-digit NAICS level rather than narrower levels of detail. By following the methodology of De Loecker, Eeckhout, and Unger (2020) we can construct these markups starting in the 1950s and running through 2016. This markup measure is not without controversey; it is obtained by multiplying the ratio of sales to cost of goods sold (a proxy for variable costs) by an estimate of the output elasticity of variable factors, though available data only permit revenue elasticity estimation. Moreover, the appropriate measure of variable costs has been disputed in the literature, as has the appropriate weighting variable for obtaining aggregate averages. Nevertheless, this form of markup has been used in widely cited papers and continues to inform discussions about market power among both researchers and policymakers.

We measure dynamism using standard measures from the literature: firm entry rates and rates of gross job reallocation, calculated in the Census Bureau's Business Dynamics Statistics (BDS) for the near-universe of private nonfarm employer businesses. These measures are available at various levels of industry detail—including the 3-digit NAICS level—and can cover the time period from the late-1970s through 2020. Combining our data on dynamism and markups, we study the period from 1980 through 2016—a period over which both dynamism and markups have seen dramatic changes.

Our results have important implications for the literatures on both dynamism and market power. Several notable papers posit a negative relationship between dynamism and market power (e.g., Akcigit and Ates 2019, 2021; De Ridder 2021; De Loecker, Eeckhout, and Mongey 2021). While this relationship is suggested by the time series patterns, its apparent absence from cross-sectional data suggests that whatever role market power has played in declining dynamism is minimal or involves complex additional channels of reverse causation. Alternatively, it could be that measurement limitations associated with markup power concepts are clouding the relationship between measured market power and dynamism.

2 Related Literature

There is a large empirical literature documenting the decline in dynamism in the U.S. since the 1980s.[2] Entry rates have fallen substantially, as shown in Figure 1 and documented more extensively in a variety of papers (Decker et al. 2014; Decker et al. 2016a; Karahan, Pugsley, and Sahin 2019; Alon et al. 2018). Closely related has been a more re-

2. Most of this literature pedates the recent pandemic; Decker and Haltiwanger (2022) provide evidence of elevated dynamism during the pandemic, though it is unclear whether this marks a durable reverse of the longer-run trend.

cent decline of entry in the high-tech sector and lower prevalence of high-growth young firms (Decker et al. 2016b; Haltiwanger, Hathaway, and Miranda 2014; Guzman and Stern 2020). The decline in entry has coincided with declining gross job reallocation and within-firm employment volatility (Davis et al. 2006; Decker et al. 2014; Decker et al. 2016b), worker flows (Hyatt and Spletzer 2013; Davis and Haltiwanger 2014), and internal migration (Molloy et al. 2016). Falling job reallocation has been associated with weaker responsiveness of firms and establishments to shocks, with potentially significant implications for aggregate productivity growth (Decker et al. 2020).

While the literature has not found one overriding cause to explain all the key dimensions of declining dynamism, several theories have found empirical support for some aspects of the decline. Given the importance of labor force growth, on net, for facilitating business entry in standard models (Hopenhayn 1992), the slowdown of labor force growth during the 1980s and related trends in population growth likely explain some of the decline in overall entry rates (Karahan, Pugsley, and Sahin 2019; Hathaway and Litan 2014; Ozimek and Wurm 2017); this theory likely has less explanatory power for the decline of high-growth entrepreneurship in the 2000s or even the decline in entry after the bulk of the labor force growth slowdown in the 1980s, and it likely does not explain declining reallocation and shock responsiveness among even older firms that has been documented by Decker et al. (2020) and others. Increasing stringency of labor market and related regulations—such as unlawful discharge regulations, occupational licensing, or land use regulations—has been empirically associated with lower entrepreneurship and job flows (Davis and Haltiwanger 2014; Autor, Kerr, and Kugler 2007; Johnson and Kleiner 2020), though simple industry-level counts of federal regulations have no empirical relationship with establishment entry rates (Goldschlag and Tabarrok 2018).

Changing business models may play an important role. For example, the retail trade sector saw a large and steady decline in entry and job flows throughout the 1980s-2000s

(Decker et al. 2016b), a time during which the sector saw significant consolidation that was productivity enhancing (Foster, Haltiwanger, and Krizan 2006). Alternatively, the decline in *employer* entry may be related to rising *nonemployer* activity as technology and other factors enable more "gig economy"-style business models; the number of nonemployer businesses has risen dramatically over this period, and this theory has been suggested by Bento and Restuccia (2022). However, much of the recent rise in nonemployers appears to be concentrated in the "ridesharing" industry (Abraham et al. 2019). Rising power of "superstar" or "frontier" firms and slowing knowedge diffusion from superstars to "laggards" likely plays some role (Andrews, Criscuolo, and Gal 2015; Akcigit and Ates 2019), particularly in the post-2000 decline of high-growth young firms and high-tech entrepreneurial growth outcomes. Relatedly, the growing importance of intangible capital could raise entry costs (De Ridder 2021).

None of these explanations need fully explain the decline in dynamism, though each likely plays some role. But an additional explanation—rising market power—has been speculated upon many times in the dynamism and related literature. Decker et al. (2020) suggest the possibility that rising market power is related with declining dynamism based in part on simple model intuition: rising market power is often modeled as increasing curvature of revenue functions, which reduces firm- or establishment-level shock responsiveness and, therefore, aggregate job reallocation. De Loecker, Eeckhout, and Unger (2020), a paper focused on measuring market power through markups, proposes rising market power as a likely explanation for declining dynamism. Most relevant is De Loecker, Eeckhout, and Mongey (2021), which notes the aggregate time series relationship and builds a rich model of market power, business dynamics, and entry; once calibrated and simulated, the model can more than explain the full decline in aggregate job reallocation.

Our paper builds on the empirical literature of markups, especially from a macroeconomic perspective, that was renewed by De Loecker, Eeckhout, and Unger (2020).

Their paper uses an approach to estimating markups that comes from Hall (1988) and De Loecker and Warzynski (2012).[3] The markup concept requires data on expenditures on any variable input along with total sales and the output elasticity of the variable input. The data that De Loecker, Eeckhout, and Unger (2020) use come from Compustat, which includes only publicly-traded firms and provides data on sales as well as cost of goods sold, which the authors use as their expenditure on variable costs.[4] Their main estimates indicate that the average markup—which is constructed as the sales-weighted average of firm-level markups—has risen from 1.2 in 1980 to 1.6 in 2016, and the manufacturing sector plays a large role in this rise. For our purposes, we take these markup estimates—which have been widely cited—as our own measure of markups, abstracting from broader debates about markup measurement.[5]

Other papers also find rising markups but with smaller increases. Traina (2018) uses the same data for public firms but includes sales and administrative expenses as a variable cost (this is a broader definition of variable costs than in De Loecker, Eeckhout, and Unger 2020). Edmond, Midrigan, and Xu (2022) also use the data on public firms but develop a model of oligopoly in which the proper measure of misallocation is a cost-weighted average markup (instead of a sales-weighted markup as in De Loecker, Eeckhout, and Unger 2020); using cost weights, the average markup has increased by much less than the sales-weighted version. Foster, Haltiwanger, and Tuttle (2022) use Census Bureau data on the universe of manufacturing establishments—a sector that is important for the

3. There is also a large econometric debate about possible issues with the De Loecker, Eeckhout, and Unger (2020) approach to estimating markups. See Flynn, Gandhi, and Traina (2019), Kirov and Traina (2021), Bond et al. (2021), Doraszelski and Jaumandreu (2019, 2021), De Loecker (2021), and De Ridder, Grassi, and Morzenti (2022).

4. Whether cost of goods sold satisfies the requirements of variable cost expenditures is an open question.

5. The De Loecker, Eeckhout, and Unger (2020) published paper comes with replication files; we directly exploit those files, running their code on Compustat data. The replication files do not include code replicating their revenue function estimation but instead provide revenue elasticities necessary for markup construction. As a result, we limit our time sample to the period covered by the replication files (i.e., through 2016), though we start in 1980 given our use of BDS data and common practice.

public firm-based markup rise—and find a smaller increase in average markups when revenue functions are estimated with more industry detail.[6] We view these measurement questions as important, but for our purposes we simply adopt the De Loecker, Eeckhout, and Unger (2020) markup estimates at face value.

