Skewed Business Cycles*

Sergio Salgado† Nicholas Bloom‡ Fatih Guvenen§

March 19, 2025

Abstract

Using Census and Compustat firm panel data we show that the skewness of four measures - sales, employment, productivity and stock value growth - are robustly cyclical. Their growth rates display a large negative left tail during recessions and a large positive right tail during expansions. We also see cyclical skewness of these four growth measures across industries and over 46 countries. Contractions display left-skewed growth rates, while expansions see right-skewed growth rates. Using a generic adjustment-cost model we argue these four measures show that recessions are a combination of a negative first moment, a positive second moment and a negative third moment shock to business conditions. Modeling recessions as this multi-moment shock makes it easier to explain large recessions and fit micro-data.

JEL Codes: E3
Keywords: Business cycles, uncertainty, procyclical skewness

*For helpful comments and suggestions we thank seminar participants at the Federal Reserve Board, Central Bank of Chile, The Econometric Society World Congress, CESifo, SED, SITE, Bank of Mexico, Cornell, Columbia, FRB Philadelphia, FRB of New York, Ohio State University, Queen's University, University of Chicago, UCL, UCLA, University of Montreal, University of Michigan, University of Toronto, and Wharton. Part of this research was performed at a Federal Statistical Research Data Center under FSRDC Projects 1694 and 2019. All results based on US Census data have been reviewed to ensure that no confidential information is disclosed. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the US Census. A replication packet for the empirical results of the paper is available at the authors' websites.

†The Wharton School, University of Pennsylvania ssalgado@wharton.upenn.edu
‡Stanford University, SIEPR, and NBER nbloom@stanford.edu
§University of Minnesota, FRB of Minneapolis, and NBER guvenen@umn.edu

1 Introduction

This paper studies the distribution of firm-level shocks over the business cycle. Recessions have classically been characterized as a combination of a negative first-moment (mean) shock and/or a positive second-moment (uncertainty) shock. We argue that recessions are also accompanied by a large negative third-moment (skewness) shock. During downturns a subset of firms does extremely poorly, leading to a left tail of large negative outcomes. At the same, time another subset of firms experiences muted growth rates, compressing the right tail of (positive) outcomes. In this sense, negative skewness captures a combination of elevated "downside risk" and muted "upside surprises." For example, although major disruptions—such as the 9/11 attacks, the Great Recession, or the COVID-19 pandemic—impact all firms, a subset in certain industries (e.g., airlines, automotive or movie theaters respectively) fared much worse. Hence, recessions can be viewed as periods of heightened occurrence of *firm-level disasters*. This is often accompanied by a deceleration of growth for firms at the top end, leading to a compression of the right tail of positive outcomes. The opposite patterns happen during expansions, with the left tail of firm growth shrinking and the right tail expanding, indicating an increase in rapid growth potential. Consequently, the skewness of firms' growth rates is procyclical.

Using firm-level panel data from the Census Bureau, Compustat, Orbis and Global Compustat data on firms from the US and 45 other countries we show that the cross-sectional skewness of four firm-level measures - sales growth, employment growth, productivity growth and stock market value growth - are robustly procyclical. As an illustration of our main empirical result, Figure 1 displays the distribution of firm sales growth from the US Census' Longitudinal Business Database (LBD). The solid line shows the empirical density of firm sales growth from the most recent three recessions: the 2002, the 2008-09 financial crisis, and the 2020 COVID recession. The dashed line shows the density for the expansion years around these recessions, the periods 2003–06, 2010–19. These have both been normalized to a median growth rate of zero. Figure 1 shows that the distribution of firm growth during recessions has a thicker left tail (solid line) than during expansions (dashed line), indicating an increase in dispersion that is mostly coming from the left tail.

