Markups and Business Dynamism across Industries

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Recent research connects rising measured market power to other macroeconomic trends in the U.S., including decades-long declines in measures of "business dynamism," such as business entry and job reallocation. Intuitively, factors that raise market power may also reduce entry, and firms with more market power are less responsive to shocks. Such theories predict a negative correlation between markups and business dynamism. We use industry-level data to study long-run trends and annual patterns of markups and dynamism. Using multiple measures of each, we find no systematic industry-level negative correlation between changes in markups and changes in dynamism from the 1980s through the 2010s. In fact, we are more likely to observe the opposite relationship.

JEL-Classification: D22, D40, L11, L26, M13

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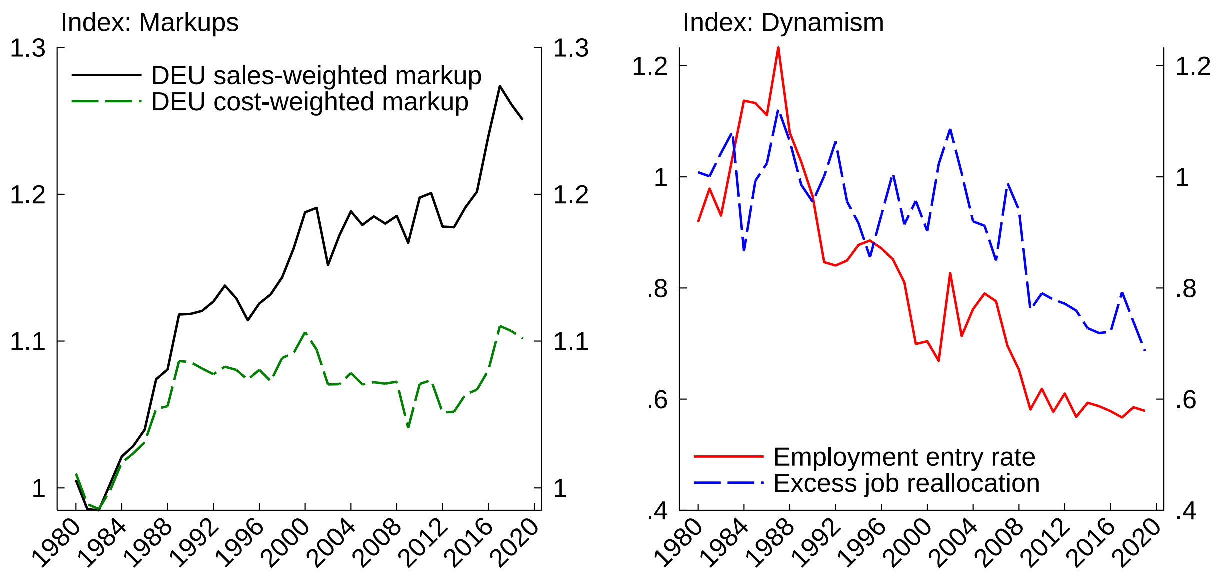
1 Introduction

Over the past four decades, the U.S. economy has experienced two notable trends that have drawn attention from researchers and policymakers, illustrated by figure 1. First, there is some evidence that an important measure of market power—the average markup—has risen significantly in recent decades (left panel; De Loecker, Eeckhout, and Unger 2020). Second, common measures of "business dynamism"—such as new business entry rates and excess job reallocation—have seen significant declines (right panel).[1] The concurrent timing of these trends raises an important question about whether these patterns are related.



Note: Index is relative to 1980-1984 average by series. Entry rate is employment based.
Excess job reallocation is gross job creation + destruction - net employment growth as a rate of employment.
Source: Business Dynamics Statistics; De Loecker, Eeckhout, & Unger (2020); and Compustat.

Figure 1: Markups and business dynamism, 1980-2019

In this paper, we ask whether rising markups are systematically correlated with the observed decline in U.S. business dynamism. While the macroeconomic time series evidence suggests a potential connection, we analyze industry cross-sectional evidence in an

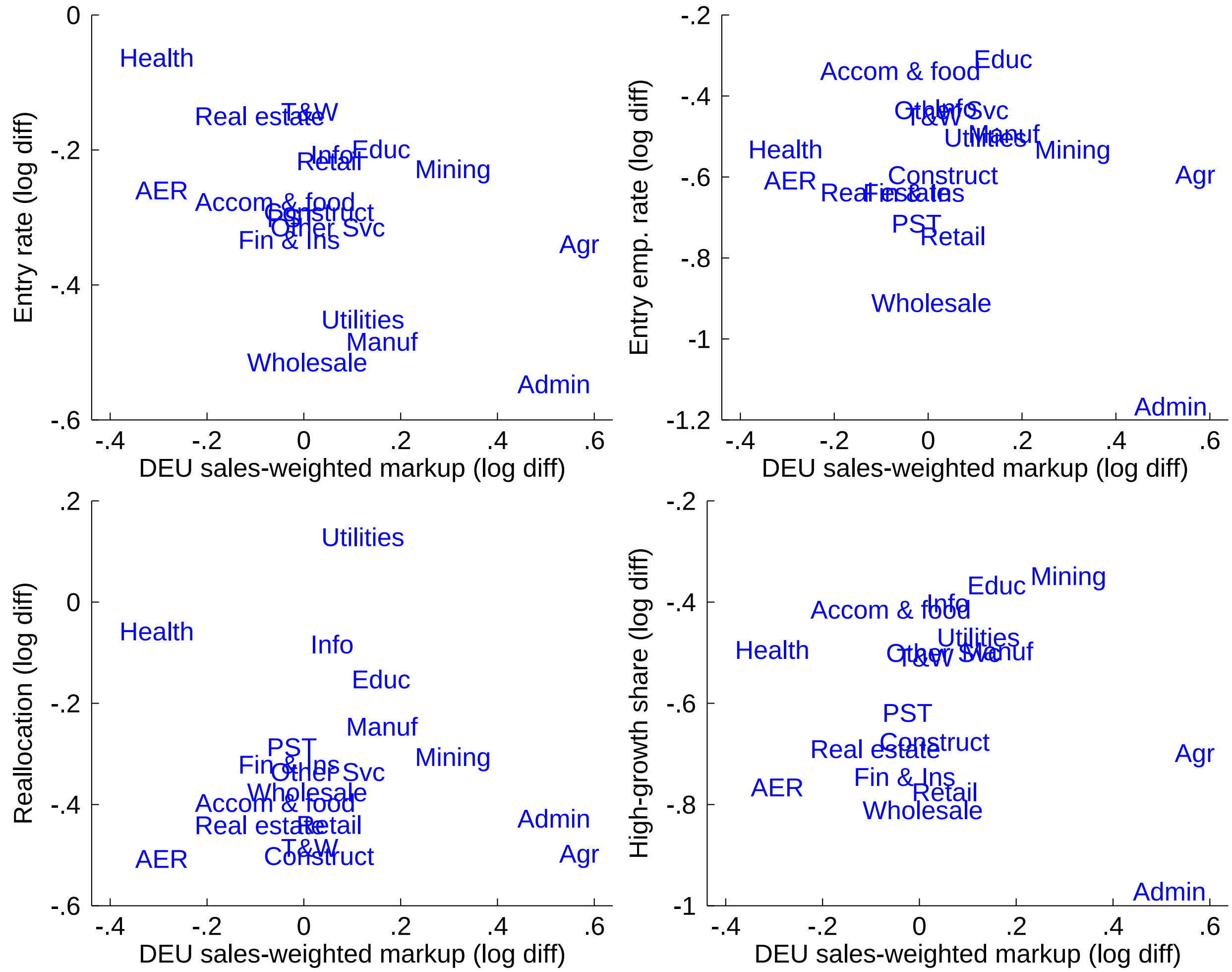
1. For example, see Decker et al. (2014), Decker et al. (2016b), and Akcigit and Ates (2023).

approach that is closer to traditional industrial organization research. Our analysis is motivated by a simple premise: if rising markups (or, more precisely, underlying industry-level drivers of rising markups) are driving the decline in dynamism, we should observe a strong negative correlation between changes in markups and changes in dynamism at the industry level.

Contrary to what the aggregate trends would suggest, our industry-level analysis reveals almost no supporting evidence for a systematic relationship. Our analysis, which employs multiple measures of both dynamism and markups and examines both long-run changes and annual fluctuations, reveals no systematic negative correlation between rising markups and declining dynamism. In fact, we are more likely to find evidence of a positive relationship.

Figure 2 provides a visual summary of our findings by plotting broad sector-level changes across four measures of business dynamism—firm entry rates, firm entry employment rates, excess job reallocation, and the share of employment at high-growth firms. These dynamism measures are plotted against changes in a popular average markup measure developed by De Loecker, Eeckhout, and Unger (2020). We focus on the change in these variables from the late 1980s through the late 2010s—the main period of focus throughout the paper. No clear negative pattern catches the eye; the broad sectors in which markups have risen most are not necessarily the sectors that have seen large declines in dynamism. Instead, the variation appears to be random, as if changes in markups and changes in dynamism have been driven by different sources. If an underlying negative relationship between market power and dynamism were a significant driver of aggregate patterns, we would expect to see a more systematic relationship at the broad sector level.

We show that drilling down to narrower industry detail, using several alternative measures of markups, exploring different regression weighting specifications, extending



Note: Difference, 2015-2019 average vs. 1988-1992 average. AER is arts, entertainment, & recreation; PST is professional & scientific services; T&W is transportation & waste management.
Source: Business Dynamics Statistics; De Loecker, Eeckhout, & Unger (2020); and Compustat.

Figure 2: Change in markups and dynamism, broad sectors

our time sample back to the early 1980s, and exploiting different time series structure do not typically yield the negative relationship seen in the aggregate time series, with relatively few possible exceptions, and sometimes yields a positive relationship.[2]

2. As we will show, in certain (but not all) econometric specifications, a modestly negative markup/dynamism relationship is observed for the unweighted firm entry rate—a measure that is susceptible to measurement issues and lacks the economic significance of our other dynamism measures. A modestly negative relationship is also sometimes seen for the markup measured specifically as the inverse of the labor share—though not for inverse energy or materials shares, nor for the widely used production function-based markup measures used by De Loecker, Eeckhout, and Unger (2020). The labor share finding seems relevant for the voluminous labor share literature but, given its marginal statistical significance and the results from our many other measures, does not seem particularly relevant for the question of ris-

Our empirical results—or, perhaps more accurately, non-results—are not trivial or inevitable. The theoretical connection between dynamism and average market power is straightforward. For example, market power makes firms less responsive to shocks via more revenue function curvature, which dampens job reallocation in canonical models (Decker et al. 2020). More generally, under common assumptions, factors that reduce the number of potential entrants to a market could be expected to manifest as both lower dynamism and higher average markups. All research to date on the connection between dynamism and markups directly or indirectly includes such a mechanism that drives markups up and dynamism down (Akcigit and Ates 2021, 2023; De Loecker, Eeckhout, and Mongey 2022; De Ridder 2024).

The positive relationships we observe suggest an alternative interpretation rooted in Schumpeterian dynamics. When markups reflect transient monopoly rents from successful innovation (rather than barriers to entry), they can both reward past innovation and incentivize future creative destruction (Aghion and Howitt 1992). Under this view, industries with rising markups may attract more entry as entrepreneurs seek to capture similar innovation rents or displace incumbent leaders. This mechanism, where markup increases signal innovation or profit opportunities rather than entry barriers, could explain why we often find that industries with larger markup increases experienced smaller dynamism declines or even increases.

Our empirical approach and inference depend heavily on measurement considerations. For our main exercises in all markup and dynamism measures, we focus on the period of 1988 through 2019; this period is covered by each of our several data sources and ends just before the COVID-19 pandemic, which led to sharp changes in measures of business dynamism. For markup measurement, we first follow the seminal work of

ing product market power and business dynamism. These exceptional results highlight the importance of considering a range of dynamism and markup measures and judging overall patterns across multiple specifications.

De Loecker, Eeckhout, and Unger (2020) (DEU), which constructed markup estimates using sales and cost data along with revenue function estimation for the universe of U.S. publicly traded firms. Since this markup measure—which we call "DEU markups"—is available at the firm level from widely available data, we can construct average markups at any arbitrary level of industry detail; we focus primarily on an industry taxonomy used in popular Bureau of Economic Analysis (BEA) datasets (described below), but we also study 2-digit (shown in figure 2) and 3-digit NAICS tabulations. This markup measure is not without controversy, but it has been used in widely cited papers and continues to inform discussions about market power among both researchers and policymakers.

To complement our analysis of DEU markups, we use industry-level measures constructed from the BEA-BLS Integrated Industry-level Production Accounts (better known as "KLEMS"). The KLEMS data offer several key advantages: comprehensive industry coverage inclusive of both publicly *and privately* owned firms, rigorous adherence to proper output measurement, and consistent industry definitions throughout the sample period. From these data, we construct several "markup" measures—admittedly using the term "markup" loosely—including basic cost share approaches and more sophisticated Hall (2018)-style instrumental variable-based estimates. KLEMS industry tabulations are constructed at a mix of 2-, 3-, and 4-digit NAICS codes and aggregations; in robustness exercises, we supplement our KLEMS analysis with similarly constructed markups in the NBER-CES Manufacturing Database, which we can study at the 4-digit NAICS level (albeit only for the manufacturing sector).

For dynamism, we examine entry employment rates (i.e., the share of employment accounted for by new firm entrants), excess job reallocation rates, and the prevalence of high-growth firms measured in the Census Bureau's Business Dynamics Statistics (BDS) for the near-universe of private nonfarm employer businesses.[3] These measures are available at various levels of industry detail throughout our sample time period.

Across these various measures, our results show a striking disconnect between aggregate time series trends and cross-sectional evidence. When studying "long differences"—industry-level changes in markups and dynamism from the late 1980s through the late 2010s—we do not generally observe that industries with large gains in markups saw larger declines in dynamism, and the opposite pattern holds in many specifications. At annual frequency, using impulse response functions from local projections, we find generally noisy and statistically insignificant results over 3- to 4-year horizons. While our exercises require many researcher decisions about model specification, we ensure our results are robust to these choices by providing entire distributions of empirical results across many specifications.

Our results have important implications for the literatures on both dynamism and market power. While several important studies hypothesize a negative relationship between dynamism and market power (e.g., Akcigit and Ates 2021, 2023; De Loecker, Eeckhout, and Mongey 2022; De Ridder 2024), we document an industry-level fact that does not provide cross-sectional support for such a relationship. Of course, our results are descriptive and do not falsify all possible mechanisms linking these aggregates. Indeed, we readily recognize that the empirical relationship or lack thereof need not be causal; various other factors could affect both markups and dynamism to produce the kind of empirical results we document. However, the absence of a clear relationship between markups and dynamism in the cross-sectional data suggests that market power likely plays at most a minimal role in explaining declining dynamism in recent decades, or that any relationship involves more complex channels than industry-specific changes. Per-

3. As noted above, we also study simpler unweighted firm entry rates, which have been used in a vast literature, though we do not focus on this measure for reasons discussed below.

haps most tellingly, we find that the major increases in markups and decreases in dynamism have largely occurred in different industries.

Explaining this empirical pattern using theories that link market power and dynamism would be difficult. But we again emphasize that our contribution is descriptive: we document a cross-sectional industry fact and explore its robustness across many measures and specifications. We do not attempt to identify causal effects.

This paper builds on an earlier short preview note (Albrecht and Decker 2024) in which we reported a smaller set of exercises focused on industry-level long differences similar to those shown in figure 2. That short note was limited in both dynamism measures and markup measures, and we did not explore annual-frequency time series relationships. The present paper is a far wider-ranging study—albeit with results confirming those of the older short note.[4]

The remainder of this paper proceeds as follows. Section 2 briefly reviews the literature on declining dynamism and rising markups, highlighting the theoretical channels through which these phenomena might be connected. Section 3 describes our data sources and measurement approaches. Section 4 presents our main empirical analyses of the long-run relationship between markups and dynamism across industries. Section 5 examines the annual-frequency relationships using local projections to generate impulse response functions. Section 6 concludes.

4. In particular, in the present paper we explore an additional dynamism measure: the prevalence of high-growth firms, a measure featured in older dynamism literature (Decker et al. 2016b) and receiving renewed attention recently (Kim et al. 2024). We also add numerous additional markup variables arising from the national accounts data and, in robustness exercises, the NBER-CES Manufacturing Database, which address the significant limitations of the public firms-based markup measures used by Albrecht and Decker (2024). Finally, while in Albrecht and Decker (2024) we focused only on long-run changes in dynamism and their relation to long-run changes in markups, in the present paper we add annual-frequency time series analysis to uncover comovement of dynamism and markups within shorter time windows. In addition, in the present paper we summarize results from a large number of robustness exercises around both our long-run change results and our annual-frequency results.