To connect declining dynamism and rising markups, the literature has proposed a variety of mechanisms that generate both phenomena: a rise in the use of intangible capital (De Ridder 2021), IT technology (Aghion et al. 2019; Lashkari, Bauer, and Boussard 2019), changes in knowledge diffusion (Akcigit and Ates 2019; Olmstead-Rumsey 2019), or demographics (Peters and Walsh 2019). Akcigit and Ates (2021) provides a summary of evidence connecting dynamism and markups to other major macroeconomic trends, such as growing concentration and rising profits. But the paper which most fully explores the direct connection between dynamism and markups is De Loecker, Eeckhout, and Mongey (2021). The authors develop a general equilibrium economy with oligopolistic output markets which matches features of the time series, such as wages and employment, entry and exit. We build on their paper by exploring the cross section in some detail, and we follow them in also adopting the De Loecker, Eeckhout, and Unger (2020) markup concept and data.

3 Cross-sectional evidence

3.1 Data

We obtain measures of business dynamism from the Census Bureau's Business Dynamics Statistics (BDS), which are publicly available tabulations from the confidential Longtitudinal Business Database (LBD) microdata. The BDS are the workhorse public-use data

6. Autor et al. (2020) find there has been a reallocation toward "superstar" firms with higher markups.

source for studying firm dynamics in the U.S., with annual data spanning from the late-1970s through 2020 and tabulations by firm size and age, establishment industry (up to 4-digit NAICS), and establishment county—among other categories—available. The data cover the near-universe of private nonfarm employer establishments and report employment and firm and establishment characteristics as of March of each reference year.[7] Most of the literature on changing business dynamism in the U.S. relies on the BDS or the confidential LBD.

Importantly, the BDS are based on high-quality firm identifiers that permit tracking of firm age, where a "firm" is distinct from an "establishment." In Census Bureau parlance, an establishment is a single operating location of a business, while a firm is a collection of one or more establishments under common operational control or ownership. Firm age in the BDS is defined consistent with most U.S. business dynamics literature (e.g. Haltiwanger, Jarmin, and Miranda 2013): upon the first observation of a firm identifier, the firm is assigned the age of its oldest establishment—where an establishment is age zero in the first year in which it has reported (March) employment.

In the BDS, we focus primarily on two common measures of business dynamics that have seen secular declines since the early 1980s. The first is the entry employment rate, which is the share of total employment accounted for by new firms (those with age 0). That is,

$$eer_t = \frac{e_t^0}{\frac{1}{2}(e_t + e_{t-1})}, \tag{1}$$

where e_t^0 is employment among firms with age 0 (i.e., new entrants) in year t, and e_t is total employment among all firms in year t. This measure of entry—sometimes referred to as the employment-based or employment-weighted entry rate—measures the economic magnitude of new entrants.

7. Railroads (NAICS 482), private households, and some smaller groups of establishments are out of scope; see Decker et al. (2021).

The second measure is excess job reallocation, which is given by:

$$ejr_t = \frac{jc_t + jd_t - |jc_t - jd_t|}{\frac{1}{2}(e_t + e_{t-1})}, \tag{2}$$

where jc_t is gross job creation (total job gains among entering and expanding establishments), jd_t is gross job destruction (total job losses among downsizing and exiting establishments), and e_t is total employment. The denominator in equation 2 is the "DHS denominator" after Davis, Haltiwanger, and Schuh (1996), which is common in the business dynamics literature. Excess job reallocation is a measure of the gross job flows that exceed what is necessary to facilitate net job growth; in this paper, we use the terms "excess job reallocation" and "job reallocation" interchangeably.

The entry employment rate and the excess job reallocation rate are reported on Figure 1. In some exercises we also report a third measure, the simple entry rate (sometimes called the "startup rate" or "unweighted entry rate"):

$$er_t = \frac{f_t^0}{f_t^{dhs}}, \tag{3}$$

where f_t^0 is the number of new firms in year t, and f_t^{dhs} is the total number of firms expressed in "DHS" terms.[8]

For markups, we use the benchmark estimates from De Loecker, Eeckhout, and Unger (2020) ("DEU markups"). A large literature has grown up debating bias and identification issues with these estimates.[9] We simply take DEU markups as given data and not

8. $f_t^{dhs} = \frac{f_t + f_{t-1}}{2}$ where f_{t-1} is longitudinally consistent and is constructed as firms in t plus firm deaths between $t-1$ and t minus firm births between $t-1$ and t.

9. See Flynn, Gandhi, and Traina (2019), Kirov and Traina (2021), Bond et al. (2021), Doraszelski and Jaumandreu (2019, 2021), De Loecker (2021), and De Ridder, Grassi, and Morzenti (2022). In addition to limitations associated with production function estimation issues, these estimates rely on Compustat data covering only publicly traded firms. The firms in Compustat account for roughly half of aggregate private sales, and this share varies widely across narrow industries (Decker and Williams 2023). Existing literature finds that the business dynamics of privately held firms differ materially from those of publicly traded

an estimated measure.[10] We rely on their benchmark sales-weighted markup but also use a cost-weighted markup. They calculate their markup estimates using a production function approach and show how the markup is given by:

$$\text{Markup} = \text{Output Elasticity of Variable Input} \times \frac{\text{Total Revenue}}{\text{Cost of Variable Input}}.$$

For their variable input, De Loecker, Eeckhout, and Unger (2020) use Cost of Goods Sold (COGS), but Traina (2018) argues for using COG plus Selling, General and Administrative Expenses (SGA). In theory, any variable input works for the estimation, although Raval (2020), using Census data on manufacturing, rejects that the markup distributions are the same whether labor or materials are used. Foster, Haltiwanger, and Tuttle (2022) argue for using material costs in the manufacturing sector.

3.2 Industry correlations

We next turn to the main exercises of the paper. Figure 1 showed a broad relationship between aggregate measures of business dynamics (entry and excess job reallocation) and markups, with the strong rise in markups from 1980-2016 matched by declines in entry and reallocation. It is this time series pattern that has led to research exploring a potential relationship between trends in dynamism and market power, a relationship that can be easily generated by standard theory (De Loecker, Eeckhout, and Mongey 2021). In this section, we exploit industry-level data in search of cross-sectional patterns consistent with the theory and time series evidence. Throughout the section we focus on "long differences"—for our measures of dynamism and markups, we look at the change from

firms, both in the cross section and over time (Davis et al. 2006; Dinlersoz et al. 2018). However, they are widely cited in the literature and policy circles and so are objects worth studying closely; readers should interpret our empirical results in the context of the limitations mentioned above as well as the importance these markup estimates have had in academic, policy, and media discussion.