This asymmetric change in the distribution of firm growth from expansion to recession years can be quantified using the Kelley skewness (Kelley, 1947), a measure of

skewness that is robust to outliers.[1] For instance, the Kelley skewness of sales growth is 0.10 in expansion years (a positively skewed distribution) and –0.15 in recession years (a negatively skewed distribution). This value of 0.10 for skewness during expansions indicates that 45% of the overall dispersion is accounted for by firms with sales growth below the median, whereas during recessions, a Kelley value of –0.15 indicates that this share increases to about 58%. Similarly, we show that employment growth, productivity growth and stock value growth also all display pro-cyclical skewness across US firms. This is robust to splits of firm size, age, industry and region, and also holds for financial strength splits across debt/assets, interest/earnings and sales growth.

Moving to the four-digit US NAICS industry data level we find a very similar pattern: the *within-industry* skewness of firm-level sales, employment, productivity and stock value growth is strongly correlated with industry growth rates. Finally, we examine data across 46 countries, showing again firm-level sales, employment, productivity and stock-value growth skewness is correlated with GDP growth.

Collectively, these results highlight how recessions are robustly characterized by negative skewness, and expansions by positive skewness of our four measures of firm growth in sales, employment, productivity and stock value. One question, however, is over causality. Is skewed firm growth an endogenous outcome of a negative macro shock, or an exogenous event that helps to drive business cycles? For example, perhaps labor adjustment costs mean that negative demand shocks generate skewed growth rates in hiring or sales (e.g. Caballero and Engel (1993); Davis and Haltiwanger (1992) and Ilut *et al.* (2018))

In the final section of the paper, we take a generic adjustment cost model and show that you need a combination of a negative first moment shock, a positive second moment shock and a negative third moment shock to generate the moments for sales, employment, productivity and stock value growth observed in empirical data. The intuition behind the result is that while some measures - like employment growth - are sensitive to adjustment costs, others like stock value and productivity are not.

A long literature has shown how non-convex fixed adjustment costs can generate Ss investment rules (e.g.), leading to jumps in labor demand. As a result first moment demand or productivity changes can generate second or third moment fluctuations in

[1]Kelley skewness is the difference between the 90th-to-50th percentile differential (a measure of dispersion in the right tail) and the 50th-to-10th percentile differential (a measure of dispersion in the left tail) divided by the difference between the 90th and 10th percentiles (a measure of the total dispersion of the distribution). For a distribution with a compressed upper half and a dispersed lower half, the Kelley skewness is negative (i.e., a left-skewed distribution).

employment levels. This makes it hard to invert employment (or capital) growth to identify the underlying driving process[2]. In contrast, "smooth pasting" optimality conditions mean that even in Ss models value growth closely tracks the underlying driving process (e.g. Dixit 1993). Similarly, if productivity growth is well measured it has a close correspondence to the underlying demand or productivity growth driving process. Hence, we argue that data on all four measures of firm growth - sales, employment, productivity and stock values - enables us to identify the moments of the underlying driving process over the cycle.

This result is important for providing empirical realism to business cycle models. There is a long literature searching for mechanisms that drive, amplify and propagate recessions, arguing that observed first and second moment shocks may not be large enough to account for observed recessions (e.g., Summers *et al.* (1986) or Bloom *et al.* (2018)). A recessionary increase in the skewness of idiosyncratic provides an additional force driving recessions. Thus, we argue modeling recessions as a multi-moment shock makes it easier to both fit micro-data and also explain large recessions.

Contribution to the literature. This paper is related to four strands of literature.

First, our paper relates to the study of the effects of uncertainty on firms' decisions. Several papers have shown that an increase in uncertainty can have important macroeconomic implications in the presence of adjustment costs, risk aversion, or financial frictions, although there is still an active debate about the size and potential duration of the drop (see, for instance, Jurado *et al.* (2015), Ludvigson *et al.* (2021), and Bachmann *et al.* (2013)).[3] Our results are complementary to this literature as we show that the rise in the dispersion of firms' outcomes—a standard measure of uncertainty—results from a widening left tail and compressing right tail.