2 Related literature

A large empirical literature documents the sustained decline in dynamism in the U.S. since the 1980s.[5] This decline appears across multiple dimensions of business activity. Entry rates and the pace of job reallocation have fallen substantially, as shown in figure 1 and documented extensively in the literature (Decker et al. 2014; Decker et al. 2016a).

Closely related has been a more recent 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; Kim et al. 2024). 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). Fewer new firms and lower job reallocation have likely had significant implications for aggregate productivity growth (Alon et al. 2018; Decker et al. 2017, 2020).

In tandem with the declining dynamism literature, a widely noted literature on rising market power has rapidly expanded. In a seminal paper, De Loecker, Eeckhout, and Unger (2020) (DEU) provide a commonly cited estimate of rising markups in the U.S. economy, showing that the average markup increased from 1.2 in 1980 to 1.6 in 2016. This paper sparked a large literature and even a book (Eeckhout 2022). DEU uses an approach to estimating markups that comes from Hall (1988) and De Loecker and Warzynski (2012). The markup concept requires data on expenditures on any variable input along with total sales and the output elasticity of the variable input. DEU use financial statement data 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.

5. Most of this literature predates the recent pandemic; Decker and Haltiwanger (2024a, 2024b, 2024c) provide evidence of elevated dynamism during the pandemic, though it is unclear whether this marks a durable reversal of the longer-run trend. We deliberately abstract from the pandemic era.

Their estimates have informed ongoing debates about market power's role in broader economic trends, and our study adopts their benchmark data to examine its connection with declining dynamism. While the validity of the DEU methodology is the subject of a substantial debate, we abstract from these concerns and focus on the empirical implications for industry-level relationships between markups and dynamism.[6]

Our approach to studying markups also builds on Hall (2018), who develops a framework for estimating markups using industry-level BEA-BLS productivity data (KLEMS). These data provide comprehensive national account-consistent coverage of all industries and carefully constructed measures of inputs and outputs. Hall develops a framework to directly measure marginal costs using these detailed industry-level productivity data, providing an alternative to the production function approach of De Loecker, Eeckhout, and Unger (2020). Intuitively, marginal cost is constructed as the elasticity of total costs to sales; to address endogeneity between these variables, Hall (2018) employs certain national defense spending categories and oil prices as instruments. Hall finds rising markups in recent decades. We adapt Hall's approach and refer to the resulting markup estimates as "Hall-style markups".

There is by now a large literature on aggregate markups, each paper relying on slightly different models or data. Traina (2018) uses Compustat 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 (2023) 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 DEU; using cost weights in DEU data, the average markup has increased by

6. There is an econometric debate about possible issues with the DEU approach to estimating markups; see Flynn, Gandhi, and Traina (2019), Kirov and Traina (2023), Bond et al. (2021), Doraszelski and Jaumandreu (2019, 2021), De Loecker (2021), and De Ridder, Grassi, and Morzenti (2024). More recent work has focused on data restrictions applied by DEU that, when loosened, significantly affect aggregate markup trends Benkard, Miller, and Yurukoglu (2025).

much less than the sales-weighted version (as can be seen on figure 1). Autor et al. (2020) find there has been a reallocation toward "superstar" firms with higher markups, a pattern also found in De Loecker, Eeckhout, and Unger (2020). Foster, Haltiwanger, and Tuttle (2022) use Census Bureau data on the universe of manufacturing establishments and find a smaller increase in average markups when revenue functions are estimated with more industry detail.

We view these measurement questions as important, but for our purposes we approach markup measurement by using a range of measures, including the DEU markups, the Hall-style markups, and looser measures constructed as the inverse of cost shares (for each of energy, materials, labor, and overall "variable" costs). That is, we do not take a stand on the best measure of markups, choosing instead to look for patterns across many measures.

The parallel trends in dynamism and market power have motivated a growing theoretical and empirical literature linking the two.[7] Decker et al. (2020) suggest the possibility that rising market power is related to 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), while focused on measuring market power through markups, suggests the rising market power that they find as a likely explanation for declining dynamism.

7. There are other proposed causes of the dynamism decline. These include declining labor force or population growth (Karahan, Pugsley, and Sahin 2019; Hathaway and Litan 2014; Ozimek and Wurm 2017), increasing stringency of regulations or frictions on factor adjustment (Autor, Kerr, and Kugler 2007; Davis and Haltiwanger 2014; Decker et al. 2020; Johnson and Kleiner 2020), changing business models like retail consolidation (Decker et al. 2016b; Foster, Haltiwanger, and Krizan 2006), or a shift toward more nonemployer activity (Bento and Restuccia 2022; Abraham et al. 2019). Using early-stage business registration data, Guzman and Stern (2020) estimate that foundings of high-potential firms have not been in secular decline, though they find that growth outcomes of such firms have cooled since the early 2000s.

De Loecker, Eeckhout, and Mongey (2022) provide the most direct examination of this relationship, developing a model where declining potential entry simultaneously reduces observed entry and raises incumbent markups. When calibrated and simulated, their model can more than explain the full decline in aggregate job reallocation. Other papers propose different channels through which these phenomena might be connected: a rise in the use of intangible capital (De Ridder 2024), information technology (Aghion et al. 2019; Lashkari, Bauer, and Boussard 2019), changes in knowledge diffusion (Akcigit and Ates 2023; Olmstead-Rumsey 2022), or demographics (Peters and Walsh 2019).

Some of these mechanisms relating market power and dynamism trends organize their predictions at a more aggregate level rather than within more narrowly defined markets or industries. For example, De Ridder (2024) models an intangible-economy channel in which high-intangible-efficiency firms expand into many product lines and sectors. In such an environment, aggregate markups can rise while measured business formation and reallocation decline even if there is no simple negative relationship *within* industries or markets, as cross-industry activity is an important characteristic of such firms. Our cross-sectional tests, therefore, do not target this class of mechanisms; rather, they document that a strong negative within-industry association is not a robust empirical regularity in our data. Our results are therefore most relevant to papers such as Akcigit and Ates (2021, 2023) and De Loecker, Eeckhout, and Mongey (2022), where the model involves industry-specific effects.

3 Data

We combine three primary datasets for our analysis, covering business dynamics (the BDS), DEU markups (Compustat), and KLEMS markups (KLEMS). We further augment our KLEMS analysis with the NBER-CES Manufacturing Database.[8]

3.1 Dynamism data

We obtain measures of business dynamism from the Census Bureau's Business Dynamics Statistics (BDS), which are publicly available tabulations from the confidential Longitudinal Business Database (LBD) microdata. The BDS are a workhorse public-use data source for studying firm dynamics in the U.S., with annual data spanning from the late-1970s through 2023. The BDS includes tabulations by firm size and age, establishment industry (up to 4-digit NAICS), and other categories. Most of the literature on changing business dynamism in the U.S. relies on the BDS or the confidential LBD.[9]

BDS data are annual with a March reference month; for example, reported job growth for the year 2015 in the BDS is a measure of job growth from April 2014 to March 2015. We adjust our other datasets—Compustat, KLEMS, and NBER-CES—to match this timing as closely as possible; in particular, we add one to the recorded year in each of these datasets prior to matching those data to the BDS. In other words, for example, we match the 2014 observations in Compustat to the 2015 observation in BDS. Throughout the paper, references to years are expressed on this BDS basis.

8. In all data sources we omit funds, trusts, and other financial vehicles (NAICS 525), lessors of nonfinancial intangible assets (NAICS 533), monetary authorities (NAICS 521), and management of companies and enterprises (NAICS 55), all of which are conceptually problematic and sometimes feature uninterpretable extreme outliers.

9. BDS data cover the near-universe of private nonfarm employer establishments, excluding only "farms" (NAICS 111 and 112), railroads (NAICS 482), private households (NAICS 814), and some other smaller categories of establishments. A separate data source for business dynamics is the Bureau of Labor Statistics' Business Employment Dynamics (BED). The BED has some key advantages in terms of frequency and timeliness, but it is not available at the narrow level of industry detail we use.

We focus on four measures of business dynamism, each capturing a distinct dimension of firm and job dynamics:

1. Entry employment rate. The entry employment rate measures 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.[10] The total employment is adjusted using the Davis-Haltiwanger-Schuh (DHS) denominator (Davis, Haltiwanger, and Schuh 1996) to ensure longitudinal consistency. This measure of entry—sometimes referred to as the employment-based or employment-weighted entry rate—measures the size of new entrants and is our preferred measure, as it captures the economic magnitude of firm entry and is robust to difficulties counting small firms and establishments.

2. Excess job reallocation rate. The excess job reallocation rate 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. Excess job reallocation is a measure of the gross job flows that exceed what is necessary to facilitate net job growth and can be thought of as a second moment of the establishment employment growth distribution. In this

10. In Census Bureau parlance, a "firm" is a collection of one or more "establishments" under common ownership or control, where an establishment is simply an operating location of an employer business.

paper, we use the terms "excess job reallocation," "job reallocation," and "reallocation" interchangeably.

3. High-growth employment share. The high-growth employment share measures the share of total employment accounted for by firms classified as "high growth." We define "high-growth firms" as those with DHS growth rates of at least 0.8%.[11] Formally, the high-growth employment share is defined as:

$$\text{HGES}_t = \frac{\sum_{f \in HG_t} e_{f,t}}{\sum_f e_{f,t}}, \tag{3}$$

where HGES_t is the high-growth employment share in year t, HG_t is the set of high-growth firms in year t, $e_{f,t}$ is the employment at firm f in year t, and the denominator sums employment across all firms. The numerator captures total employment at high-growth firms, while the denominator reflects total employment across the entire economy (or industry). Declining high-growth firm activity has been seen as one of the indicators of declining dynamism (Decker et al. 2016b; Kim et al. 2024).

4. Simple entry rate. In addition, in appendix material we report some results for a fourth measure, the simple or unweighted entry rate (often called the startup rate). This entry rate measures the share of *firms* in the economy that are new entrants, regardless of their size:

$$er_t = \frac{f_t^0}{\frac{1}{2}(f_t + f_{t-1})}, \tag{4}$$

11. DHS growth rates are given by $(e_{f,t} - e_{f,t-1})/(0.5e_{f,t-1} + 0.5e_{f,t})$, where $e_{f,t}$ is employment at firm f in year t. For example, a firm that had 50 employees in year $t-1$ would have to have gained another 67 employees by year t to have a DHS growth rate of at least 0.8. Notably, new firms have DHS growth rate of 2 and are therefore included in our definition of high-growth firms; while the BDS tabulations allow for excluding new firms from this set, such tabulations produce data suppression within industry cells.

where f_t^0 is the number of new firms in year t. This measure has been widely used in the dynamism literature but has two key limitations. First, the simple entry rate is heavily influenced even by very small entrants and is therefore less indicative of the overall economic magnitude of business entry than is the entry employment rate described above. Second, the simple entry rate is not robust to increasingly noticeable measurement challenges associated with identifying and appropriately categorizing small firms and establishments; small business units are the subject of considerable (and rising) disagreement between the Census Bureau's business register (underlying the BDS) and the Bureau of Labor Statistics (BLS) business register.[12] The two data sources are much closer for employment figures, prompting us to prefer the entry employment rate to the simple entry rate.

3.2 Compustat-based markup measures

For our first set of markup measures, we use the benchmark estimates from De Loecker, Eeckhout, and Unger (2020) ("DEU markups"). DEU markups are calculated with a production function approach where the markup is given by:

$$\text{Markup} = \text{Output elasticity of variable input} \times \frac{\text{Revenue}}{\text{Cost of variable input}}.$$

For their variable input, De Loecker, Eeckhout, and Unger (2020) use cost of goods sold (COGS), but Traina (2018) argues for using COGS plus selling, general and administrative expenses (SGA). In theory, any variable input works for the estimation, although Raval (2023), 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.

12. By 2021 there were roughly 2 million more establishments in BLS data than in Census Bureau data. See discussion slides here: https://rdeckernet.github.io/website/2024CRIW_discussion_CHMS.pdf.

We obtain these estimates by using DEU's published replication files and Compustat data. While these files provide the estimated output elasticities necessary for markup construction, they do not include code for the original revenue function estimation. Their replication files' coverage extends through 2017; we extend the DEU markup estimates through 2019 using Compustat data.[13] When aggregating across firms, we rely on the DEU benchmark sales-weighted markup for most exercises but also sometimes report results using a cost-weighted markup.[14]

A large literature has grown up debating bias and identification issues with these estimates.[15] 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 (even running well above 100 percent in some cases; see Decker and Williams 2023). Existing literature finds that the business dynamics of privately held firms differ materially from those of publicly traded firms, both in the cross section and over time (Davis et al. 2006; Dinlersoz et al. 2018).

Despite these limitations, DEU markup measures are widely cited in the literature and policy circles and so are objects worth studying closely. For econometric purposes, we simply take DEU markups as given data and not as an estimated object.[16] Readers should interpret our empirical results in the context of both the limitations mentioned

13. We use DEU's output elasticities as provided in their replication files through 2017 then assume the elasticities are constant through 2019, avoiding using pandemic years to estimate output elasticities through the DEU process of five-year rolling windows.

14. Firms in Compustat are labeled with detailed NAICS industry codes of varying NAICS vintage; we adjust these codes to match the NAICS 2017 vintage as described in Albrecht and Decker (2024). We drop industries that cannot be easily mapped to NAICS 2017 format.

15. See Flynn, Gandhi, and Traina (2019), Kirov, Mengano, and Traina (2023), Bond et al. (2021), Doraszelski and Jaumandreu (2019, 2021), De Loecker (2021), and De Ridder, Grassi, and Morzenti (2024)

16. 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.

above and the importance these markup estimates have had in academic, policy, and media discussion.

3.3 KLEMS industry data

In addition to the popular DEU markup measure, we use a variety of separate measures that rely on the BEA-BLS Integrated Industry-level Production Accounts. This is also known as the "KLEMS" dataset—the acronym stands for inputs of capital (K), labor (L), energy (E), materials (M), and services (S).[17] The data are annual beginning in 1988 (defined on BDS basis as described above), and we use the version covering roughly 60 distinct non-overlapping industries. KLEMS industry codes map to standard NAICS industries at varying levels of detail; for example, within the "2-digit" NAICS manufacturing sector (NAICS 31-33) there are nearly 20 KLEMS industries, while the 2-digit NAICS educational services sector (NAICS 61) is a single KLEMS industry.[18] We are not concerned about this variation in the level of industry detail across sectors (which is also a feature of the standard NAICS industry taxonomy) as most of our results are constructed on an activity-weighted basis (i.e., employment or sales weighted). KLEMS industries are defined such that data formatted with standard NAICS industry codes can be matched to KLEMS codes through appropriate aggregation; this is convenient given that the BDS and Compustat are both on a NAICS basis. We use KLEMS data from 1988-2019 to avoid any changes related to the pandemic.

17. The BLS and BEA provide extensive technical documentation of the data at https://www.bls.gov/productivity/articles-and-research/bea-bls-integrated-production-accounts.htm

18. As mentioned above, we omit NAICS 521 (monetary authorities) from all exercises. The KLEMS industry setup combines NAICS 521 with NAICS 522 (credit remediation and related activities) into the KLEMS industry 521CI, which we omit from all KLEMS exercises. Similarly, we omit NAICS 533 (lessors of nonfinancial intangible assets) from all exercises. The KLEMS industry setup combines NAICS 533 with NAICS 532 (rental and leasing services) into the KLEMS industry 532RL, which we omit from all KLEMS exercises.

The KLEMS data offer several key advantages compared to data used in earlier markup measurement work. First, the data maintain rigorous adherence to proper measurement of output and other variables (resulting from their origin in the national accounts) using appropriate methodologies to track levels and growth.[19] Second, they employ uniform and modern NAICS industry definitions throughout the sample period, and the available level of industry detail does not present concerns about sparsely populated cells, as in Compustat data. Third, they provide a comprehensive breakdown of inputs into five categories: capital, labor, energy, materials, and services.

These measurement advantages make the KLEMS data particularly well-suited for examining markups, despite being aggregated to the industry level rather than providing firm-level variation. The tradeoff is between more granular but less comprehensive data from individual firms (and associated firm-level production function estimation) versus broader but more carefully measured industry aggregates. Given our focus on industry-level relationships, the measurement advantages of KLEMS are worth considering as an alternative to DEU firm-level markup measures.