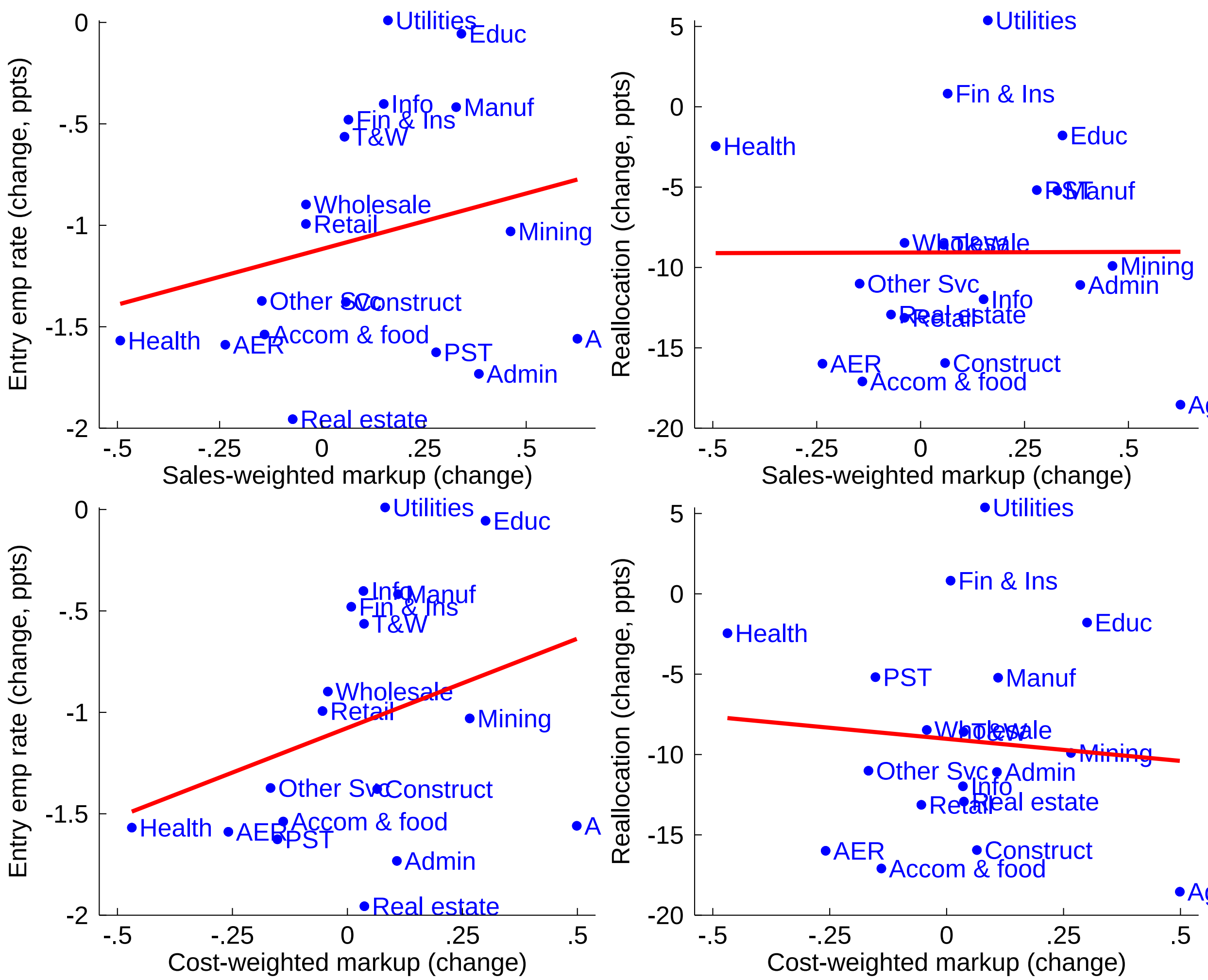
10. This also means that we do not address the concern of generated regressors (Murphy and Topel 1985; Oxley and McAleer 1993), so our standard errors are likely understated.

the 1980-1984 period (on average) to the 2012-2016 period (on average). If markups are an important explanatory factor for changing dynamism between these time periods, we should expect industries with larger increases in markups to also exhibit larger declines in dynamism.

To fix ideas, Figure 3 shows the relationship between the change in markups and the change in dynamism measures at the broad sector level. The left panels relate the employment-based entry rate with markups, while the right panels relate excess reallocation with markups; the top panels measure industry-level markups using sales weights, while the bottom panels use cost weights. The red lines show simple regression fit; given the theoretical and aggregate empirical considerations discussed above, we expect these lines to have negative slope.

We first focus on the top-left panel, which relates the change in the entry rate to the change in the sales-weighted markup. In contrast to the simple theory, we observe a striking *positive* relationship between entry and markups. Some sectors with large declines in entry—such as healthcare and social assistance services and arts, entertainment, and recreation (AER)—actually saw declines in markups, despite the aggregate increasing markup pattern. On the other hand, some sectors with large increases in markups—such as mining or, especially, manufacturing and education—saw relatively little decline in entry rates. This relationship between entry rates and markups is broadly similar when markups are constructed with cost weights, as in the bottom-left panel.

The left panels of Figure 3 illustrate a central challenge to theories relating recent trends in business entry and markups. Certain critical sectors where large gains in markups are evident have not seen large declines in entry. Manufacturing accounts for a disproportionate share of the increase in aggregate markups, but it has seen little decline in entry; and the tech-intensive information sector—often a focus of public discussion about market power—has likewise seen material increases in markups alongside little decline



Note: Difference, 2012-2016 average vs. 1980-1984 average. Entry rate is employment based.
Source: Business Dynamics Statistics and Compustat following De Loecker, Eeckhout, & Unger (2020).

Figure 3: Change in dynamism and markups, broad sectors

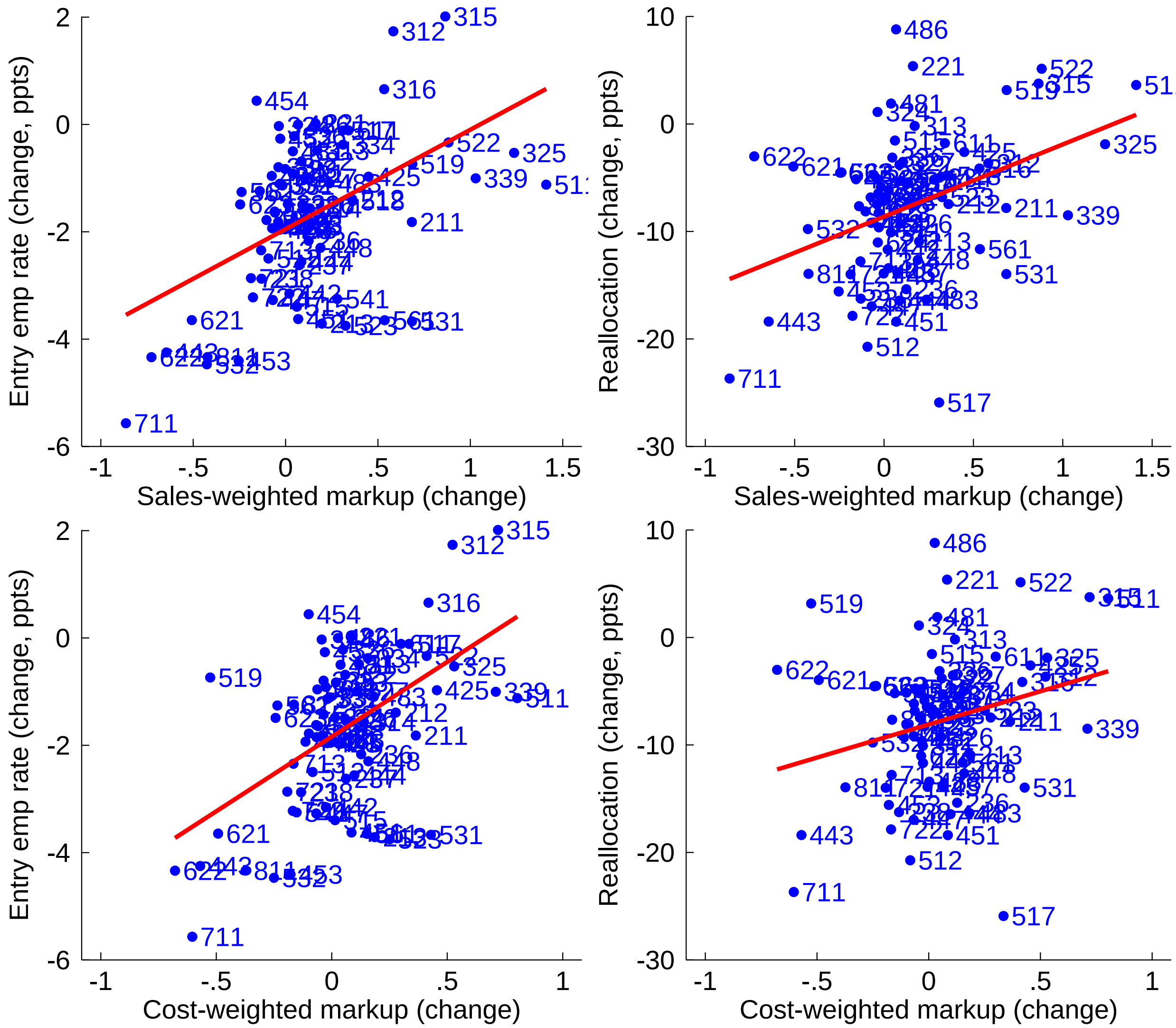
in entry.[11] The main sectors where the theory may work well, with important broader implications, are professional, scientific, and technical services (PST) and administrative and support services ("Admin" in the figure). The PST sector includes critical service industries like law, accounting, and marketing as well as technology-intensive industries like engineering, computer system design, and research and development services; Ding et al. (2022) shows that this sector has played a large role in aggregate employment dynamics and firm-level restructuring in the U.S. in recent decades. The administrative and support services sector includes key business support industries such as employment placement and temporary help services, which may have important labor market implications.