Second, several authors have suggested that rare disasters—presumably arising from an asymmetric distribution of shocks—can generate large fluctuations in economic activity, such as the Great Recession. Reviving the ideas introduced first by Rietz (1988), Barro (2006) considers a panel of countries to estimate the probability of large macroeco-

[2]This non invertability with adjustment fixed-costs is why Olley and Pakes (1996) rules out fixed-costs in their productivity estimator. They note that with fixed-costs you cannot invert investment rates to determine productivity shocks.

[3]Other important papers in the literature are Arellano *et al.* (2018), Fernandez-Villaverde *et al.* (2011), Schaal (2017), Bachmann and Bayer (2014), Gilchrist *et al.* (2014), Jurado *et al.* (2015), Leduc and Liu (2016), Basu and Bundick (2017), Berger *et al.* (2017), Kozeniauskas *et al.* (2018), Bloom *et al.* (2018), Bachmann *et al.* (2017). See also Bloom (2014) and Fernández-Villaverde and Guerrón-Quintana (2020) for recent surveys.

nomic disasters and shows that these low-probability events can have substantial implications for aggregate economic activity and asset pricing. Several papers have confirmed the importance of fluctuations in disaster risk for aggregate economic activity.[4] The results of our paper can be seen as evidence that rare disasters also occur at the microeconomic level, and because firms are not typically perfectly insured against microeconomic risk, these firm-level disasters have large economic effects.

Third, our paper also contributes to a growing literature that studies the cyclical patterns of micro-skewness in individual labor earnings risk (e.g., Guvenen *et al.* (2014), Harmenberg and Sievertsen (2017), and Busch *et al.* (2022)), firm productivity (Kehrig, 2011), employment and sales growth (e.g., Davis and Haltiwanger (1992), Decker *et al.* (2015), among others), stock returns (e.g., Harvey and Siddique (2000), Oh and Wachter (2018), and Ferreira (2018), and several others), and option-implied skewness (e.g., Bollerslev and Todorov (2011), Conrad *et al.* (2013), an more recently Dew-Becker (2022)).[5] An older literature by Higson *et al.* (2002), Higson *et al.* (2004) and Döpke *et al.* (2005) document a counter-cyclical patterns of firm sales growth skewness using data from publicly traded firms in the US, the UK, and Germany respectively. This analysis, however, drops firms outside certain growth thresholds—for example, firms with sales changes outside $\pm 25\%$ in Higson *et al.* (2002)—which leads to highly cyclically sample selection, which reverses the underlying procyclical skewness in the full data set. It also typically focuses on only one or two measures of firm growth - usually employment or sales - which we argue due to lumpy adjustment costs may not reliable indicators of the underlying driving process.

Finally, another set of papers highlights the mapping from third-moment shocks to the driving process. Dew-Becker (2022) uses data from publicly traded firms to show that the firm-level option implied (i.e., forward-looking) skewness is procyclical, consistent with our results on value growth. Ilut *et al.* (2018) focus on employment in large US manufacturing plants from 1972–2011, finding that employment growth skewness is procyclical but negative. Bachmann *et al.* (2017) use German firm-level data on investment expectations, finding investment innovations are acyclical. Our model highlights how non-convex adjustment costs can impact the relationship between the driving process and control processes like hiring and investment, making these results harder to map

[4] See, for instance, Gabaix (2008, 2012), Gourio (2008, 2012, 2013), Wachter (2013), Kilic and Wachter (2015), Kozlowski *et al.* (2018, 2016), Venkateswaran *et al.* (2015), and Jordà *et al.* (2020).

[5] We also relate to the vast literature on the asymmetric behavior of the business cycle at the macro level (e.g., Colacito *et al.* (2016); McKay and Reis (2008); Veldkamp (2005); Segal *et al.* (2015) and several others), that tend to show sharp declines during recessions and slow recoveries during expansions.

back to productivity or demand growth moments.

The rest of the paper is organized as follows. Section 2 describes the data we use and the statistics discussed in the empirical section. Section 3 shows the main empirical results of our paper, that is, that the skewness of several firm-level outcomes and productivity shocks is procyclical. Section 4 describes a simple model to account for the empirical evidence. Section 5 summarizes our results.