KLEMS inverse cost-share markups

We construct several KLEMS-based markup measures. Our first approach exploits input cost shares to infer markups based on the ratio of (nominal) revenue to (nominal) expenditures on a specific input category.

$$\text{Inverse cost-share markup} = \frac{\text{Industry revenue}}{\text{Industry cost of variable input}}.$$

The variable inputs we consider are labor, materials, energy, and total "variable" costs (which we define as the sum of labor, materials, energy, and services).

19. DEU markups can be corrected to match more features of the national accounts. See Hasenzagl and Pérez (2023).

The cost-share approach requires three conditions: (i) first-order cost minimization for the chosen variable inputs on average; (ii) constant returns to scale (CRS); and (iii) *constant output elasticities* for those inputs (for our comparisons over time). Notably, when expressed as log differences over time—as we do in most of our main exercises—these inverse cost shares are equivalent to the DEU markup under constant output elasticities. While these are strong assumptions, the cost share approach has advantages over alternatives—notably not requiring output quantity data or imposing more restrictions, such as Hicks-neutral productivity.

Our inverse cost–share objects should be interpreted as descriptive proxies for markups under the conditions above. Violations of constant returns to scale or time–invariant elasticities (e.g., due to technological change or input reclassification) would break the tight mapping to a structural markup. Consistent with this, we treat these measures as reduced–form indicators and place emphasis on patterns across industries and specifications rather than levels.

NBER-CES Manufacturing Database

In robustness exercises, we apply the KLEMS inverse cost share approach described above to the NBER-CES Manufacturing Database. These data currently extend through 2019 (on a BDS basis). While the NBER-CES Manufacturing Database is limited to manufacturing industries, it permits finer industry detail than our KLEMS or Compustat-based exercises (up to 6-digit NAICS); we focus on 4-digit NAICS tabulations since these can be merged with our BDS dynamism measures. The data are structured similarly to KLEMS and we construct markups in an identical manner. NBER-CES data come from a variety of sources, most notably the Census Bureau's annual surveys and semidecadal censuses of the manufacturing sector; see Bartelsman and Gray (1996) and Becker, Gray, and Marvakov (2021) and citations therein for detail.

KLEMS Hall-style markups

Using KLEMS data for 1988-2019 and following Hall (2018), we specify an industry-level regression that allows for a time trend in industry-specific markups:

$$\sum_i \alpha_{i,t} \Delta x_{i,t} = (\phi - \psi t) \Delta \log y_t - a_t, \tag{5}$$

where $\alpha_{i,t}$ is the input share for factor i, $x_{i,t}$ is a (real) factor input quantity, y_t is real industry output, t is time, and we omit industry index subscripts for simplicity. Equation (5) is the Hall-style measurement identity: with Hicks-neutral technology, the coefficient on output growth identifies the price–marginal-cost wedge (or its inverse in our parameterization). The left-hand side, $\sum_i \alpha_{i,t} \Delta x_{i,t}$, is constructed directly from KLEMS as the difference between output growth and the published Solow residual, so no firm optimality conditions are imposed beyond production feasibility.[20] To address endogeneity with a_t, we follow Hall (2018) and use national instruments in log differences——federal purchases of military equipment, ships, software, military R&D; and the WTI oil price——under the assumption that these series are orthogonal to contemporaneous industry-specific a_t while correlated with output and inputs.[21]

Hall (2018) shows the implied functional form for the ratio of price to marginal cost is:

$$\mu_t = \frac{1}{\phi - \psi_t}. \tag{6}$$

Rather than study the full markup formula (6), we simply focus on ψ to measure the direction and magnitude of industry-level markup growth. We therefore read $\psi > 0$ as a

20. Aggregation similarly comes from KLEMS: $\Delta \log y_t$, $\Delta \log x_{i,t}$, and Törnqvist revenue shares $\alpha_{i,t}$ for K, L, E, M, and S.
21. The regression we describe in equation 5 matches equation (19) from Hall (2018).

rise over time in the Hall-style price–marginal-cost wedge at the industry level, without attributing the change to a specific source of market power.

4 Long-run industry trends

Figure 1 showed opposite movements between aggregate measures of business dynamics (entry and excess job reallocation) and markups, with the strong rise in markups during 1980-2019 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 (Akcigit and Ates 2021, 2023; De Loecker, Eeckhout, and Mongey 2022). For example, declining competition resulting from fewer potential entrants results in lower entry and reallocation alongside higher average markups. If this kind of mechanism is an important explanatory factor for declining dynamism and rising markups from the 1980s through the 2010s, we should expect industries with larger increases in markups to also exhibit larger declines in dynamism over this period. In this section we present our primary empirical tests of this prediction using cross-sectional industry-level data.

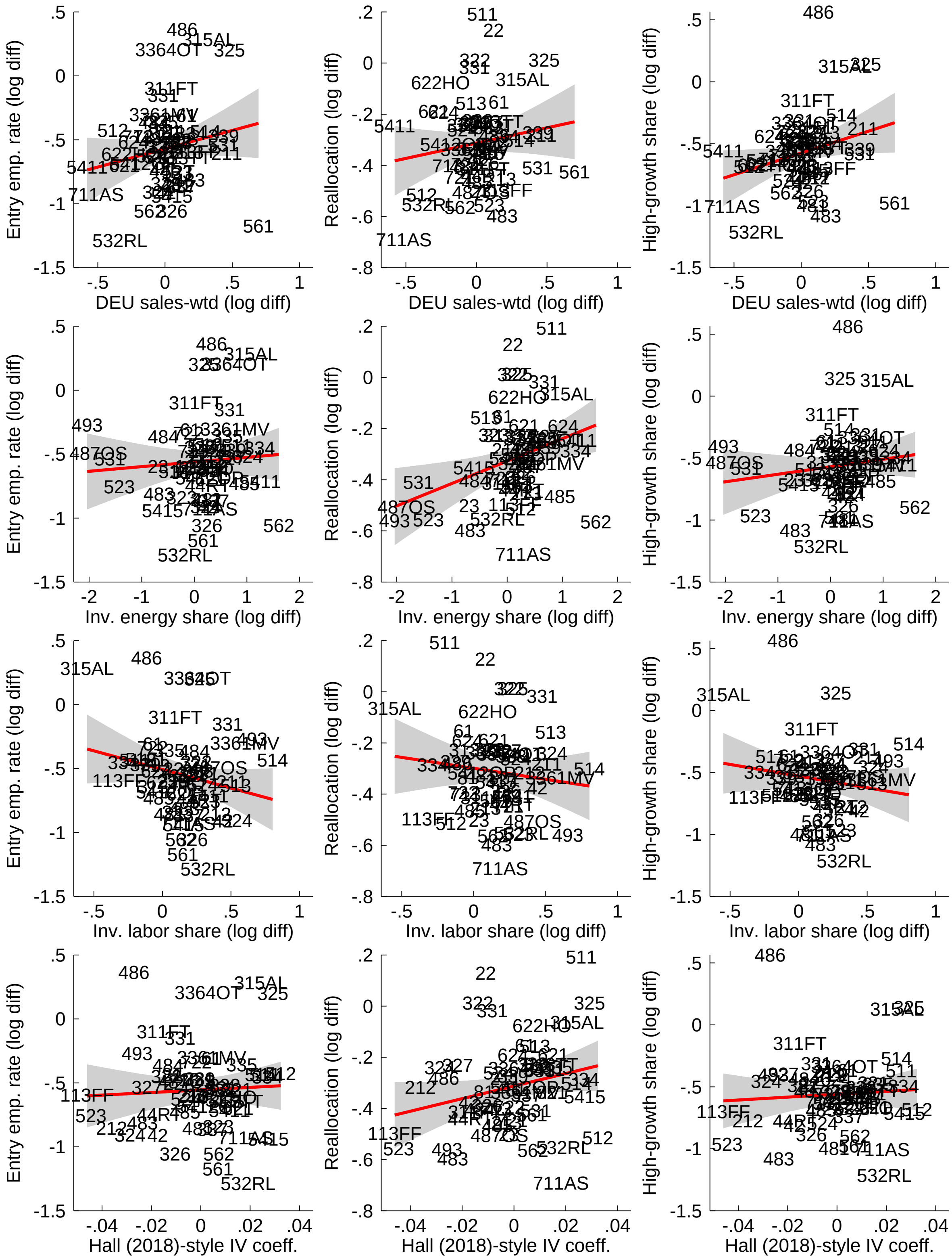
4.1 Plotting long-run industry trends

Figure 3 shows the reduced-form relationship between our three main business dynamism measures and four different markup specifications within detailed industries. For this figure, industries are defined on a KLEMS basis, the most detailed industry taxonomy available for all of our markup measures. Since, in this section, we are interested in long-run trends, each variable is expressed as a log difference between the 2015-2019 average and the 1988-1992 average (the earliest period available for KLEMS data). The exception is the Hall (2018)-style markup, which is simply measured as the estimated slope coefficient as described above (estimated on data for 1988-2019). In the figure, each row of panels corresponds to a different markup measure—here we show the DEU sales-weighted markup, the inverse energy cost share, the inverse labor cost share, and the Hall (2018)-style markup coefficient estimated using instrumental variables. The columns correspond to our main three dynamism measures—the entry employment rate, excess job reallocation, and the high-growth firm share of employment.

Rather than examining whether markup levels in an early time period predict dynamism levels in a later period, this exercise shows how the accumulation of markup changes relates to the cumulative change in dynamism measures. This approach captures the possible accumulation of both rising market power and declining dynamism. If underlying changes to industry structure are causing lower dynamism and higher market power, then industries that experienced larger increases in markups over these decades should show correspondingly larger declines in measures of dynamism.

We can focus on the top-left panel, which relates the change in the entry employment rate to the change in the DEU sales-weighted markup. In contrast to the theory in papers like Akcigit and Ates (2021, 2023) and De Loecker, Eeckhout, and Mongey (2022), we observe a striking *positive* relationship between entry and markups in these long differences. Many industries with large *declines* in markups saw large declines in entry rates, while industries with large gains in markups often feature smaller declines (or even increases) in entry rates. And we observe a wide range of entry rate outcomes among those industries with little or no markup change. We observe similar patterns across all dynamism measures (i.e., all columns of figure 3) for three of the four markup measures (i.e., rows).

The noteworthy exception is the *inverse labor share* markup measure (the third row of the figure), which actually does appear to have a negative relationship with the dynamism measures; the slope of the line is not statistically significant, though we do ob-



Note: Difference, 2015-2019 average vs. 1988-1992 average except the Hall-style coefficent.
Shaded area is 95% confidence interval.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure 3: Change in dynamism and markups, KLEMS industries

serve significance in some specifications discussed below.[22] That said, none of the other markup measures exhibit this negative relationship with dynamism.

This can be further seen in appendix figure A2, which shows scatterplots for the remaining markup measures: the DEU cost-weighted markup, the inverse materials share, the inverse variable cost share, and the OLS version of the Hall (2018)-style markup coefficient. In this appendix figure, a flat or positive relationship is observed in each case, with the closest call being the variable cost (driven by the inclusion of labor costs in the variable cost aggregate).

Finally, we consider our results' robustness to industry definitions. Appendix figure A3 reports 4-digit NAICS-based results (though only for manufacturing) in the NBER-CES data; again we note, if anything, a positive correlation. And appendix figure A4 reports economywide results at the 3-digit NAICS level, where we again observe positive slopes relating (DEU) markup and dynamism changes.[23]

4.2 Limitations

Here we pause to emphasize three 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—including, for example, the mass of *potential* entrants as in De Loecker, Eeckhout, and Mongey (2022)—and are ultimately jointly determined. Our scatterplots and regression results

22. Additionally, a partial exception among the dynamism variables is the *unweighted* firm entry rate. Appendix figure A1 reports scatterplots showing the long (log) difference in unweighted entry rates against changes in all eight of our markup measures. Some of these show a modestly negative slope, though in unreported regressions using many different specifications only a few produce statistically significant negative relationships.

23. The KLEMS scatterplots feature at most 56 industries, the NBER-CES scatterplots feature 86 industries, and the 3-digit NAICS scatterplots feature at most 77 industries. The data shown in figure A4 cover the period 1988-2019 to be consistent with our main exercises, but in unreported exercises (and earlier drafts of this paper) we exploit the longer time series available for Compustat data to study long differences starting in the early 1980s, with similar results.

are simply reduced-form moments that are naturally implied by rich models of firm dynamics. In a sense, we are providing reduced-form empirical tests of such models using cross-sectional variation. If, indeed, the same underlying causal mechanisms are driving higher market power and lower business dynamism, we should observe a negative reduced-form correlation between changes in markups and changes in dynamism at the industry level.

Second, the interpretation of these cross-industry patterns merits careful consideration. If changes in both markups and dynamism were driven by a common economy-wide force, this would not necessarily generate any cross-sectional correlation. Common shocks are differenced out when comparing across industries within the same time period. Our tests therefore speak to whether industries experiencing relatively larger markup increases also experience relatively larger dynamism declines.

Third, our markup measures are subject to a range of measurement limitations. And some of them (the DEU markups and the Hall-style coefficients) are econometrically estimated objects with their own sampling variation; considerations for "imputed regressors" described by Murphy and Topel (1985) likely apply to these markups. We will next turn to formal regressions, which we will estimate with commonly used "robust" standard errors, but we acknowledge that we may be underestimating the standard errors given the nature of the markup measures. For these reasons, we study this issue with a large number of empirical specifications, including not only multiple "markup" measures but many different econometric setups, as we will show below.

4.3 Baseline regression specifications

In table 1, we present baseline regression results examining the relationship between changes in markups and dynamism measures across industries. The table reports coefficients from separate regressions of long (log) differences in dynamism measures on long (log) differences in various markup measures at the KLEMS industry level; these correspond closely with the regression lines displayed in figure 3, with a key exception: the regressions shown in table 1 systematically omit outliers, that is, industries whose respective markup change is in the top or bottom 2 percent of industries (we relax this constraint for robustness discussions further below). Slope coefficients from both unweighted (panel A) and employment-weighted (panel B) regression specifications are shown, where employment weights are constructed based on the average of industry employment in the earlier and later periods of the long differences.

Panel A, reporting unweighted regressions, is consistent with the results of figure 3 already shown. We only observe negative slopes for regressions using the inverse labor share markup measure, though in unweighted regressions these negative coefficients are not statistically significant. Slopes are generally positive elsewhere and are even statistically significantly positive in a few cases—mainly the DEU sales-weighted markup and the inverse energy share markup.[24]

Importantly, though, our motivations for this paper—summarized by figure 1—are the aggregate patterns. We are interested not only if markups and dynamism relate negatively at the industry level, but also if a negative markup/dynamism relationship can explain aggregate patterns of markups and dynamism. The regression results of panel A could simply reflect small industries that are not important for aggregate economic activity. Panel B therefore reports employment-weighted regressions, such that industries with larger employment shares have larger influence on regression coefficients.[25] This

24. The statistical significance of coefficients corresponding to the DEU sales-weighted markup is specification dependent. For example, regressions using a longer time period (starting in 1980 instead of 1988) still have positive coefficients but without statistical significance.

25. Weighted regressions also mitigate concerns about arbitrary industry definitions or levels of detail. For example, if an industry taxonomy features greater detail in, say, manufacturing than in services, then manufacturing industries will unduly influence unweighted coefficients in industry-level regressions. Weighted regressions alleviate this concern by ensuring that small industries—which may be "small" simply because they are targeted by narrower industry definitions—have appropriately small influence on regression coefficients.