Changes in excess reallocation rates—shown on the right panels of Figure 3—are less puzzling, with a flat relationship in the case of sales-weighted markups or a modestly negative relationship in the case of cost-weighted markups. The sector-level comparisons, then, leave some ambiguity about the relationship between dynamism and markups. The broad sector level is still quite aggregated, though, so we next turn to more detailed industry comparisons.

Figure 4 reports scatterplots at the 3-digit industry level; this affords much more disaggregation than the sector-level plots of Figure 3, and given sparseness of Compustat data on which markups are estimated we judge the 3-digit level to be as detailed as can be reasonably studied in these data.

At this narrower level of industry detail, we observe consistent *positive* correlations throughout. On average, both entry rates and excess reallocation are *increasing* in both sales- and cost-weighted markups. The differences between the correlations in Figure 3 and Figure 4 illustrate the importance of drilling down on cross-sectional relationships,

11. Importantly, the information sector exhibits significant time series heterogeneity over this time period, with flat or even rising entry into the 1990s followed by a decline in the 2000s; see Decker et al. (2016b). In future drafts we will study such time series variation in more detail.



Note: Change, 2012-2016 average vs. 1980-1984 average.
Source: Business Dynamics Statistics and Compustat following De Loecker, Eeckhout, & Unger (2020).

Figure 4: Change in dynamism and markups, 3-digit industries

as significant aggregation has large effects on dynamism versus markup patterns. In short, at this level of industry detail we find no reduced-form support for the theory that declining dynamism is a result of rising markups. Whatever causal effect market power may have on dynamism is not evident in these simple cross-sectional moments.

The cross-sectional relationships shown on Figure 4 form the core of our empirical results, so we explore them in more detail with regressions reported on Table 1. We regress the change in dynamism measures (with specific measures indicated by column headings) on the change in markups (with weighting indicated on the table); these regressions correspond closely with the fit lines shown on Figure 4. The top panel of Table 1 reports simple unweighted regressions, while the bottom panel reports regressions weighted by the average industry employment in 1980-1984 and 2012-2016. While we use simple long differences on Table 1, we report the same regressions using *log* long differences on Table A1 in the appendix; results are qualitatively similar.

Here we pause to emphasize two limitations of our empirical exercises. First, of course, we are not uncovering causal relationships between markups and dynamism measures. Both markups and dynamism are endogenous to various other economic forces and are ultimately jointly determined. Our scatterplots and regression results are simply reduced form moments that are naturally suggested by rich models of firm dynamics like De Loecker, Eeckhout, and Mongey (2021); in a sense we are providing reduced form empirical tests of such models using cross-sectional variation. Second, our markup measure is an estimated object with its own sampling variation as well as potential biases arising from measurement limitations; considerations for "imputed regressors" described by Murphy and Topel (1985) likely apply to markups. We estimate our regressions with standard robust standard errors but acknowledge that we may be underestimating the standard errors given the nature of the markup measure. As we will see, these considerations—while noteworthy—are not of critical importance for our empirical results.

Table 1: Dynamism vs. markups at the industry level

	(1) Entry emp	(2) Reallocation	(3) Entry rate	(4) Entry emp	(5) Reallocation	(6) Entry rate
A. Unweighted regressions						
Markup	1.852***	6.716***	1.549	2.783***	6.164	1.496
	(4.07)	(3.64)	(1.17)	(4.48)	(1.89)	(0.72)
Constant	-1.949***	-8.618***	-3.987***	-1.838***	-8.090***	-3.868***
	(-12.89)	(-11.15)	(-8.75)	(-12.44)	(-10.27)	(-8.30)
Markup weighting	Sales	Sales	Sales	Cost	Cost	Cost
Observations	74	74	74	74	74	74
B. Employment-weighted regressions						
Markup	1.447*	3.662	-1.268	2.921***	2.529	-0.786
	(2.38)	(1.08)	(-0.89)	(5.35)	(0.53)	(-0.49)
Constant	-2.258***	-8.931***	-3.800***	-2.072***	-8.653***	-3.892***
	(-10.64)	(-7.56)	(-8.97)	(-10.27)	(-7.78)	(-7.36)
Markup weighting	Sales	Sales	Sales	Cost	Cost	Cost
Observations	74	74	74	74	74	74

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Regressions of long differences (2012-16 vs. 1980-1984) at 3-digit NAICS level.
Weighted regressions are weighted by average employment in 1980-84 and 2012-2016.
Source: Business Dynamics Statistics, Compustat, and author calculations.

The first column in the top panel of Table 1 reports the regression of the change in entry employment rates from 1980-84 to 2012-2016 on the change in sales-weighted markups among 3-digit industries (as in the left panels of Figures 3 and 4). The coefficient is *positive* and highly statistically significant; in other words, we find a strong positive relationship between sales-weighted markups and entry rates. Column 4 shows an even more positive result when markups are constructed with cost weights. The second column shows a positive, highly statistically significant relationship between changes in reallocation and sales-weighted markups (as in the right panels of Figures 3 and 4); the relationship is quantitatively similar, though statistically noisier, for cost-weighted markups. Additionally, columns 3 and 6 report results for the simple firm entry rate from equation 3, where coefficients are positive but not statistically significant. All measures of dynamism are positively related to markups at the 3-digit level, and some are statistically significantly so—though in light of the "imputed regressor" issue mentioned above, this statistical significance may be sensitive to the markups' sampling variation (but the signs of the coefficients are not). Most of the average decline in entry and reallocation is therefore captured by the constant regression terms.

The simple regressions on the top panel of Table 1 may be misleading if a small number of large industries do exhibit a negative relationship between dynamism and markups. Such industries could potentially account for much of the aggregate trend such that the simple theory is a good guide to aggregate patterns despite positive correlations in the unweighted cross section. The bottom panel of Table 1 therefore reports results from regressions that are weighted by average industry employment in 1980-1984 and 2012-2016. Indeed, the regression coefficients are generally lower in the weighted regressions than in the unweighted regressions (with only one exception in column 4). In two cases—columns 3 and 6—the coefficients are actually negative, though without statistical significance.[12] Apparently it is the case that the strong positive relationship we observe among industries on average is weaker, or even negative, among some large industries. We next study these industries and assess their role in aggregate patterns.