2 Data and Measurement

2.1 Data and Sample Selection

Our analysis is based on five large datasets that encompass firm- and establishment-level information for the United States and for a combined sample of 46 other countries.[6] The breadth of our dataset allows us to provide a detailed description of the cyclical patterns of the distribution of the growth rate of firm-level outcomes and firm productivity.

First, we extract panel data on firm employment and sales from the US Census Bureau's LBD. The LBD provides high-quality measures of employment, wage bill, industry, and age for the entire US non-farm private sector, linked over time at the establishment level from 1976 to 2021. Skewness measures are extremely sensitive to outliers, so having several million observations per year for the aggregate sample, and for sub-sample cuts by age, size, industry, and other observables is critical. Starting in 1998, the LBD also contains information on firm-level revenues which we also use in our analysis (Haltiwanger *et al.*, 2019).[7] From the LBD, we calculate cross-sectional moments of the distribution of employment and sales growth within narrow firm population groups. The LBD contains over six million firms per year which, for measuring higher-order moments like skewness, is a major advantage. For consistency across datasets, and because our primary unit of analysis is the firm, we aggregate establishment data up to the US firm level.

Second, we obtain data on employment, revenues, capacity utilization, and productivity for a panel of manufacturing establishments by combining information from three Census data sets, the Census of Manufacturing (CM), the Annual Survey of Manufactures (ASM), and the Quarterly Survey of Plant Capacity Utilization (QPC), covering

[6] Table B.2 in Appendix B.4 shows the list of countries in our dataset.

[7] The revenue data at Census is collected at the firm-level and is available from 1998 to 2018. Approximately 30 percent of firms that have employment information but do not have revenue information. A significant fraction of these firms (about 25%) are in the NAIC 81 code (Other Services). The cross-sectional moments for the employment growth distribution do not change when we focus in the sample of firms that have employment and revenue data. See Haltiwanger *et al.* (2016) for additional details on this data.

years from 1976 to 2021. From the merged dataset, we select establishments with at least ten years of non-missing, non-negative observations on employment and sales which, by the ASM methodology, oversamples larger establishments (and thus, implicitly, larger firms). We use this dataset to construct measures for firm-level (revenue) productivity and corresponding cross-sectional moments of the distribution of productivity shocks.

Third, we draw panel data of publicly traded firms from Compustat. Although this dataset contains mostly large established firms, it provides several additional variables that are helpful in our analysis. In particular, we use data on quarterly and annual sales, annual employment, and daily stock prices from 1970 to 2024, and we restrict attention to a sample of firms with more than ten years of data to reduce the types of compositional issues identified in Davis *et al.* (2006). Finally, by providing data on firms' entire global sales and employment—rather than just the US component in the Census—we can confirm that skewness of growth rates also pertains in firms' global sales, employment, and productivity data.[8]

Fourth, we study whether the patterns we document for the United States are also observed in other both developed and developing. To that end, we use cross-country firm-level panel data on publicly traded firms containing sales and employment information between 1986 and 2018 from the Osiris dataset collected by Bureau van Dijk (BvD). In order to maintain homogeneous sampling criteria, we only consider firms with ten or more years of data. Additionally, we restrict our sample to country-year bins with more than one hundred firms. Our main results are based on an unbalanced panel of firms spanning 42 countries from 1984 to 2018. We complement this dataset with information on firm-level stock prices obtained from the Global Compustat dataset. Applying similar selection criteria, we obtain a sample of daily stock price information for firms in 29 countries from 1985 to 2020.

Finally, we obtain firm-level panel data from the Amadeus dataset also collected by the BvD. This dataset comprises a smaller sample of countries, for a shorter timespan, but with rich firm-level information for small and large firms, both publicly traded and privately held. In particular, Amadeus provides information on sales, employment, value added, capital, and labor input cost so that we can estimate firm-level TFP. Our sample contains information for 12 European countries starting in the mid 1990s.[9] All com-

[8]This is important because many large US firms have substantial activity outside the US, engaging in transfer pricing to shift activity (and profits) across borders, which could potentially be cyclical.