Table 1: Long run markups vs. dynamism: Baseline specification

	Entry Employment Rate	Reallocation	High-Growth Share
A. Unweighted regressions			
DEU sales-weighted markup	0.54**	0.22*	0.62***
	(0.22)	(0.13)	(0.19)
Observations	53	53	53
Inverse energy share	0.12*	0.11***	0.12**
	(0.06)	(0.03)	(0.05)
Observations	54	54	54
Inverse labor share	-0.19	-0.05	-0.13
	(0.18)	(0.12)	(0.17)
Observations	54	54	54
Hall-style IV markup	0.82	2.85*	1.26
	(3.39)	(1.54)	(3.43)
Observations	54	54	54
B. Employment-weighted regressions			
DEU sales-weighted markup	0.36*	-0.15	0.35*
	(0.19)	(0.20)	(0.18)
Observations	53	53	53
Inverse energy share	0.01	0.11***	0.03
	(0.05)	(0.03)	(0.04)
Observations	54	54	54
Inverse labor share	-0.47**	-0.13	-0.41***
	(0.20)	(0.12)	(0.15)
Observations	54	54	54
Hall-style IV markup	1.29	5.54***	2.90
	(3.47)	(1.48)	(2.69)
Observations	54	54	54

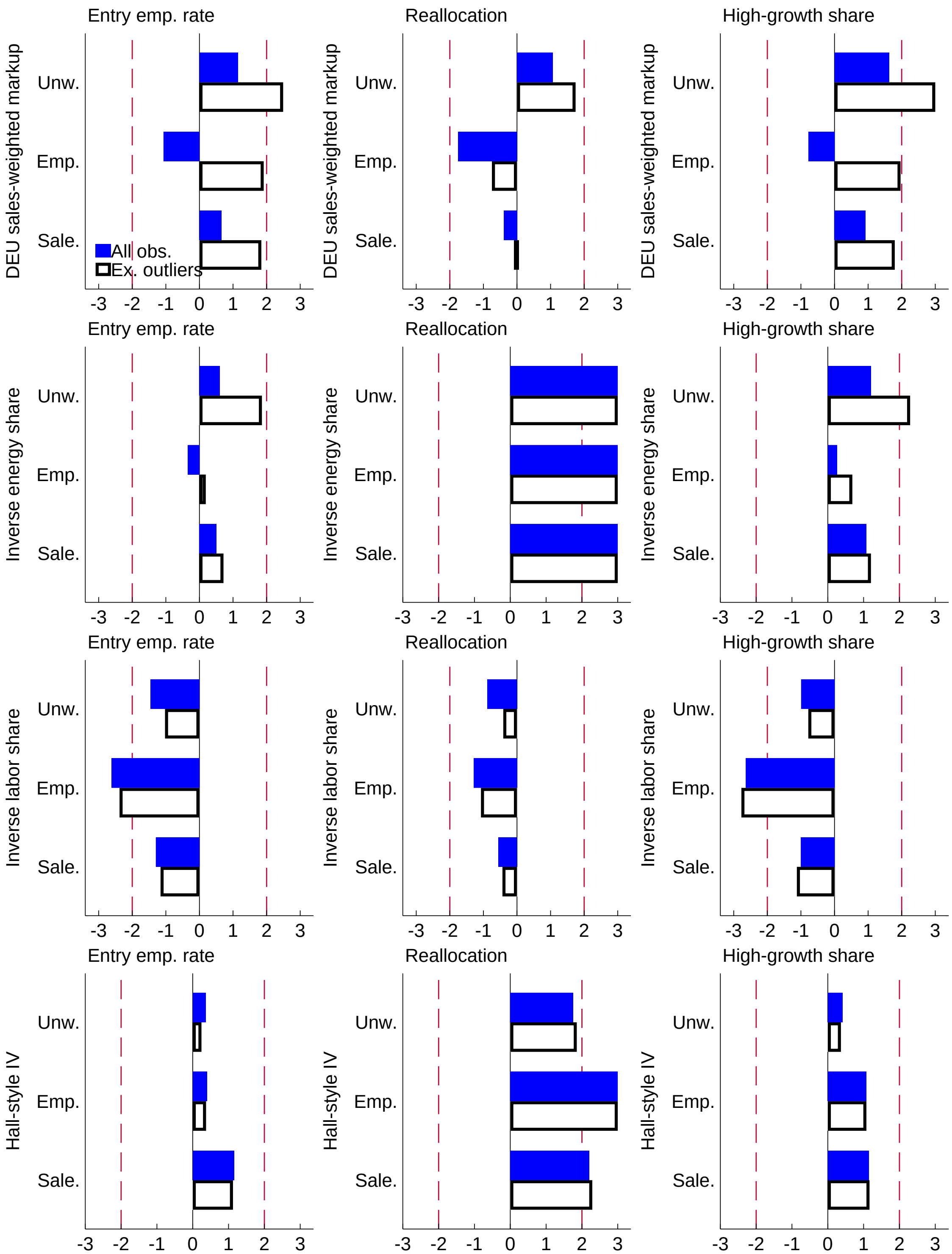
Note: SE in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
Long log differences at KLEMS industry level, 2015-2019 average vs. 1988-1992 average.
Weighted regressions use average employment 2015-2019 and 1988-1992.
2% outlier markup changes omitted.

adjustment clearly matters: coefficients are generally lower in panel B than in panel A. In the weighted regressions we observe less statistical significance for positive coefficients than in the unweighted regressions, and we now observe statistical significance for two of the three negative coefficients on the inverse labor share markup—especially in the case of high-growth firm shares. On balance, the weighted regressions still cast considerable doubt on theories linking market power and dynamism, but the labor share exception is noteworthy.

4.4 Alternative regression specifications

These baseline results are robust to numerous alternative specifications. We estimate these regressions on KLEMS industries with and without outliers and with three different regression weighting schemes (unweighted, employment weighted, and real sales weighted).[26] The results are summarized in figure 4, which corresponds to the markup variables shown on table 1 (DEU sales-weighted markups, the inverse energy share, the inverse labor share, and the Hall-style IV coefficients). In this figure, we report t statistics from a number of regressions, allowing for quick analysis of both the direction and the statistical significance of each regression's estimated markup/dynamism relationship. Each panel of the figure corresponds to a single dynamism variable and a single markup variable and reports three sets of bars corresponding to unweighted regressions ("Unw."), employment-weighted regressions ("Emp."), and real sales-weighted regressions ("Sale."). Within each weighting scheme, we report t statistics from regressions using all observations (solid bars, "All obs.") and regressions in which 2 percent outliers are excluded as in table 1 (hollow bars, "Ex. outliers"). We include vertical dashed lines indicating t statistics of -2 and 2, a rule of thumb for statistical significance.

26. We deflate industry nominal sales data using the U.S. GDP deflator. This deflation does not matter for these exercises.



Note: Each panel shows t statistics from unweighted, employment-weighted, and sales-weighted regressions (described in text). t statistics truncated below -3 and above 3. KLEMS industry-level regressions.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure 4: Long-run markup vs. dynamism coefficients t statistics, KLEMS industries

To understand figure 4, start on the top left panel. The first hollow bar (corresponding with the unweighted "Unw." row of the panel) shows the t statistic from an unweighted regression of the (log differenced) entry employment rate on the (log differenced) DEU sales-weighted markup, with outliers excluded. This bar corresponds exactly to the first regression coefficient reported on table 1. This top left panel generally suggests only borderline statistical significance for regressions of entry employment rates on DEU sales-weighted markups; only one of the bars clears the rule-of-thumb for statistical significance (the bar corresponding to the unweighted regression excluding outliers). In these regressions (again, still focused on the top left panel of figure 4), outliers do appear to matter: excluding outliers results in higher coefficients that are closer to statistical significance.

Looking across the panels of figure 4 generally, we observe that, regardless of regression weights and outlier inclusion, results are usually statistically indistinguishable from zero. The most glaring exception comes from the middle panel of the second row, corresponding to the regressions of reallocation rates on the inverse energy share, all of which feature large, highly significant, positive t statistics. A couple exceptions can be seen on the third row, corresponding to the inverse labor share and discussed above, though in broader context these exceptions are not so striking or persuasive.

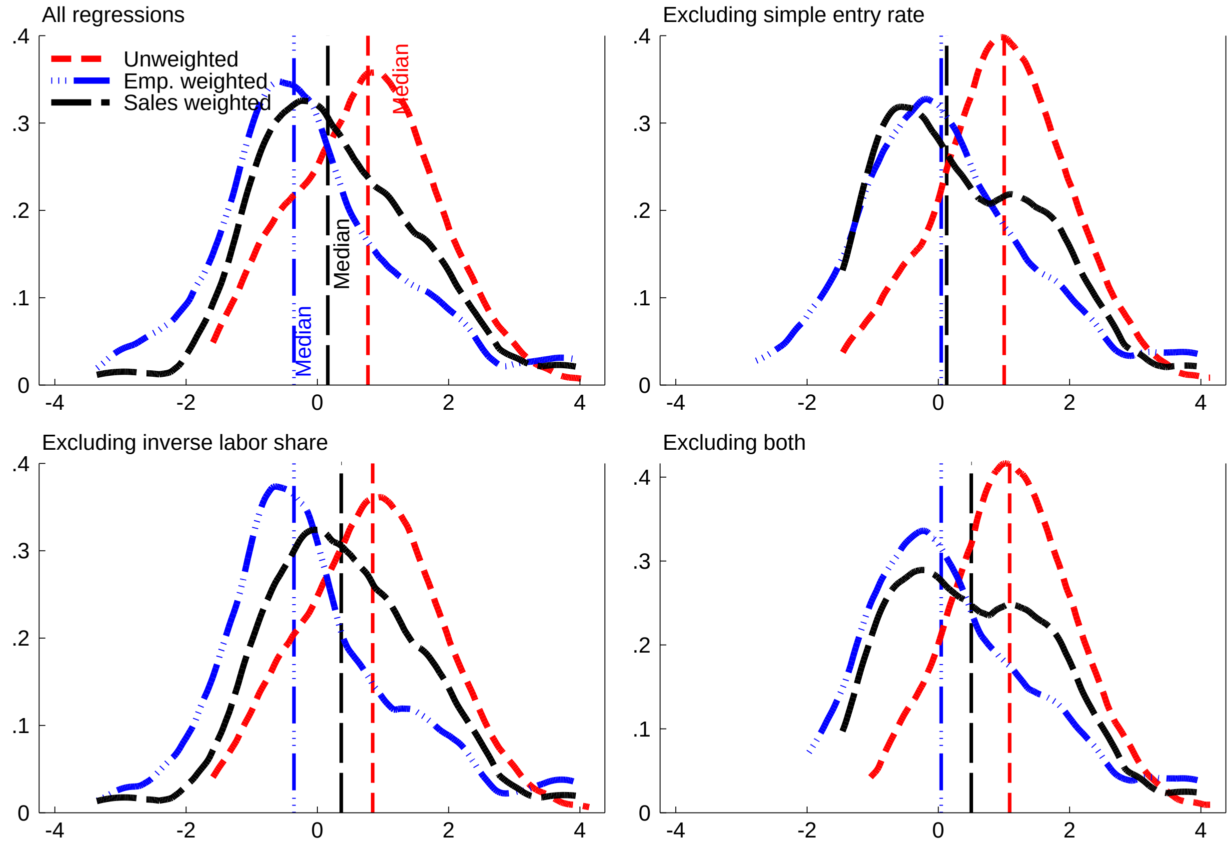
Appendix figure A5 is similar to figure 4 but corresponds to our remaining four markup variables in KLEMS data: DEU cost-weighted markups, the inverse materials share, the inverse variable cost share, and the OLS version of the Hall-style markup growth coefficient. The only statistically significant bars in figure A5 are in the positive direction, suggesting that industries with larger markup gains saw smaller dynamism declines. Figure A6 in the Appendix reports t statistics associated with 3-digit NAICS-level regressions. Again, these only permit use of the DEU markups, but they allow for slightly more industry detail. In these regressions, most coefficients are positive, though few approach statistical significance.[27]

While the bar charts just described show little or no clear, consistent relationship between markups and dynamism across a wide range of regression and measurement specifications, these figures still do not fully capture the many regression specifications we have investigated. Other specifications include all specifications with the simple entry rate dynamism variable and all specifications expressed in long *level* differences (instead of log differences). Rather than report dozens more regressions one by one, we summarize *all* regression t statistics—including those we have already shown—using kernel densities, shown in figure 5.

The top left panel of figure 5 reports kernel densities of t statistics, separately by regression weighting scheme, for all regression specifications (over 400 of them). Along with the standard kernel densities, we report medians of each distribution. Roughly speaking, the distribution of unweighted regression t statistics has a clear majority of its mass above 0 and a nontrivial portion even above 2, the rule of thumb for statistical significance. Weighted regression distributions are shifted to the left of the unweighted one, centered close to or just below zero. That is, among hundreds of regressions, the coefficients relating markups and dynamism have a central tendency very close to zero.

The top right panel of figure 5 excludes the simple entry rate and therefore is limited to the other three dynamism variables on which we have focused in the main text. This shifts the distributions a bit to the right, at least for unweighted regressions, suggesting more prevalence of positive relationships between markups and dynamism. The bottom left panel reports all regressions excluding the inverse labor cost share, which we exclude due to its unusual behavior relative to other markup measures documented above (though

27. Figure A6 reports regressions using the 1988-2019 period, but results are not materially different when using the 1980-2019 period.



Note: Kernel density of t statistics from long difference regressions in two datasets: KLEMS industries with all markup variables (384 regressions) and 3-digit NAICS industries with DEU markup variables (64 regressions). Separate densities shown for unweighted regressions, employment-weighted regressions, and sales-weighted regressions. Regression specifications include level differences and long differences; including and excluding outliers. All dynamism variables included. Vertical lines indicate median t statistic across regressions.
Source: Business Dynamics Statistics, Compustat, and KLEMS.

Figure 5: Kernel density of t statistics from long difference regressions

this panel does include regressions using variable costs generally, which include payroll). Finally, the bottom right panel excludes both the simple entry rate regressions and the inverse labor cost share regressions.

Observe several additional patterns exhibited in figure 5. Notably, across all panels, there is almost no density below t statistics of -2. This reinforces our main finding that evidence for a relationship between rising markups and declining dynamism is extremely limited. A nontrivial amount of density appears above 2, but the bulk of the t-statistic distributions falls between -2 and 2, indicating that many of our estimated relationships are not statistically significant. If we focus in on the medians (shown by vertical lines), they differ across weighting schemes: employment-weighted and sales-weighted specifications tend to produce t-statistic distributions centered close to zero compared to positive-median unweighted specifications. This suggests that the positive relationship we saw in some scatterplots is being driven by smaller industries; once industries are weighted, the median specification finds essentially no positive *or* negative correlation between markups and dynamism.

Wrapping up these "long difference" analyses of industry-level trends in markups and dynamism: across hundreds of regression specifications we find minimal evidence for the negative reduced-form relationship between dynamism and markups that is posited by some theories. We find nontrivial but limited evidence for positive relationships.

4.5 The special case of the inverse labor share

The negative relationship we find between the inverse labor share measure and dynamism metrics—in some though not all specifications—warrants further discussion, as it connects to a broader literature on the secular decline in labor's share of income. Recent work by Autor et al. (2020), Karabarbounis and Neiman (2014), and others documents this decline and explores various potential explanations including technological change, globalization, and changes in market structure.

While our inverse labor share results might appear to support theories linking market power to declining dynamism, we interpret that result cautiously for several reasons. First, the labor share can decline for many reasons unrelated to product market power, such as capital-biased technological change, increased automation, or changes in the relative prices or availability of capital and labor. Our inverse labor share measure, as a simple ratio of nominal sales to nominal payroll, fails to adequately account for such changes; a more rigorous markup measure using appropriately estimated output elasticities might do so. Indeed, the DEU markup measure, which incorporates time-varying output elasticities, likely picks up labor costs as a significant component of its cost of goods sold measure of factor costs; regressions involving this markup measure do not suggest a negative relationship.

Second, if declining labor shares primarily reflected rising product market power, we would expect to see similar negative relationships with our other markup measures, which we do not.[28] Third, the broad sectors driving the declining labor share in the literature and our data do not have clear systematic patterns in relation to declining dynamism; for example, while retail trade sees a large decline in the labor share and in some dynamism measures, manufacturing sees a large decline in the labor share with a relatively *small* decline in our main three dynamism measures.

Thus, while our labor share results are intriguing and connect to important trends in factor shares, they do not appear likely to be driven by broader theories attempting to link product market power and business dynamism.

28. An important reminder is that, in these log long difference specifications, each of our markup variables—assuming they capture the revenue share of variable inputs—is equivalent to the more rigorous DEU markup concept under the assumption of constant production function elasticities.

4.6 Reconciling aggregate and industry patterns

Our findings present a puzzle: aggregate time series show markups rising while dynamism falls (figure 1), yet cross-sectional industry-level evidence reveals no systematic negative relationship between these trends. How can both patterns be true simultaneously?

One resolution lies in an accounting phenomenon akin to Simpson's Paradox. At the aggregate level, changes over time in markups correlate negatively with changes in dynamism. But the industries experiencing the largest markup increases are largely independent of the industries experiencing the largest dynamism declines. In the language of the Simpson's Paradox, after controlling for the industry, the correlation between markups and dynamism disappears or reverses. The scatterplots show this; rising markups and declining dynamism have occurred in different parts of the economy.