3.3 Exploring key industries

We next identify and study "key industries" in which a negative relationship between dynamism and markups is apparent, and we ask whether these key industries can account meaningfully for aggregate trends in dynamism and markups. We illustrate our appo-

12. We find no negative coefficients when we use log long differences instead of differences in levels; see Table A1 in the appendix.

rach to identifying key industries by studying the simple correlation coefficient. Let r be the correlation between changes in entry and changes in markups at the 3-digit industry level. Then r is given by:

$$r = \frac{\sum_{i=1}^{I}(e_i - \bar{e})(m_i - \bar{m})}{\sqrt{\sum_{i=1}^{I}(e_i - \bar{e})^2(m_i - \bar{m})^2}}, \tag{4}$$

where i indexes industries (of which there are I), e_i is the long difference in the entry rate for industry i, m_i is the long difference in the sales-weighted markup for industry i, and $\bar{e}$ and $\bar{m}$ are the average long differences of entry and markups, respectively. We know from the previous subsection that r is positive in general; but the weighted regressions on Table 1 suggest that some large industries contribute negatively (or at least less positively) to the overall correlation. We consider a simple decomposition of equation 4:

$$r = \frac{\sum_{i \in K}(e_i - \bar{e})(m_i - \bar{m})}{\sqrt{\sum_{i=1}^{I}(e_i - \bar{e})^2(m_i - \bar{m})^2}} + \frac{\sum_{i \notin K}(e_i - \bar{e})(m_i - \bar{m})}{\sqrt{\sum_{i=1}^{I}(e_i - \bar{e})^2(m_i - \bar{m})^2}}, \tag{5}$$

where K is the set of all industries for which $e_i - \bar{e} < 0$ and $m_i - \bar{m} > 0$; that is, K is the set of industries where the decline in entry is larger than average and the increase in markups is larger than average. By construction, the first term of equation 5 is negative; this set of "key industries," if it is not empty, contributes negatively to the overall correlation, consistent with the theory of De Loecker, Eeckhout, and Mongey (2021) and others in which markups are negatively related with dynamism. We identify these key industries in the data; we do so both for employment-based entry rates and, separately, for excess job reallocation. With this set of industries identified, we will be able to assess their contribution to the aggregate patterns of dynamism and markups. In other words, we identify industries in which the theory of higher markups being associated with lower dynamism is empirically evident, then we determine whether the aggregate trends can be explained by these theory-consistent industries.

With our construction of the set of key industries we are intentionally selecting on the dependent variable, giving the theory of negatively correlated dynamism and markups the best possible chance of explaining the aggregate trends. While the negative correlation does not hold among all industries, it may hold in some industries that are sufficiently large (or have extremely large changes in dynamism or markups) to substantively help explain aggregate patterns. Table 2 lists the "key industries" we identify in terms of employment-based entry (top panel) and excess job reallocation (bottom panel).

Table 2: Key industries

A. Key industries in terms of employment-based entry

NAICS	Title
211	Oil and gas extraction
213	Support activities for mining
236	Construction of buildings
448	Clothing and clothing accessories stores
523	Securities, commodity contracts, and other financial investments and related activities
531	Real estate
541	Professional, scientific, and technical services
561	Administrative and support services

B. Key industries in terms of excess job reallocation

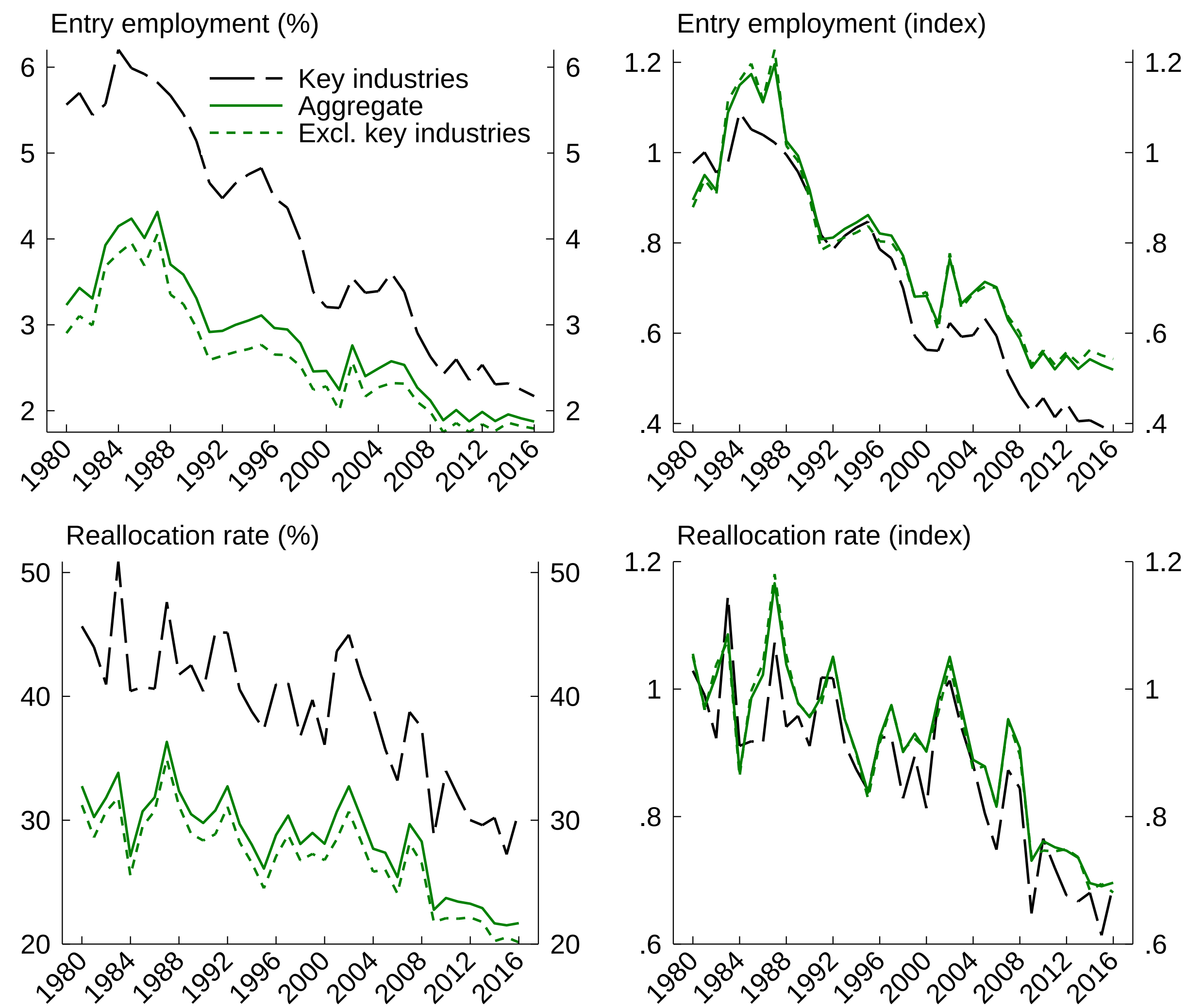
NAICS	Title
213	Support activities for mining
236	Construction of buildings
339	Miscellaneous manufacturing
448	Clothing and clothing accessories stores
483	Water transportation
517	Telecommunications
531	Real estate
561	Administrative and support services

Note: Key industries are those with larger-than-average increases in markups and larger-than-average decreases in employment-based entry rates (top panel) or excess job reallocation (bottom panel).

Of the 74 3-digit industries we study, only 8 industries satisfy the criteria for key industries in terms of employment-based entry; these industries account for about 18 percent of 1980-1984 and 2012-2016 average employment. Similarly, only 8 industries (with some overlap) satisfy the criteria in terms of excess job reallocation, accounting for 13 percent of 1980-1984 and 2012-2016 average employment. While we did not deliberately choose the set of key industries to be small, it is a natural result of our criteria requiring both larger-than-average declines in entry (or reallocation) and larger-than-average increases in markups. This limited set of industries is the set of industries that can contribute negatively to the correlation between changes in entry (or reallocation) and changes in markups at the industry level. Since the theorized negative relationship is not common across industries, the set of key industries in which it holds is small. As a result, it is not likely that these industries can account for a significant portion of the decline in overall dynamism or the rise in average markups. Figure 5 illustrates this by showing the entire time series of aggregate entry (top panel) and reallocation (bottom panel) for three groups of industries: key industries (black long-dashed line), all industries (i.e., the aggregate pattern—the green solid line), and all industries excluding the key industries (green short-dashed line). The left panel of the figure shows the actual aggregate entry or reallocation rates, while the right panel shows the trends indexed to their respective average 1980-1984 pace.