We can shed more light on this by separating industries into four groups based on each industry i's long-difference (log) change in dynamism (Δe_i) and change in markups (Δm_i) relative to the average industry ($\bar{\Delta e}$ and $\bar{\Delta m}$, respectively). Consider four groups of industries:

I. Those with large declines in dynamism and large increases in markups: $(\Delta e_i - \bar{\Delta e}) < 0$ and $(\Delta m_i - \bar{\Delta m}) > 0$

II. Those with small declines (or even increases) in dynamism and large increases in markups: $(\Delta e_i - \bar{\Delta e}) > 0$ and $(\Delta m_i - \bar{\Delta m}) > 0$

III. Those with large declines in dynamism and small increases (or even declines) in markups: $(\Delta e_i - \bar{\Delta e}) < 0$ and $(\Delta m_i - \bar{\Delta m}) < 0$

IV. Those with small declines (or even increases) in dynamism and small increases (or even declines) in markups: $(\Delta e_i - \bar{\Delta e}) > 0$ and $(\Delta m_i - \bar{\Delta m}) < 0$

Focusing on the entry employment rate dynamism variable and the DEU sales-weighted markup variable common in the literature, we calculate each group's employment share (averaged across the earlier and later periods of our long differences) and report it on table 2.

Table 2: Industry employment shares by markup and entry patterns

	Entry pattern	
	Larger decline	Smaller decline
Markup pattern		
Larger increase	0.26	0.19
Smaller increase	0.35	0.21

Note: Cells show share of 1988-2019 average employment in industries with the corresponding patterns. "Larger" and "smaller" refer to above- and below-average changes relative to the cross-industry mean.

Table 2 reveals the independence of markup and dynamism variation across industries. The on-diagonal panels—the upper-left and lower-right quadrants—represent industries whose experiences are consistent with a theory in which market power and dynamism are inversely related.[29] If rising markups were systematically negatively correlated with dynamism, we would expect employment to concentrate in on-diagonal quadrants. But these industry groups only account for 47 percent of employment. Instead, employment is dispersed almost equally across all four quadrants, with more than half of employment in the off-diagonal cells.

Despite this apparent independence, the on-diagonal industries could still be important and play a decisive role in aggregate trends if they included industries with extremely large markup increases and entry declines that disproportionately influenced economy-wide patterns. The "key industries" analysis that follows explores this possibility.

29. This assertion can be thought of quite literally. Consider the correlation coefficient relating changes in markups and dynamism across industries: $\frac{\sum_{i=1}^{I}(\Delta e_i - \bar{\Delta e})(\Delta m_i - \bar{\Delta m})}{\sqrt{\sum_{i=1}^{I}(\Delta e_i - \bar{\Delta e})^2(\Delta m_i - \bar{\Delta m})^2}}$. The on-diagonal industries from table 2 contribute negatively to this correlation, while the off-diagonal industries contribute positively.

Key industries

We now focus on industries in the top-left quadrant of table 2—these "key industries" feature both larger-than-average markup increases and larger-than-average entry declines. The key industries both (a) fit the theory of a negative markups/dynamism relationship, *and* (b) have the potential to explain the observed aggregate pattern of rising markups and declining dynamism.[30] We can study these industries further to quantify their importance, intentionally selecting on the dependent variable to give the theory of negatively correlated dynamism and markups the best possible chance of explaining the aggregate trends.

Table 3 lists the "key industries" we identify in terms of employment-based entry and DEU sales-weighted markups. There are 13 key industries (out of 55 total KLEMS industries in our main analysis) and, as shown on table 2, they account for about one-quarter of employment.

Table 3: Key industries

KLEMS code	Title
481	Air transportation
483	Water transportation
44RT	Retail trade
213	Support activities for mining
523	Securities, commodity contracts, and investments
113FF	Forestry, fishing, and related activities
326	Plastics and rubber products
313TT	Textile mills and textile product mills
561	Administrative and support services
211	Oil and gas extraction
5415	Computer systems design and related services
212	Mining, except oil and gas
337	Furniture and related products

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

30. The bottom-right quadrant of the table, while important for generating a negative markup/dynamism correlation, is not important for aggregate patterns since, by construction, that group features industries with relatively small markup increases and dynamism declines.

The top panels of figure 6 illustrate the role of these industries in aggregate dynamism declines by showing the entire time series of aggregate entry rates (left) and the entry rates indexed to their 1988 levels (right). Unsurprisingly, the key industries (black long-dashed line) see a larger decline in entry than the overall aggregate (solid green line). But the aggregate series *excluding the key industries from table 3*—the dashed green line—exhibits a decline that is only slightly less than the overall aggregate. In other words, most of the aggregate decline in entry rates is occurring in other industries that do not satisfy the criteria of larger-than-average entry decline and larger-than-average markup increase. For example, the industries in the bottom-left quadrant of table 2 above account for one-third of employment and, by construction, have larger-than-average entry rate declines; these industries likely account for a large share of the aggregate entry rate pattern.

The bottom two panels of figure 6 are analogous but for the reallocation rate (where the key industries are defined based on reallocation decline rather than entry decline); here the key industries make even less difference for the aggregate dynamism decline. Notably, the key industries started in 1988 with higher reallocation than other industries; this fact is consistent with earlier work arguing that declining dynamism is in part a "convergence" story, with industries that started the 1980s with higher dynamism converging toward lower-dynamism industries (e.g., Decker et al. 2016b).

Similarly, the key industries cannot account for the rise of average markups. Figure 7 reports aggregate sales-weighted DEU markups for all industries, key industries, and all industries excluding key industries in similar fashion to figure 6; in the top panel, key industries are defined based on entry employment rates, while in the bottom panel key industries are defined in terms of excess job reallocation.

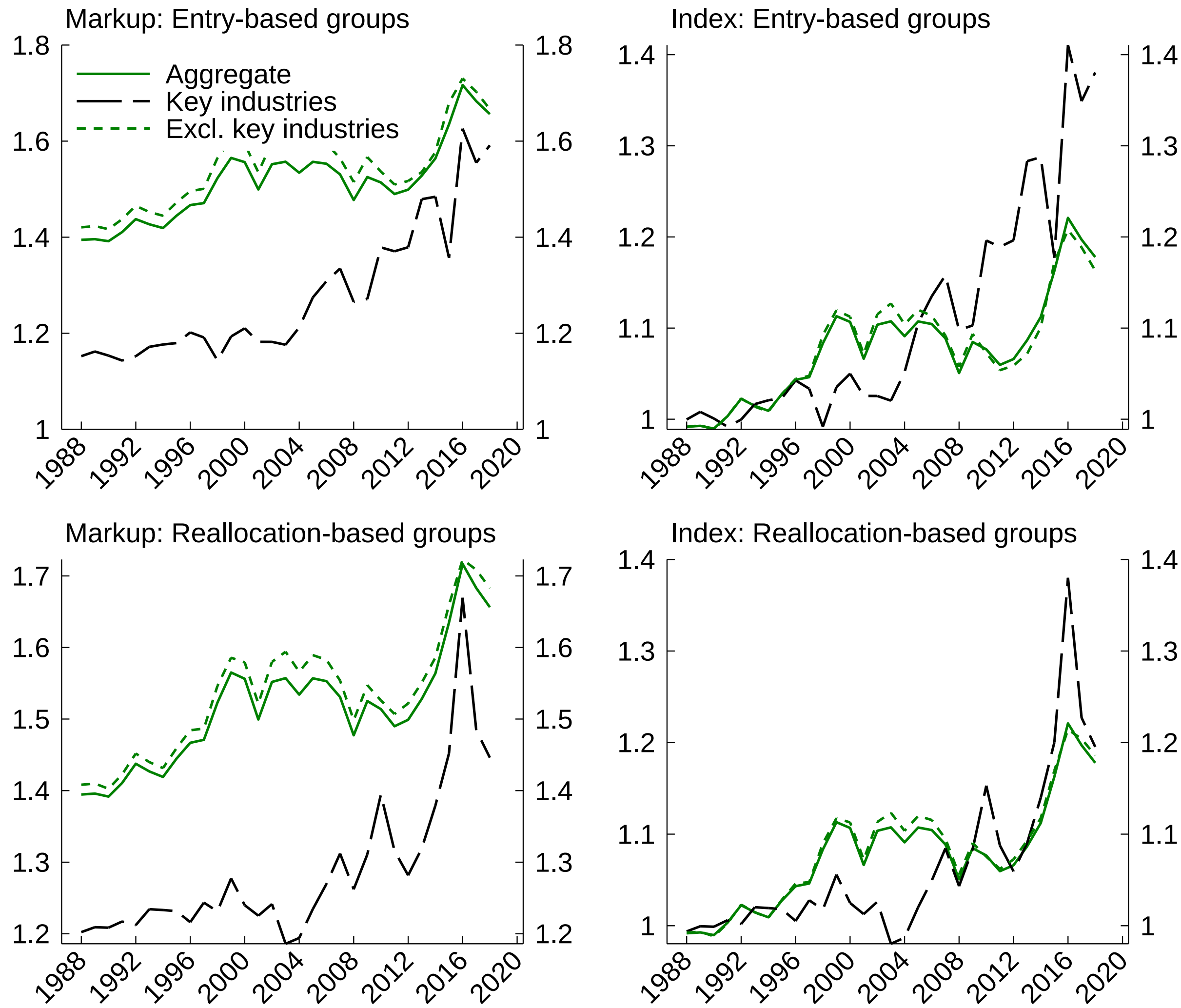
Key industries—by construction—have larger-than-average increases in markups; but they matter little for the aggregate trend, which is virtually identical to the trend among all industries excluding the key industries. Moreover, the "convergence" story is very ap-

Note: DEU sales-weighted markups. Key industries have larger-than-average increases in markups and decreases in entry employment rates (top) or reallocation (bottom). Indexes are based on 1988 levels.
Source: Business Dynamics Statistics, Compustat, and author calculations.

Figure 6: Dynamism trends with and without key industries

parent from figure 7; the key industries started the time period with much lower markups than other industries, such that their relatively large markup increases appear to reflect convergence.

The inability of the key industries to explain aggregate patterns of dynamism and markups suggests that the apparent negative relationship between dynamism and markups



Note: DEU sales-weighted markups. Key industries have larger-than-average increases in markups and decreases in entry employment rates (top) or reallocation (bottom). Indexes are based on 1988 levels. Source: Business Dynamics Statistics, Compustat, and author calculations.

Figure 7: Sales-weighted markup trends with and without key industries

from figure 1, while interesting, is spurious with regard to theories in which markups and dynamism are negatively related at the industry level. The decline in business dynamism is not explained by rising markups (or determinants of rising markups); other factors—present in industries where dynamism and markups are not negatively correlated—must explain the aggregate patterns of business dynamism.

5 High-frequency analysis: Impulse response functions

The foregoing analysis is all focused on long-run trends, with correlations specified in terms of industry-level long differences. One possible critique of this approach is that the relationship between market power and dynamism may occur within a smaller time window than three decades such that our trend-based exercises obscure the underlying relationship. We next analyze the contemporaneous, high-frequency comovement of dynamism and markup variables using local projections following Jordà (2005). This allows us to assess the short-to-medium-run comovement predicted by theories linking market power and dynamism. Notably, we have annual variation in all of our dynamism variables and in all of our markup variables except for the Hall-style market coefficients.

The local projection method involves estimating a series of separate regressions for each forecast horizon h, where the outcome variable of interest is regressed on the contemporaneous shock and relevant controls. Specifically, for each h, we estimate the following equation:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \tau_t + \sum_{l=0}^{L} \beta_l^h \Delta x_{i,t-l} + \sum_{l=1}^{L} \gamma_l \Delta y_{i,t-l} + \epsilon_{i,t+h}, \tag{7}$$

where $y_{i,t}$ is the dynamism variable of interest (e.g., entry employment rates, reallocation, or the high-growth share) for industry i in year t, and $x_{i,t}$ represents the markup variable (both y and x are expressed in logs). Industry fixed effects, α_i, and year fixed effects, τ_t, control for unobserved persistent heterogeneity across industries and macroeconomic shocks. The inclusion of lagged changes in x and y ensures that the regressions control for potential persistence in both shocks and outcomes. The β_0^h coefficient measures the cumulative response of $y_{i,t+h}$ to $\Delta x_{i,t}$, accounting for both immediate and lagged effects of the change in x.

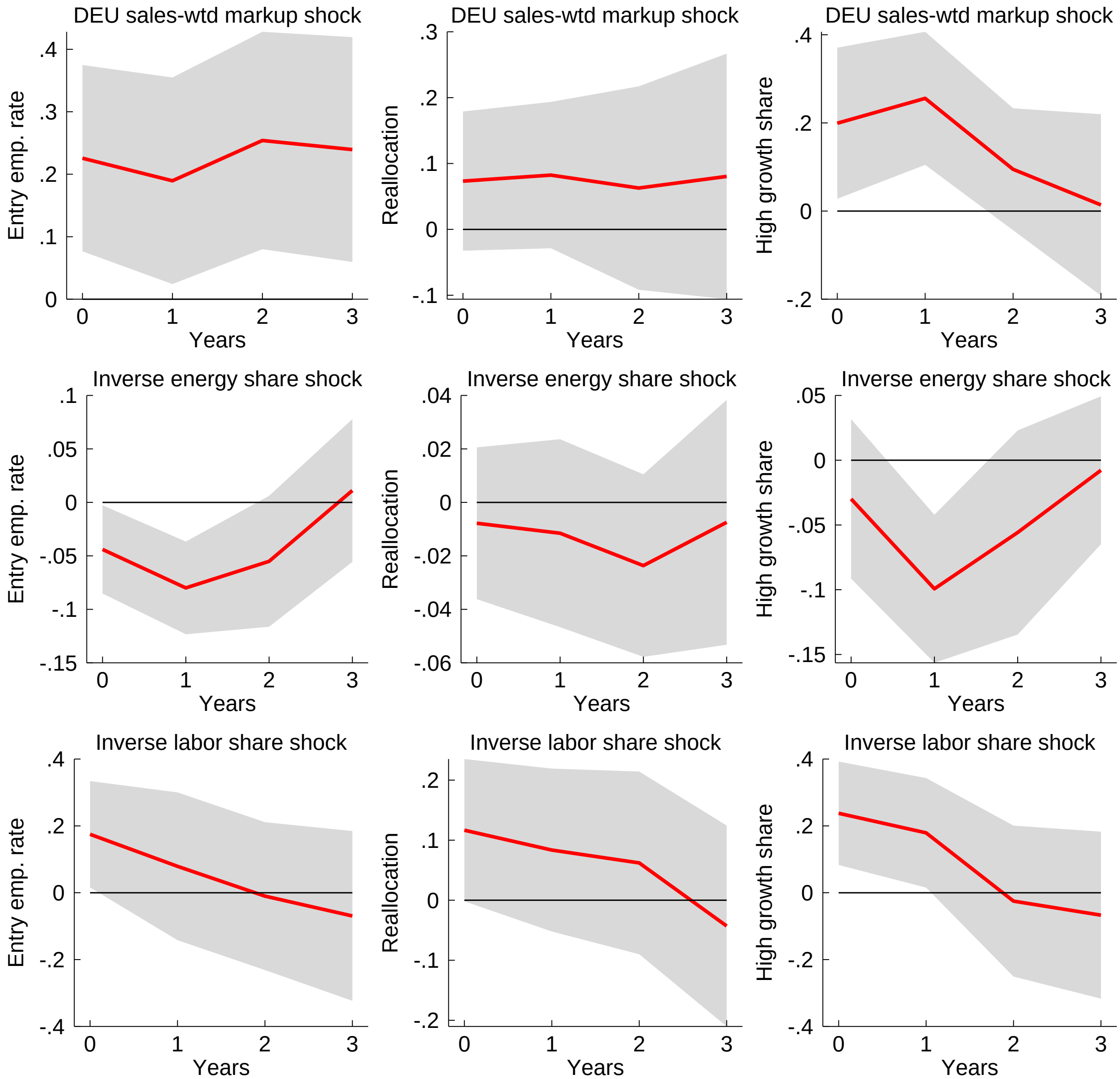
Our local projection explicitly accommodates concurrent effects at $h = 0$, which allow for the immediate impact of shocks, in line with a theory where a shock moves markups and dynamism at the same time (De Loecker, Eeckhout, and Mongey 2022). For our main results, we set the maximum horizon H at 3, balancing our interest in observing as wide a window as practical against the short nature of our time series datasets; we later discuss results for $H = 4$. We set the maximum lag L at 3 but also discuss results for $L = 2$.And our main results feature employment-weighted regressions, consistent with our interest in understanding drivers of aggregate patterns; we explore this specification choice below as well.

Importantly, while impluse response functions (IRFs) resulting from local projection specifications often take on a natural causal interpretation, in our setting we do not claim to be recovering exogenous shocks and causal responses. We employ the local projection methodology and IRFs simply to uncover high-frequency reduced-form comovement of markups and dynamism variables when controlling for persistent industry heterogeneity and aggregate temporal shocks. This allows us to isolate these comovements in a much narrower window than our long difference exercises above and to abstract from prominent sources of variation that could cloud the reduced-form relationship between markups and dynamism.