Unsurprisingly, key industries (black long-dashed line) show very different patterns than the aggregate series: both for entry and reallocation, the key industries start higher and fall by more. The larger decline is a mechanical result of the key industry selection criteria: we intentionally selected industries with larger-than-average declines in entry or reallocation. The fact that the key industries started in the 1980s with higher rates of entry and reallocation was not inevitable but is consistent with earlier work arguing that declining dynamism is in part a "convergence" pattern, with industries that started the 1980s with higher dynamism declining toward lower-dynamism industries (e.g., Decker et al. 2016b).

If the key industries play an important role in accounting for the aggregate dynamism trends, we should expect to see large differences between the aggregate series (green solid line) and the series that excludes key industries (green short-dashed line); in particular,



Note: Key industries have above-average increase in sales-weighted markups and above-average declines in entry employment (top) or reallocation (bottom). Indexes are based on 1980-84 average.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Figure 5: Dynamism trends with and without key industries

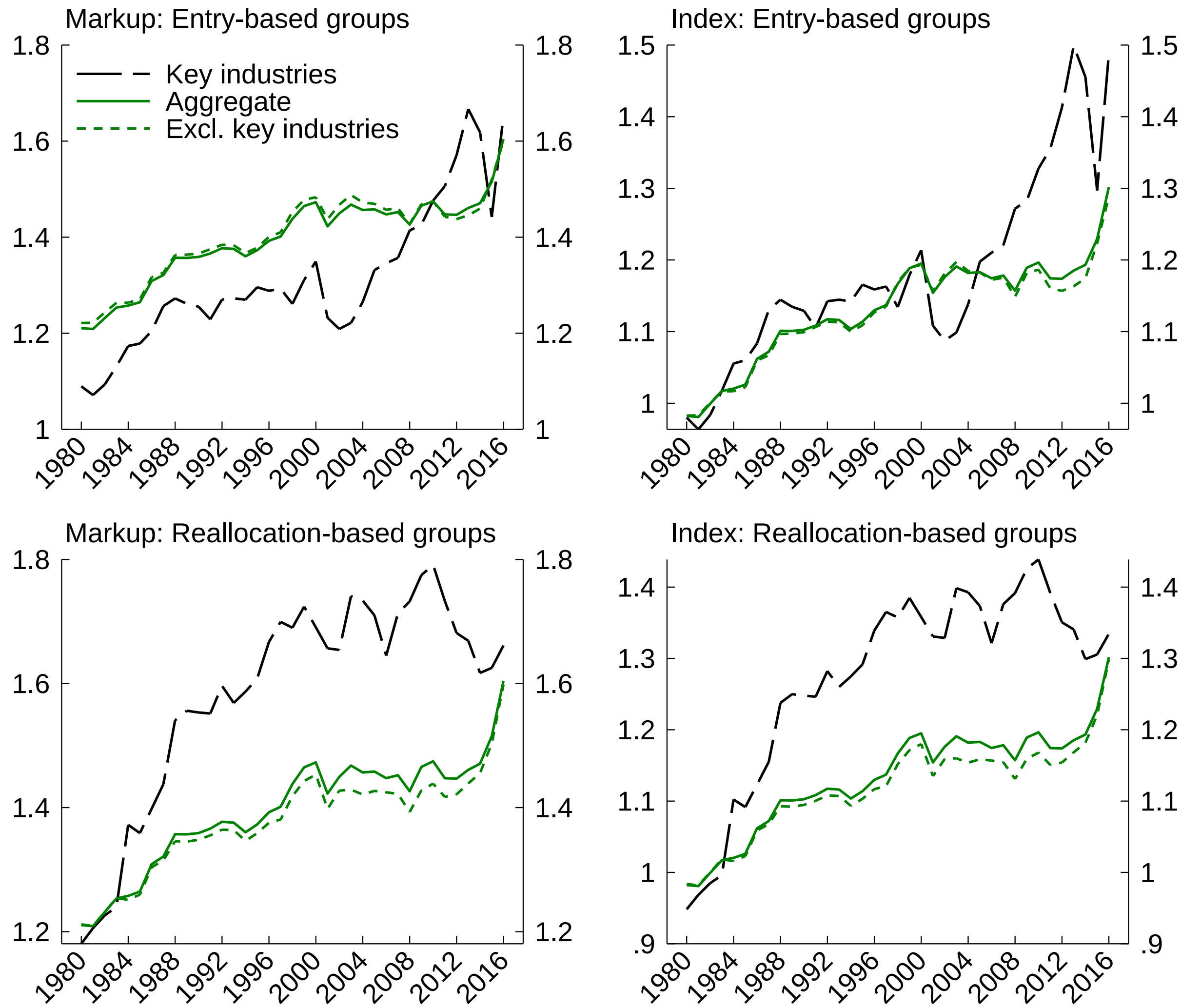
we should see much smaller declines in the latter series, as the key industries that would be driving the aggregate trend are excluded. Figure 5 shows this is not the case: the aggregate series and the series excluding key industries are nearly identical. In other words: most (or all) of the decline in aggregate entry rates and excess reallocation rates is accounted for by industries other than the key industries that are necessary for producing a meaningful negative correlation between dynamism and markups.

Similarly, the key industries cannot explain rising average markups. Figure 6 reports aggregate sales-weighted markups for key industries, all industries, and all industries excluding key industries in similar fashion to Figure 5; in the top panel, key industries are defined based on employment-based entry, while in the bottom panel key industries are defined in terms of excess job reallocation.

Key industries—by construction—have larger-than-average increases in markups; but they matter little for the aggregate trend, which is virtually identical to the trend among all industries excluding the key industries. Figure A1 in the appendix shows results for cost-weighted markups, which are broadly similar. Key industries have little or no explanatory power for aggregate markup trends.

This result is unsurprising in light of the small economic magnitude of the key industries from Table 2: the key industries, as a group, are simply too small to meaningfully matter for the aggregate trends. But that is precisely the point: this result was not inevitable but instead arises from the fact that the negative correlation between dynamism and markups is simply not common at the industry level, nor is it present in sufficiently large industries to be economically substantial. The apparent negative relationship between dynamism and markups suggested by Figure 1, while interesting, is apparently spurious with regard to theories in which markups and dynamism are negatively related. The decline in business dynamism is not explained by rising markups; other factors—present in industries where dynamism and markups are not negatively correlated—must explain the aggregate patterns of business dynamism.[13]

13. Some readers may have noted that our set of key industries are not the only industries that would contribute negatively to the correlation in equation 4. Our key industries are those in which entry (or reallocation) declined by more than average and markups rose by more than average; but industries in which entry declined by *less* than average and markups rose by *less* than average would also contribute negatively to the overall correlation. In unreported results we find that expanding the definition of key industries in this manner, while increasing the share of the economy covered by the key industries, does not meaningfully change our main result that key industries do not account for a sizeable portion of the



Note: Key industries have above-average increase in sales-weighted markups and above-average declines in entry employment (top) or reallocation (bottom). Indexes are based on 1980-84 average.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Figure 6: Sales-weighted markup trends with and without key industries

4 High-frequency patterns [INCOMPLETE]

Our results thus far focus on long-run changes in markups and dynamism, consistent with the motivation for the paper, that is, literature on multi-decade trends in markups

aggregate trends. This is unsurprising, since the additional key industries included by expanding the rule in this way, by definition, do not see large declines in dynamism or large increases in markups, so they are not important for the aggregate trends.

and dynamism. But our results raise questions about the relationship between markups and dynamism at higher frequency, as long-run changes may obscure important short-run dynamics. In this section, we briefly study the relationship between markups and dynamism at annual frequency, still focusing on industry-level patterns.

Table 3 reports industry-level regressions using annual data, where we regress dynamism measures on contemporary markups ("Markup" in the table) and on the average of the prior two years' markups ("Markup t-1/2") for slightly delayed relationships (where industry-level markups are constructed with sales weights). We use data for 1978-2016 and include industry and year fixed effects to abstract from permanent differences across industries and from aggregate shocks.