5.1 Baseline impulse response specifications

The results of the local projections using the KLEMS industry-level data are presented in figure 8, which plots the *cumulative* IRFs of industry-level dynamism measures to markup "shocks". The panels show responses of entry employment rates (first column), reallocation (second column), and the high-growth share (third column) to three markup shocks: DEU sales-weighted markup shocks (first row), inverse energy share shocks (second row), and inverse labor share shocks (third row).

For DEU markups (top row), we generally observe positive responses of dynamism variables to markup shocks, though with varying levels of statistical significance. Inverse



Note: Cumulative impulse response of dynamism variable to markup variable (both in log differences); employment-weighted regressions with industry and year fixed effects and 3 lags. 1988-2019. KLEMS industries.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure 8: Cumulative impulse responses of dynamism measures to DEU markup and cost share shocks, KLEMS industries

energy share shocks (second row) are associated with statistically significant drops in entry rates and high-growth firm shares for the first couple of years, but these responses are quite short-lived (consistent with our long difference results, which find an eventual positive, and often statistically significant, relationship between dynamism and inverse energy shares). Inverse labor share shocks (third row) prompt no significant response of entry employment rates and reallocation, though a borderline statistically significant negative response of high-growth firm shares is detectable for the first couple years.

In the appendix, figure A7 presents a similar variety of KLEMS-based results using alternative markup measures: DEU cost-weighted markups, inverse material share shocks, and inverse variable cost share shocks. With these alternative measures, we still observe largely non-statistically significant results, with some modest exceptions. We also estimate these KLEMS-based IRFs for the simple (unweighted) entry rate, reported in appendix figure A8. The entry rate response to markups is typically positive though not typically statistically significant. Finally, appendix figure A9 reports impulse response functions based on 3-digit NAICS industry codes (and limited to DEU markups), with generally positive and sometimes statistically significant results.[31]

On balance, the IRFs across the two datasets point to statistically minor high-frequency responses of dynamism variables to markups, with little evidence of negative relationships aside from the inverse labor share—which we discussed at length above. In short, we do not observe compelling, widespread negative relationships as posited by theory.

The often positive——though often not statistically significant——relationships we observe between markup shocks and dynamism measures are consistent with a Schumpeterian interpretation of market dynamics. When markup changes reflect quality improvements, they predict future entry and reallocation as followers invest to catch up. This

31. We again limit the 3-digit NAICS-based exercises to our usual time period, 1988-2019. In unreported exercises, we include data starting in 1980, finding no statistically significant impulse response functions.

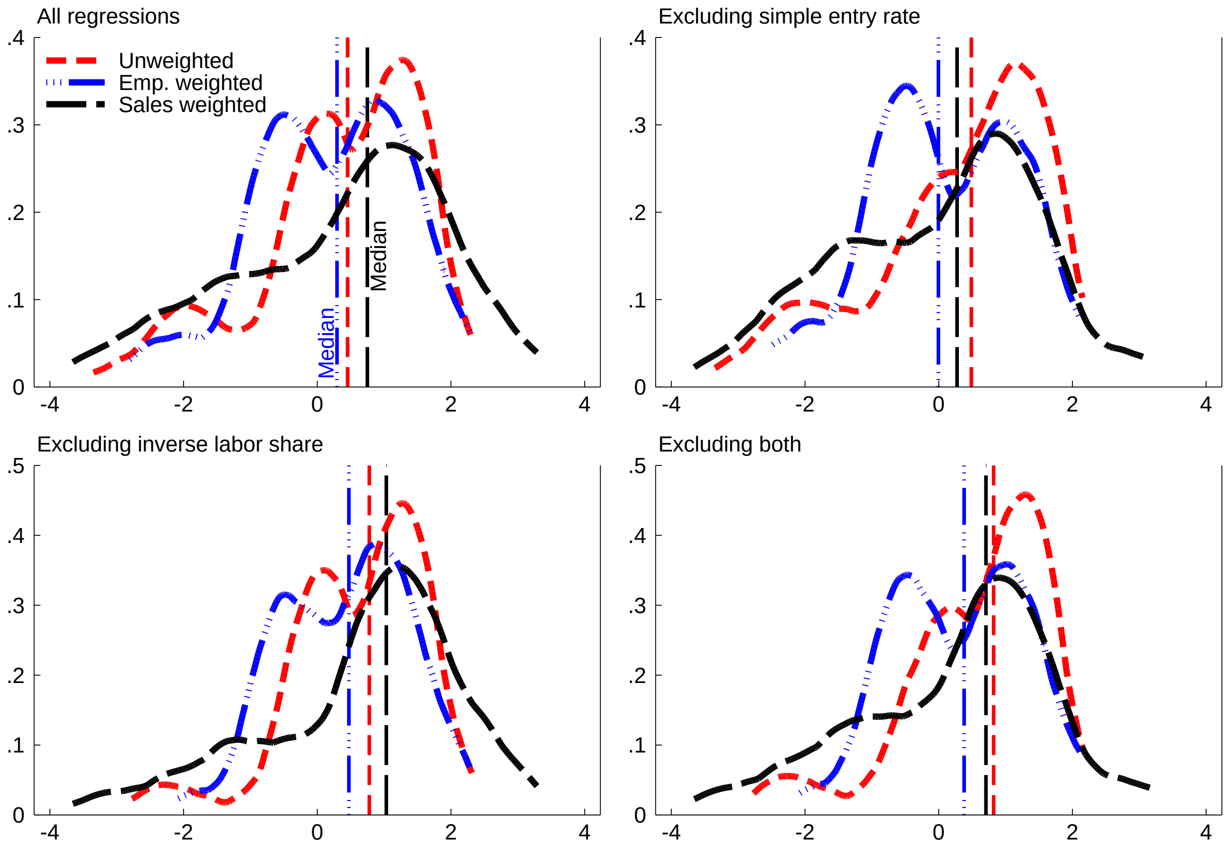
mechanism naturally links higher markups to subsequent entry and reallocation, exactly the pattern suggested by our positive impulse responses. This Schumpeterian framework offers one explanation for why markup increases need not suppress dynamism.

5.2 Alternative specifications

As with our long difference regressions, we estimate these IRFs under a number of alternative specifications beyond those described above. These include:

- With and without year fixed effects.
- Unweighted and real sales-weighted regressions in addition to the employment-weighted regressions of the main results.
- Without allowing contemporaneous effects of markups on dynamism measures (i.e., require the first effect to be lagged one year).
- Extending the maximum lead horizon H to 4 (allowing for a more comprehensive time window of observation).
- Shortening the maximum lag L to 2 (allowing for a slightly longer available dataset coverage period).

Once again we use kernel densities to display the range of outcomes from these many specifications; we focus on the t statistic associated with the IRF coefficient timed at the maximum H horizon ($H = 3$ in our main exercises). That is, we study the range of possibilities for the end-of-window cumulative "effect" of markups on dynamism. Figure 9 reports kernel densities in the same format as figure 5 described above. The top left panel shows the t statistic distributions across all specifications under the three different regression weighting schemes.



Note: Kernel density of t statistics for cumulative response at end of 3 years in two datasets: KLEMS industries with all markup variables (576 estimated models) and 3-digit NAICS industries with DEU markup variables (128 models). Separate densities shown for unweighted regressions, employment-weighted regressions, and sales-weighted regressions. All dynamism variables included. Includes models with and without year effects. Includes models with simultaneous response to markup shocks and one-year lagged response. Vertical lines indicate median t statistic across regressions.
Source: Business Dynamics Statistics, Compustat, and KLEMS.

Figure 9: Kernel density of t statistics from cumulative impulse responses of dynamism measures to markup shocks (horizon H = 3)

The medians of all distributions are slightly positive but close to zero, indicating that the cumulative response of dynamism shocks after 3 years tends to be close to zero. Appendix figure A10 reports the same kind of kernel densities but for the longer cumulative time horizon, $H = 4$. The longer time horizon does result in some distributions shifted slightly to the left, though we still observe medians close to zero with the bulk of each t-statistic distribution lying between -2 and 2.

These annual-frequency results largely corroborate our long-run analyses: there is little or no robust, systematic negative relationship between industry-level markups and dynamism.

Before concluding, we make a short digression: As noted in numerous places above, theories linking dynamism with markups need not feature direct causality from markups to dynamism. A third factor could cause both dynamism to fall and markups to rise. The example from De Loecker, Eeckhout, and Mongey (2022) is a decline in the number of potential entrants, which both reduces entry and, in a Cournot setting, raises markups due to fewer competitors. While we cannot observe the number of potential entrants, we can observe firm counts by industry. In unreported exercises, we estimate impulse response functions of markup measures to firm count shocks. Results are decidedly mixed and heavily dependent on specification, with cumulative effects that are sometimes positive, sometimes negative, and typically not statistically significant. When firm counts are normalized by employment (i.e., firms per employee, the inverse of average firm size), markups often respond negatively to firms per employee, especially in weighted regressions (equivalently, markups respond positively to average firm size shocks). A more thorough investigation of this topic is beyond the scope of this paper but an interesting avenue for further research.

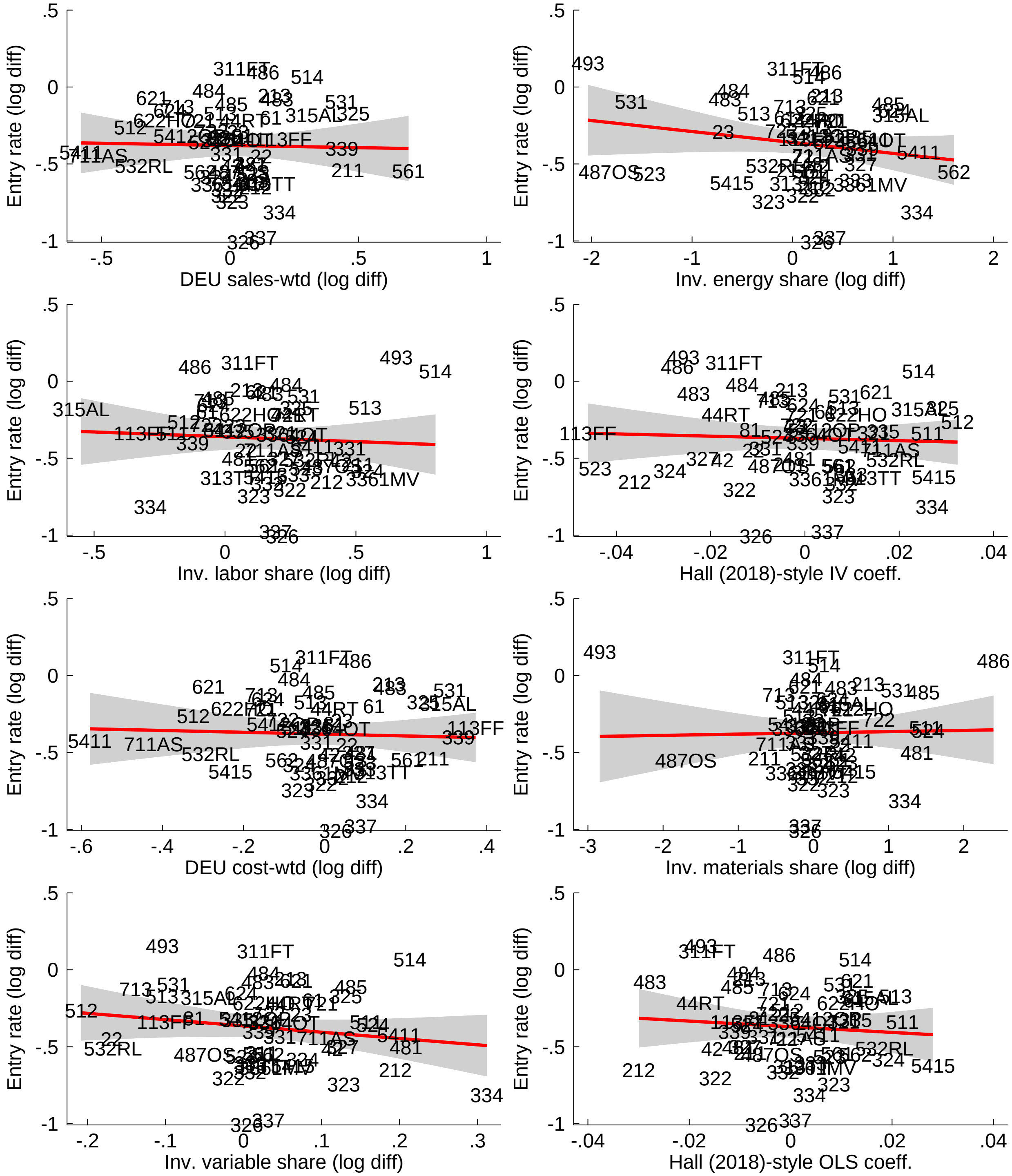
6 Conclusion

Recent literature has argued that aggregate trends of rising markups and declining business dynamism are causally connected. The aggregate approach has been fruitful in bringing attention to macroeconomic implications of market power, but aggregate markups and dynamism variables could comove for any number of reasons (or for spurious reasons). We instead exploit industry-level variation, tying the macroeconomics literature back to a more traditional industrial organization viewpoint in which market power is a market- or industry-level phenomenon related to industry-level business dynamics.

Our analysis employing multiple measures of markups and dynamism, at varying levels of industry detail, and in a range of cross-sectional and time-series specifications, reveals a disconnect between theoretical predictions and empirical evidence at the industry level. We find almost no empirical support for a negative markup/dynamism relationship within industries between the 1980s and late 2010s. In fact, several specifications relating long-run trends in these variables suggest a positive correlation, indicating that industries experiencing larger increases in measured markups often saw smaller declines, or even increases, in various measures of business dynamism. The primary exception to our general result—which appears only in certain specifications—corresponds to markups measured as the simple inverse labor share of sales which, as we discuss in the text, could arise from a number of other factors unrelated to the central motivation of the paper.

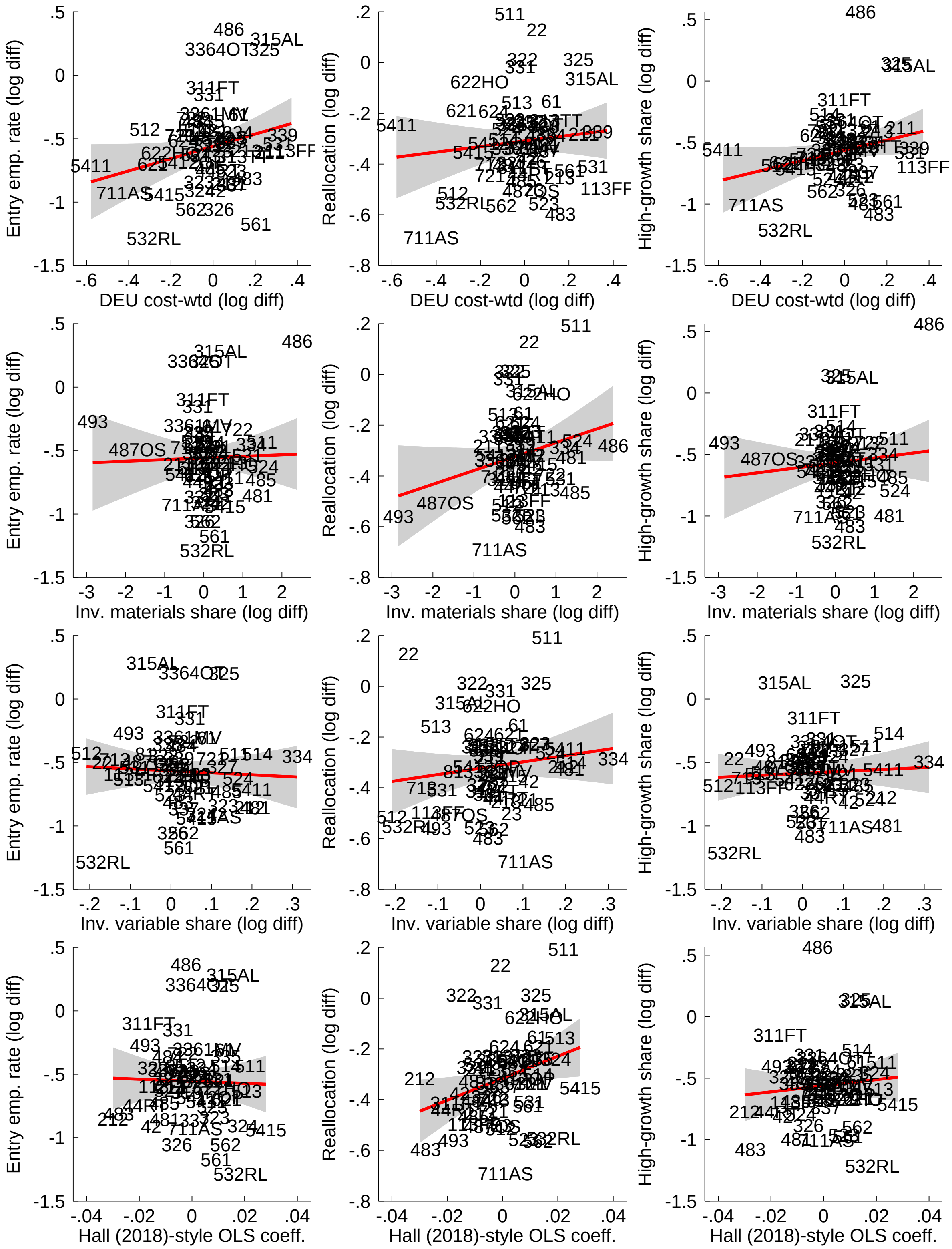
We emphasize that our results are not necessarily causal, and they do not necessarily speak to theories in which market power in one industry is causally related to dynamism in other industries. But our simple, robust result is that the aggregate trends in dynamism and market power have been driven by different industries, and any theory linking these two topics of wide-ranging interest must account for this new fact.

A Appendix



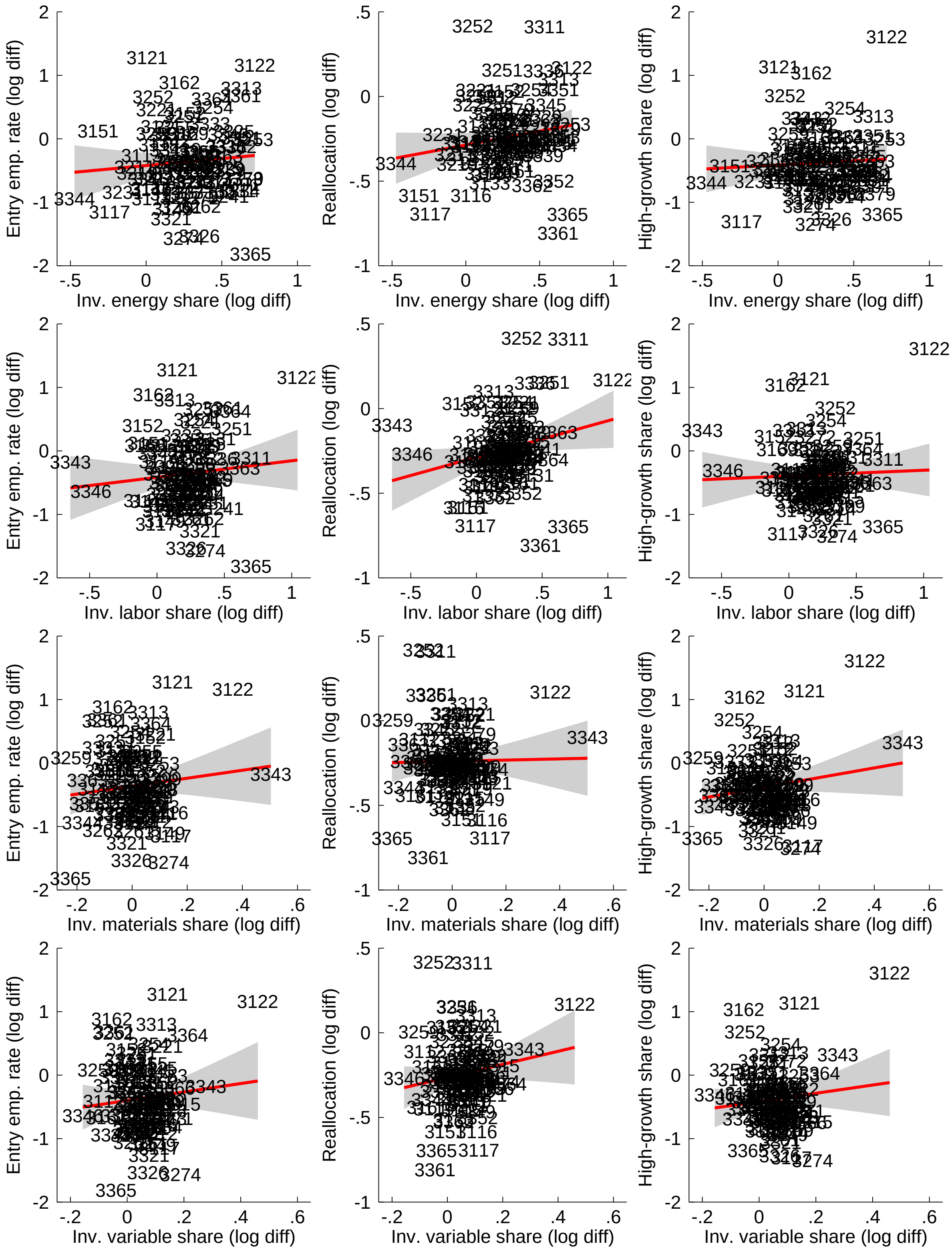
Note: Difference, 2015-2019 average vs. 1988-1992 average except Hall-style coefficents.
Shaded area is 95% confidence interval.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A1: Change in unweighted entry rates and markups, KLEMS industries



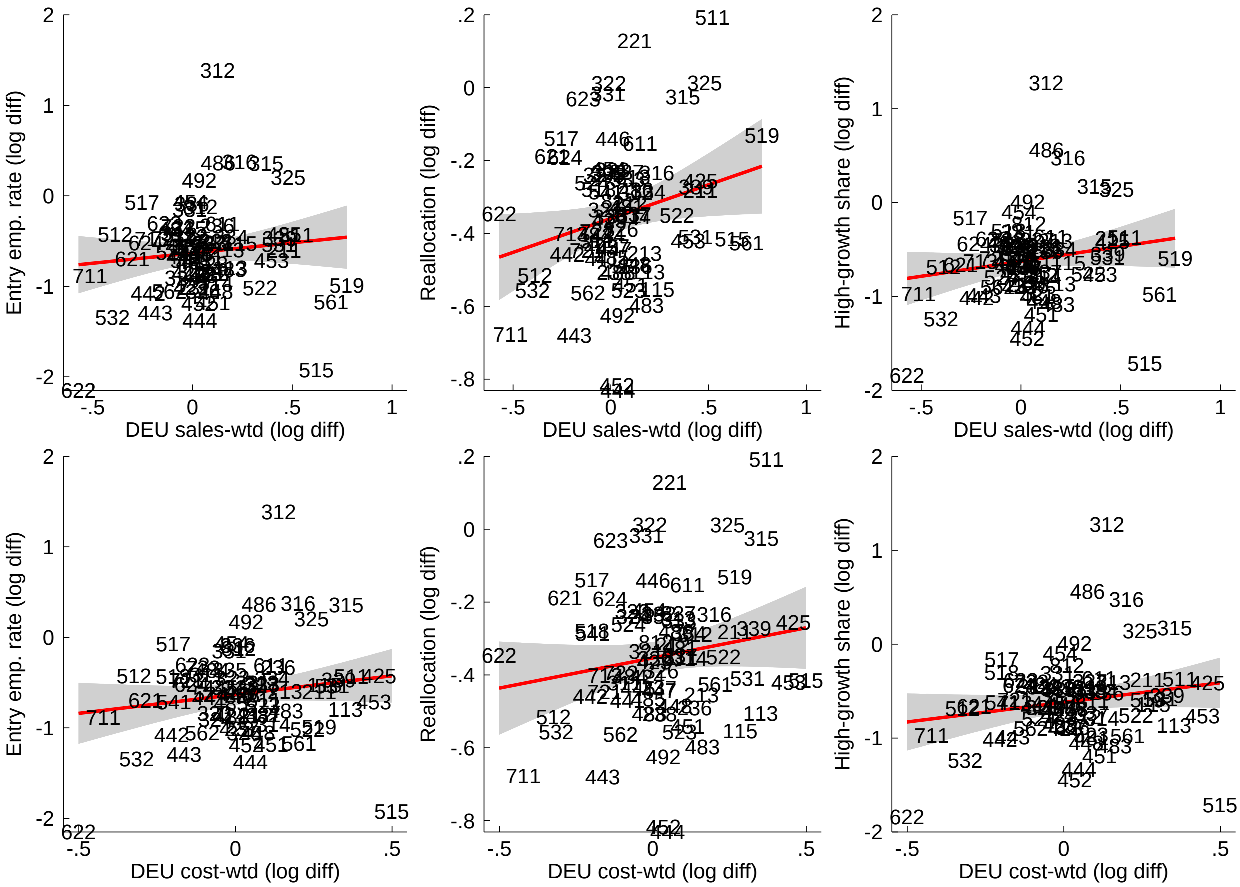
Note: Difference, 2015-2019 average vs. 1988-1992 average except the Hall-style coefficent.
Shaded area is 95% confidence interval.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A2: Change in dynamism and markups, KLEMS industries (alternative markup measures)



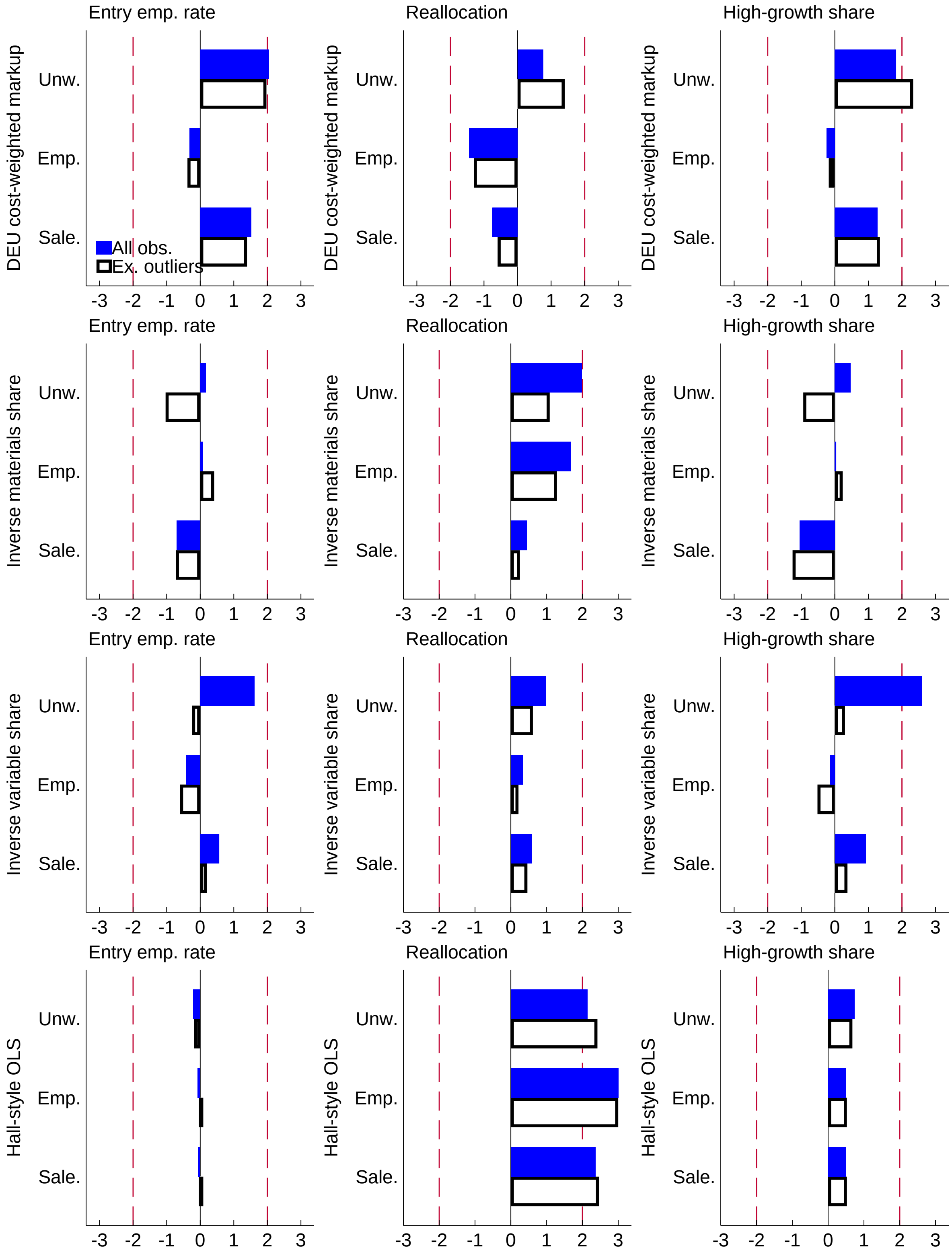
Note: Difference, 2015-2019 average vs. 1988-1992 average.
Shaded area is 95% confidence interval.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A3: Change in dynamism and markups, NBER-CES, 4-digit NAICS industries for manufacturing



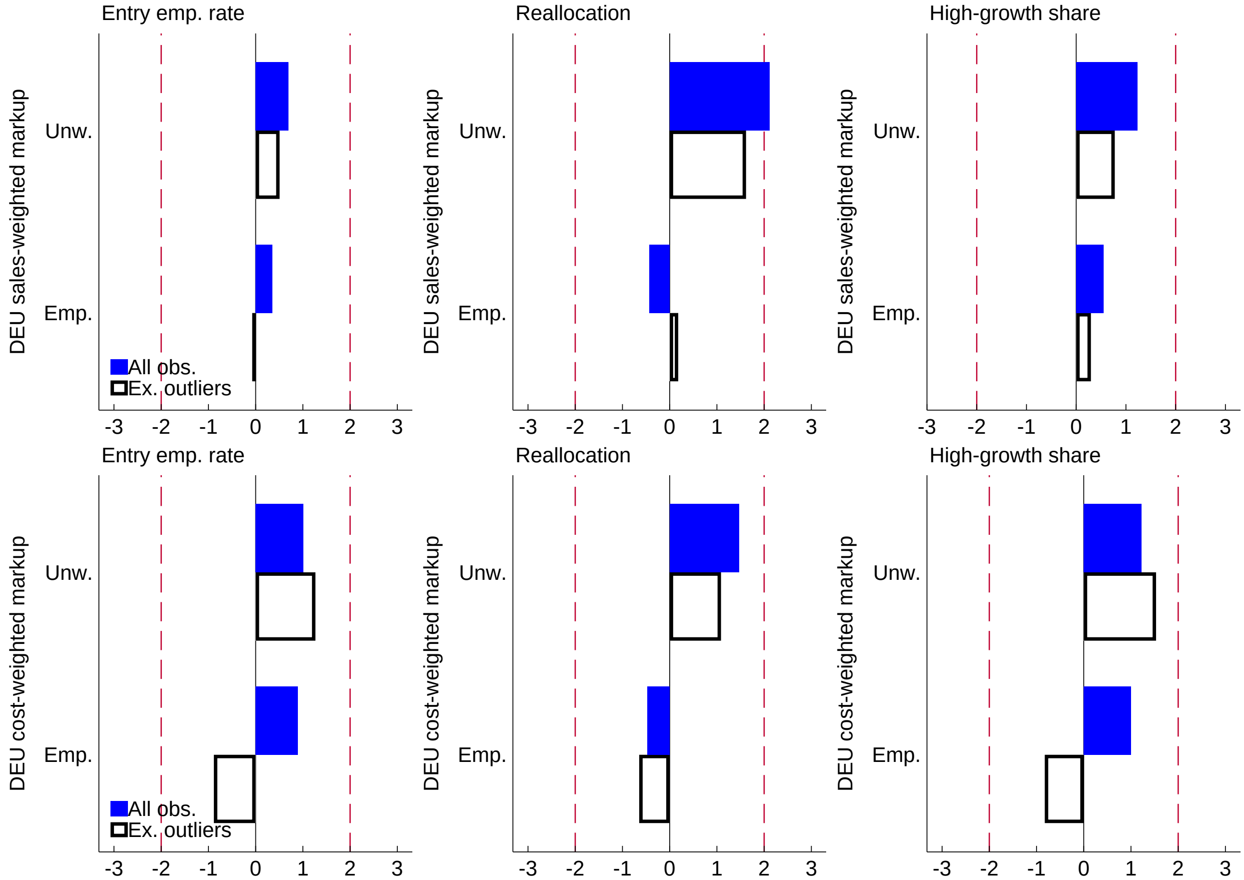
Note: Difference, 2015-2019 average vs. 1988-1992 average.
Shaded area is 95% confidence interval.
Source: Business Dynamics Statistics; Compustat.