Consistent with the long difference results described above, Table 3 again suggests a *positive*—though not always statistically significant—relationship between markups and dynamism measures, both in contemporaneous comparisons and with a delay of 1-2 years. We observe the most significant effects for job reallocation, while entrants' employment share exhibits a marginally statistically significant relationship with markups while the unweighted entry rate shows only a non-statistically significant relationship. This positive relationship appears to be most significant in smaller industries, as the employment-weighted regressions shown on the bottom panel of table 3 shows smaller coefficients with no statistical significance.

Table 4 reports the same regressions but using cost-weighted industry markups instead of sales-weighted markups. The regression coefficients remain mostly positive with cost-based industry markups, though they are generally further from statistical significance. Additional robustness explorations are found in the appendix on table A2, which omits year fixed effects, and table A3, which reports regressions using all variables in log form. In unreported exercises, we find similar results using a simple (single) lag of the markup. Overall, we find no evidence of a negative relationship between markups

Table 3: Dynamism vs. markups at annual frequency (sales-weighted markups)

	(1) Entry emp	(2) Entry emp	(3) Reallocation	(4) Reallocation	(5) Entry rate	(6) Entry rate
A. Unweighted regressions						
Markup	0.621*		2.400**		0.693	
	(2.23)		(2.81)		(1.35)	
Markup (t-1/2)		0.774*		3.042**		0.442
		(2.54)		(3.07)		(0.74)
Constant	1.717***	1.452***	23.36***	22.38***	8.653***	8.850***
	(4.49)	(3.48)	(19.88)	(16.50)	(12.24)	(10.78)
Observations	2984	2827	2984	2827	2984	2827
B. Employment-weighted regressions						
Markup	0.458		1.405		-0.0300	
	(1.51)		(1.46)		(-0.06)	
Markup (t-1/2)		0.582		1.542		-0.454
		(1.56)		(1.22)		(-0.74)
Constant	2.143***	1.942***	25.10***	24.91***	9.530***	10.00***
	(5.29)	(3.92)	(19.61)	(14.88)	(14.68)	(12.30)
Observations	2984	2827	2984	2827	2984	2827

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data for 1978-2016. Regressions (in annual data) of dynamism measures on same-year sales-weighted industry markups ("Markup") or average of prior two years' sales-weighted industry markups ("Markup (t-1/2)"). Fixed industry and year effects included. Standard errors clustered by industry. Weighted regressions are weighted by average of current and prior year employment.
Source: Business Dynamics Statistics, Compustat, and author calculations.

and business dynamism; while we do not claim to have identified causal effects, the evidence suggest that higher measured markups are not associated with lower entry or job reallocation at the industry level. We find some limited evidence of opposite association: markups may be positively related with entry (particularly of larger firms) and job reallocation, which would be consistent with a theory in which elevated markups inspire entrepreneurial entry to take advantage of profit opportunities. In work in progress, we are applying panel vector autoregressions to this question to uncover richer time series relationships.

Table 4: Dynamism vs. markups at annual frequency (cost-weighted markups)

	(1) Entry emp	(2) Entry emp	(3) Reallocation	(4) Reallocation	(5) Entry rate	(6) Entry rate
A. Unweighted regressions						
Markup	0.732		1.980*		0.553	
	(1.94)		(2.00)		(0.93)	
Markup (t-1/2)		0.994*		2.676		0.242
		(2.35)		(1.89)		(0.31)
Constant	1.620**	1.225*	24.09***	23.08***	8.888***	9.142***
	(3.31)	(2.24)	(18.74)	(12.62)	(11.53)	(9.16)
Observations	2984	2827	2984	2827	2984	2827
B. Employment-weighted regressions						
Markup	0.687		1.104		0.175	
	(1.55)		(1.23)		(0.40)	
Markup (t-1/2)		0.989		0.800		-0.487
		(1.94)		(0.53)		(-0.69)
Constant	1.895***	1.483*	25.59***	25.96***	9.272***	10.01***
	(3.42)	(2.34)	(22.82)	(13.91)	(17.05)	(11.44)
Observations	2984	2827	2984	2827	2984	2827

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data for 1978-2016. Regressions (in annual data) of dynamism measures on same-year cost-weighted industry markups ("Markup") or average of prior two years' cost-weighted industry markups ("Markup (t-1/2)"). Fixed industry and year effects included. Standard errors clustered by industry. Weighted regressions are weighted by average of current and prior year employment.
Source: Business Dynamics Statistics, Compustat, and author calculations.

5 Conclusion

The U.S. economy has experienced several possibly troublesome trends over the past few decades: productivity growth has slowed, profit shares have increased, the labor share has fallen, and the high pace of business and labor market dynamics commonly associated with the U.S. economy has declined. Many researchers and policymakers have speculated on relationships between these various trends. This paper adds to the empirical literature by studying two trends in particular: rising markups and declining dynamism. Instead of focusing on the time-series evolution of average markups and aggregate dynamism, we study the cross-section of industry-level patterns.

The industry-level evidence does not support the notion that the aggregate time series are causally related. In fact, the opposite relationship emerges. Instead of increases in markups correlating with decreases in dynamism, industries with larger increases in markups saw a smaller decline in dynamism. To be clear, it is not true that high-markup-growth industries saw an *increase* in dynamism. The decline in dynamism has been widespread in the U.S. economy.

To examine why our results differ from most of the literature, we focus on "key industries" that have seen larger-than-average increases in markups and larger-than-average decreases in dynamism. Any story about how markups have caused a decline in dynamism must center around these industries. These key industries, which we selected deliberately to focus on negative relationships between markups and dynamism, explain almost none of the aggregate trends in either dynamism or markups: omitting these industries entirely leaves the aggregate trends little changed.

In preliminary exercises, we also find that markups and dynamism measures are not negatively related at annual frequency and, in many specifications, are significantly positively related. Simply put, it is difficult to find empirical specifications in which markups and dynamism are negatively related at the industry level.

Our results suggest that economists must be careful when explaining the dynamism decline by markups or market power. The situation is more complicated than the simple theory that firms with more market power are less responsive to shocks or industries with market power may have (or create) significant barriers to entry.

While we do not establish causal relationships or establish alternative theories for the empirical relationships we observe, our findings strongly suggest that theories relating changing dynamism and rising markups do not have explanatory power. Why not? We can speculate on three possible explanations for our results. First, our simple regressions may capture the underlying reality: basic theory suggests that higher markups (and likely higher profits) can actually attract more entrants with the promise of profits in excess of entry costs, and that force may offset or completely reverse the negative relationship between markups and dynamism. Second, the empirical failure of theories proposing a negative markups/dynamism relationship may be a data issue; for example, while our measures of dynamism include the near-universe of firms, our measure of markups from De Loecker, Eeckhout, and Unger (2020) only includes publicly-traded firms—a small minority of all private firms and roughly half of overall economic activity (Davis et al. 2006). Publicly-traded firms differ from private firms, and these differences are likely time varying (Davis et al. 2006; Dinlersoz et al. 2018). Moreover, the literature has not provided direct evidence that cost of goods sold—or any other expenditures reported on standard financial statements—is a pure measure of variable factor expenditures. Third, even if the underlying accounting data capture well each firm's marginal costs, there is still an ongoing debate about the estimation technique used to generate markups (Flynn, Gandhi, and Traina 2019; Kirov and Traina 2021; Bond et al. 2021; Doraszelski and Jaumandreu 2021; De Loecker 2021). In other words, the DEU measure of markups may not be capturing theoretically meaningful measures of markups or market power.