Figure A4: Change in dynamism and markups, 3-digit NAICS industries



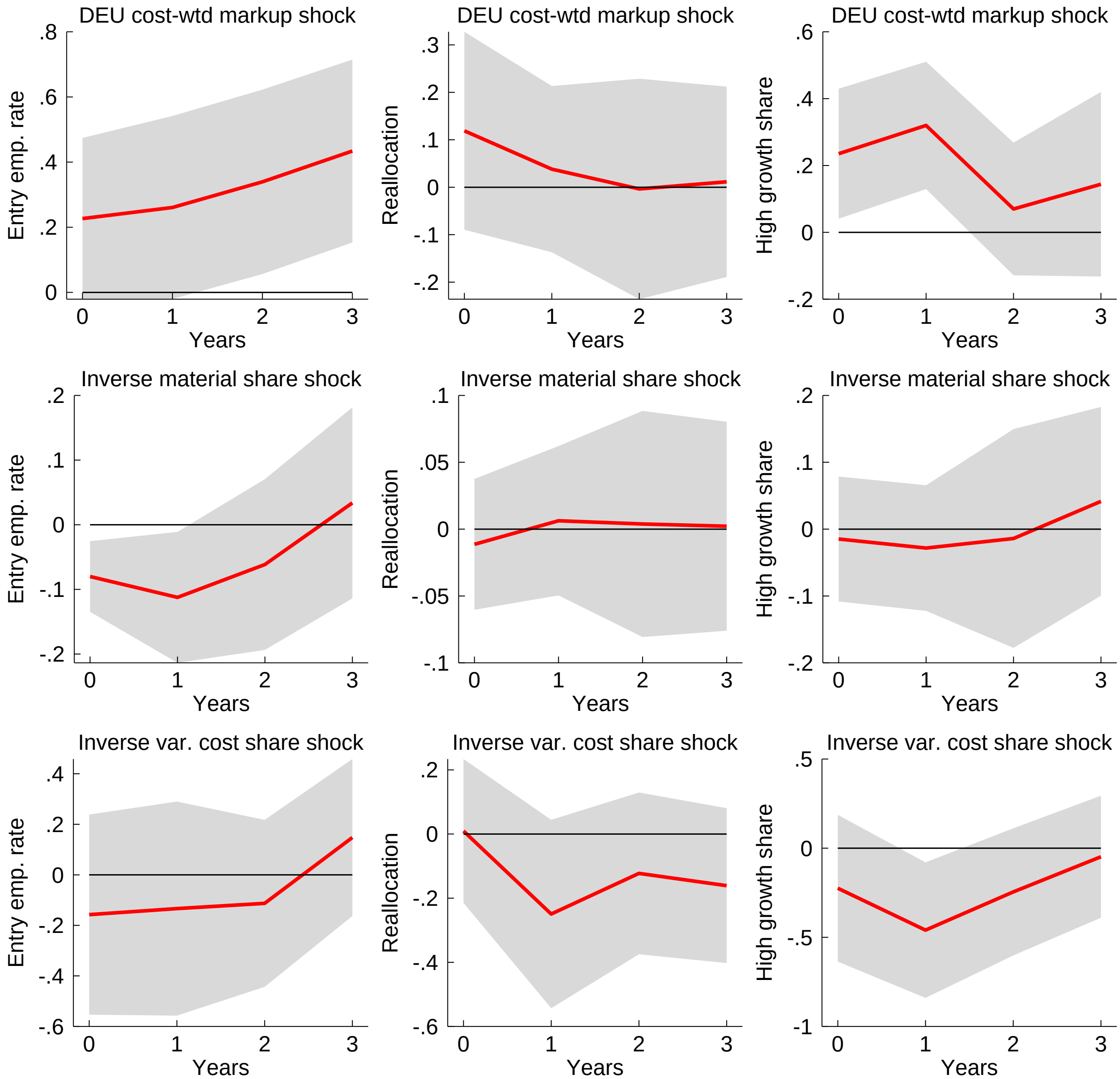
Note: Each panel shows t statistics from unweighted, employment-weighted, and sales-weighted regressions (described in text). t statistics truncated below -3 and above 3. KLEMS industry-level regressions.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A5: Long-run markup vs. dynamism coefficients t statistics, KLEMS industries (alternative markup measures)



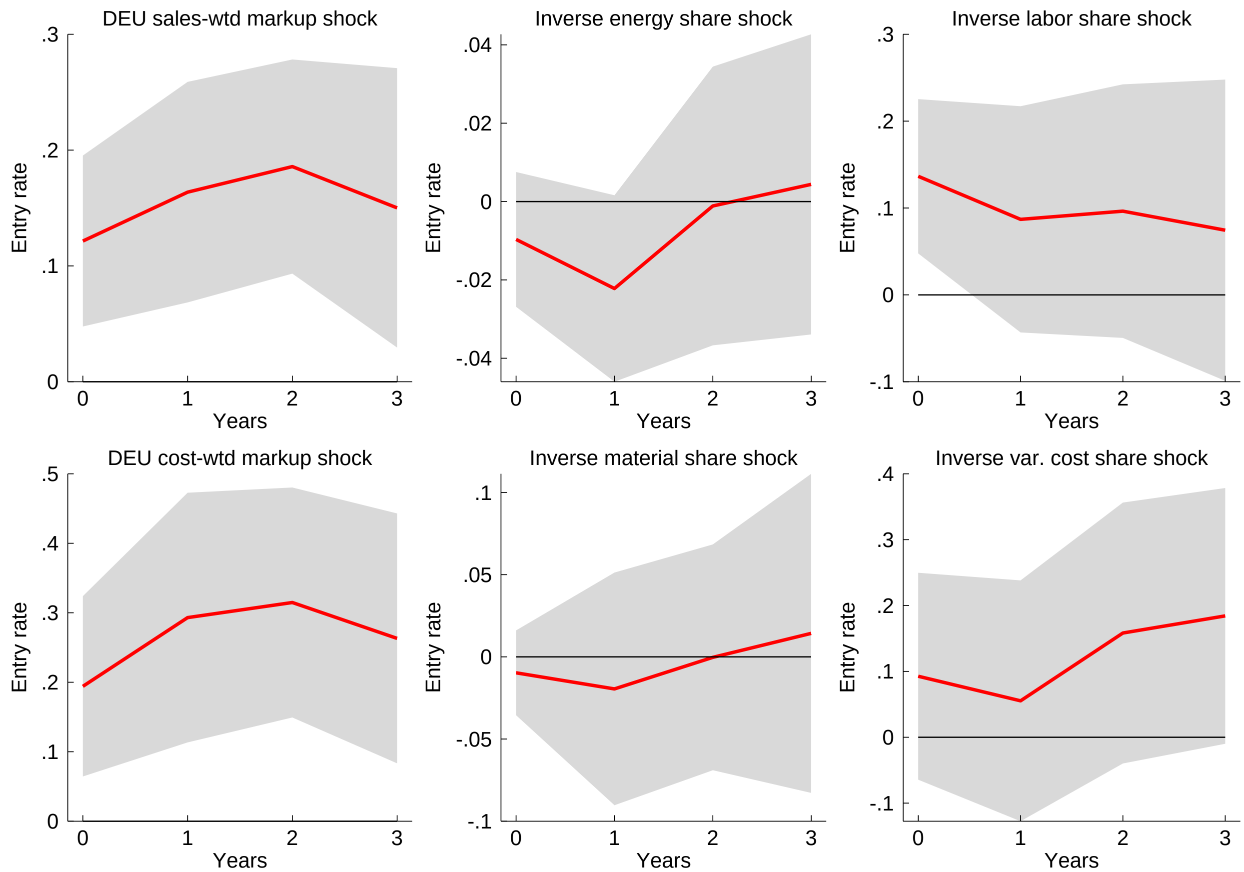
Note: Each panel shows t statistics from unweighted, employment-weighted, and sales-weighted regressions (described in text).
t statistics truncated below -3 and above 3. 3-digit NAICS level regressions.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A6: Long-run markup vs. dynamism coefficients t statistics, 3-digit NAICS industries



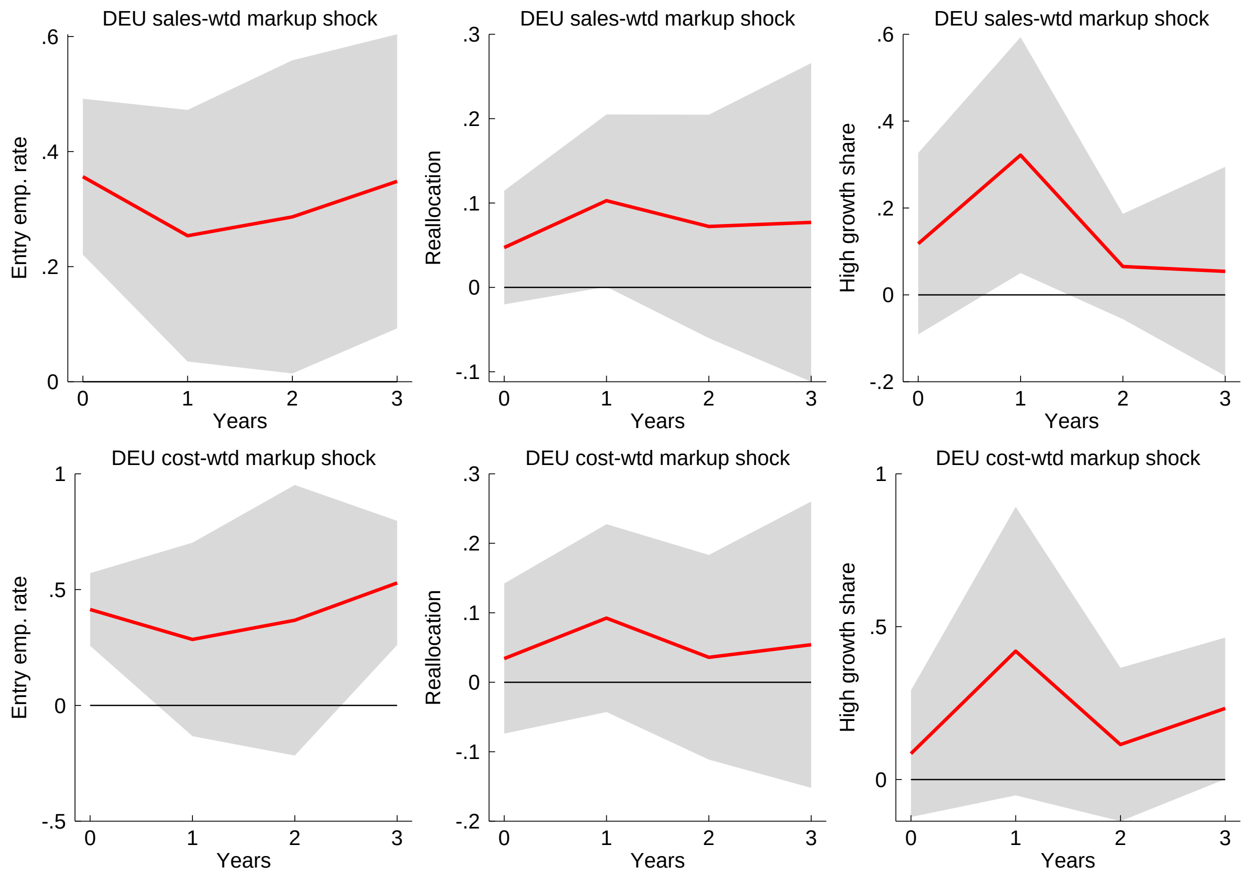
Note: Cumulative impulse response of dynamism variable to markup variable (both in log differences); employment-weighted regressions with industry and year fixed effects and 3 lags. 1988-2019. KLEMS industries.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A7: Cumulative impulse responses of dynamism measures to DEU markup and cost share shocks, KLEMS industries (alternative markup measures)



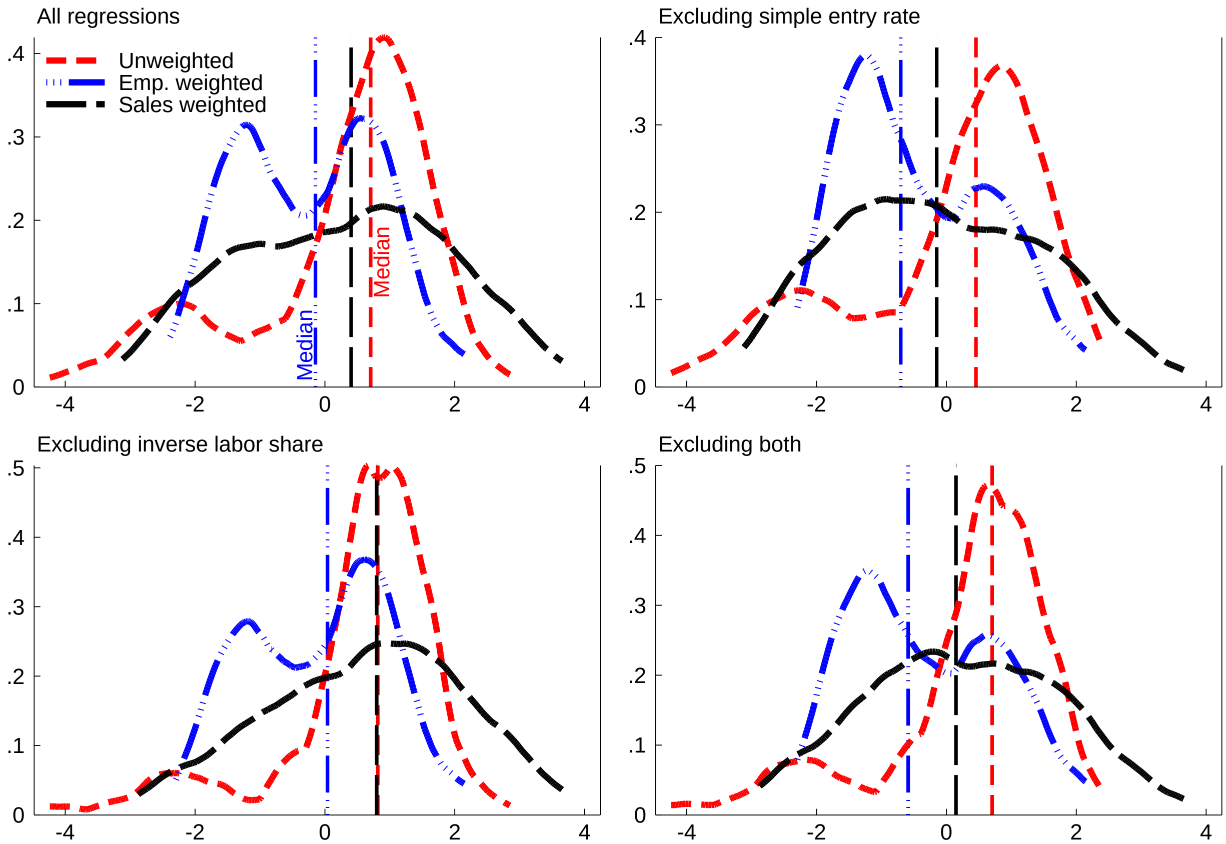
Note: Cumulative impulse response of dynamism variable to markup variable (both in log differences); employment-weighted regressions with industry and year fixed effects and 3 lags. 1988-2019. KLEMS industries.
Source: Business Dynamics Statistics; Compustat; KLEMS.

Figure A8: Cumulative impulse responses of simple (unweighted) entry rate to DEU markup and cost share shocks, KLEMS industries



Note: Cumulative impulse response of dynamism variable to markup variable (both in log differences); employment-weighted regressions with industry and year fixed effects and 3 lags. 1988-2019. 3-digit NAICS industries.
Source: Business Dynamics Statistics; Compustat.

Figure A9: Cumulative impulse responses of dynamism measures to DEU markup shocks, 3-digit NAICS industries



Note: Kernel density of t statistics for cumulative response at end of 4 years in two datasets: KLEMS industries with all markup variables (576 estimated models) and 3-digit NAICS industries with DEU markup variables (128 models). Separate densities shown for unweighted regressions, employment-weighted regressions, and sales-weighted regressions. All dynamism variables included. Includes models with and without year effects. Includes models with simultaneous response to markup shocks and one-year lagged response. Vertical lines indicate median t statistic across regressions.
Source: Business Dynamics Statistics, Compustat, and KLEMS.

Figure A10: Kernel density of t statistics from cumulative impulse responses of dynamism measures to markup shocks (horizon H = 4)

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