A Appendix

Table A1: Dynamism vs. markups at the industry level - Log differences

	(1) Entry emp	(2) Reallocation	(3) Entry rate	(4) Entry emp	(5) Reallocation	(6) Entry rate
A. Unweighted regressions						
Markup	0.994*	0.384***	0.170	1.308*	0.339*	0.168
	(2.53)	(3.92)	(1.01)	(2.56)	(2.55)	(0.72)
Constant	-0.828***	-0.321***	-0.450***	-0.796***	-0.305***	-0.444***
	(-11.54)	(-11.84)	(-10.96)	(-12.20)	(-10.75)	(-10.35)
Markup weighting	Sales	Sales	Sales	Cost	Cost	Cost
Observations	74	74	74	74	74	74
B. Employment-weighted regressions						
Markup	1.322	0.293	0.00510	1.972	0.244	0.0800
	(1.52)	(1.91)	(0.03)	(1.82)	(1.30)	(0.50)
Constant	-0.924***	-0.336***	-0.431***	-0.829***	-0.322***	-0.428***
	(-6.89)	(-10.31)	(-10.97)	(-9.38)	(-9.30)	(-9.81)
Markup weighting	Sales	Sales	Sales	Cost	Cost	Cost
Observations	74	74	74	74	74	74

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Regressions of long log differences (2012-16 vs. 1980-1984) at 3-digit NAICS level.
Weighted regressions are weighted by average employment in 1980-84 and 2012-2016.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Table A2: Dynamism vs. markups at annual frequency (no year effects)

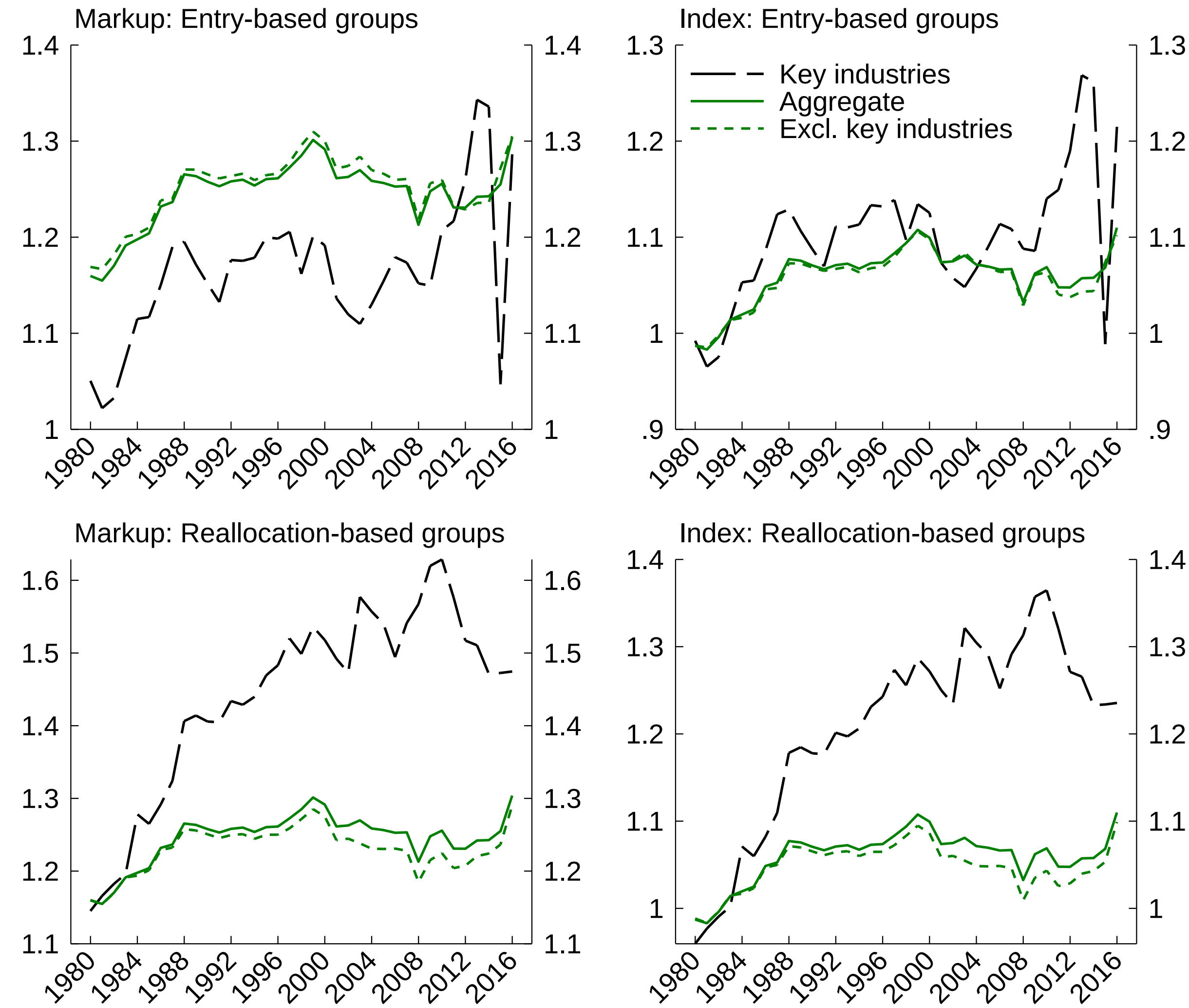
	(1) Entry emp	(2) Entry emp	(3) Reallocation	(4) Reallocation	(5) Entry rate	(6) Entry rate
A. Unweighted regressions						
Markup	0.293		1.027		-0.0578	
	(0.97)		(1.07)		(-0.08)	
Markup (t-1/2)		0.382		1.341		-0.398
		(0.97)		(1.07)		(-0.45)
Constant	2.169***	1.989***	25.25***	24.71***	9.684***	9.999***
	(5.22)	(3.70)	(19.07)	(14.43)	(9.82)	(8.27)
Observations	2984	2827	2984	2827	2984	2827
B. Employment-weighted regressions						
Markup	0.373		0.854		-0.206	
	(0.81)		(0.62)		(-0.27)	
Markup (t-1/2)		0.482		0.932		-0.627
		(0.79)		(0.54)		(-0.70)
Constant	2.256***	2.075*	25.83***	25.72***	9.764***	10.23***
	(3.68)	(2.56)	(14.11)	(11.19)	(9.63)	(8.63)
Observations	2984	2827	2984	2827	2984	2827

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data for 1978-2016.
Regressions (in annual data) of dynamism measures on same-year sales-weighted industry markups (“Markup”) or average of prior two years’ sales-weighted industry markups (“Markup (t-1/2)”). Fixed industry effects included. Standard errors clustered by industry.
Weighted regressions are weighted by average of current and prior year employment.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Table A3: Dynamism vs. markups at annual frequency (in logs)

	(1) Entry emp	(2) Entry emp	(3) Reallocation	(4) Reallocation	(5) Entry rate	(6) Entry rate
A. Unweighted regressions						
Markup	0.509^{**}		0.183^{***}		0.154	
	(2.79)		(3.90)		(1.97)	
Markup (t-1/2)		0.538^{*}		0.217^{***}		0.106
		(2.59)		(4.23)		(1.29)
Constant	0.486^{***}	0.463^{***}	3.160^{***}	3.147^{***}	2.131^{***}	2.131^{***}
	(9.32)	(7.86)	(235.80)	(215.70)	(94.94)	(91.42)
Observations	2984	2827	2984	2827	2984	2827
B. Employment-weighted regressions						
Markup	0.761		0.199^{**}		0.113	
	(1.63)		(2.80)		(1.18)	
Markup (t-1/2)		0.801		0.212^{**}		0.0492
		(1.58)		(2.89)		(0.52)
Constant	0.485^{***}	0.468^{***}	3.167^{***}	3.164^{***}	2.132^{***}	2.140^{***}
	(4.01)	(3.59)	(171.60)	(167.47)	(86.14)	(88.24)
Observations	2984	2827	2984	2827	2984	2827

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data for 1978-2016.
Regressions (in annual data) of (log) dynamism measures on same-year (log) sales-weighted industry markups ("Markup") or (log) average of prior two years' sales-weighted industry markups ("Markup (t-1/2)"). Fixed industry and year effects included. Standard errors clustered by industry.
Weighted regressions are weighted by average of current and prior year employment.
Source: Business Dynamics Statistics, Compustat, and author calculations.



Note: Key industries have above-average increase in sales-weighted markups and above-average declines in entry employment (top) or reallocation (bottom). Indexes are based on 1980-84 average.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Figure A1: Cost-weighted markup trends with and without key industries

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