[9]Table A.1 in the Appendix summarizes the data sources and provides basic sample statistics for each of datasets we use in our analysis. Appendix Table B.2 shows a list of the countries we consider in our analysis and the data available for each of them.

bined, our dataset spans 46 countries. Additional details on data construction, sample selection criteria, and moment calculation for each dataset used in our analysis can be found in Appendix B. A full replication packet for the empirical results of the paper can downloaded from the authors' website.

Measuring Dispersion and Skewness. To minimize the impact of outliers, we measure the growth rate of firm-level outcomes, such as employment, sales, and revenue per worker, by the arc-percent change between period t and $t+k$, defined as $2 \times (x_{t+k} - x_t) \,/\, (x_{t+k} + x_t)$. This measure is bounded between –2, in the case a firm exits the market, and 2, in the case a firm enters the market. Returns instead are computed as the percentage change of prices within a calendar year.

To further control for potential outliers, we measure dispersion and skewness using quantile-based measures. As we shall see, they also have magnitudes that are easy to interpret. Our measure of dispersion is the 90th to 10th percentiles differential, denoted by $P9010_t$, where t is a quarter or a year depending on the dataset. Additionally, we use the 90th to 50th percentiles differential, $P9050_t$, and the 50th to 10th percentiles differential, $P5010_t$, as measures of dispersion in the right and left tails, respectively. Finally, our preferred measure of skewness is the Kelley skewness (Kelley, 1947), which is defined as

$$KSK_t = \underbrace{\frac{P9050_t}{P9010_t}}_{\text{Right Tail Share}} - \underbrace{\frac{P5010_t}{P9010_t}}_{\text{Left Tail Share}} \in [-1, 1]. \tag{1}$$

This measure is useful as it provides a simple decomposition of the share of total dispersion that is accounted for by the left and the right tails of a distribution. A negative value of Kelley skewness indicates that the left tail accounts for more than one-half of the total dispersion and the distribution is negatively skewed, and vice versa for a positive value. Notice also that the Kelley skewness is invariant to 20 percent of the observations in the sample (the top and bottom 10 percent of the distribution are not considered). In principle, the Kelley skewness can be computed using any two symmetric percentiles, such as the 95th and 5th or 97.5th and 2.5th percentiles. Our results are robust to these choices and to using the third standardized moment.

3 Skewness over the Business Cycle

In this section, we show that firm employment and sales growth is positively skewed during expansions and negatively skewed during recessions in the United States (Section 3.1), across firms characteristics (Section 3.1.1), within industries (Section 3.2), and across several countries (Section 3.3).

3.1 US Macro Evidence

The first contribution of our paper is to show that the skewness of the growth rates of firm-level outcomes varies over the business cycle Top panels show the distribution of sales growth and employment growth. As in Figure 1, we plot the distribution for recessions and expansions, both of them adjusted to have the same median, so the densities overlap. It is clear that relative to expansions, recessions display a a more dispersed distribution of firm growth but also negative skewness, with a left tail that is thicker. The right tail instead does not show significant changes. The bottom two panels of Figure 2 show two additional variables that are closer to the underlying exogenous process that affects firm profitability, namely, revenue per worker growth and firm annual returns. Similarly to what is observed for sales and employment, the skewness of these variables is procyclical, declining significantly during recessions, mostly coming from a left tail that expands.

Simple time series analysis show this point more clearly. Table 1 shows a series of regressions where the left hand side is the skewness of the growth rate our four main variables against the annual growth rate of GDP, which has been standardized to have a variance equal to 1 to better comparison. As expected, the skewness of all variables strongly commove with the business cycle, including firm productivity and returns. In the following section we expand on these results to show that hold across firms with different characteristics. different industries, and countries.

3.1.1 Firms Size, Age, Industry, and Region

How does the cyclicality of skewness vary across firms characteristics? It is well-known, for instance, that small and young firms account for an oversized fraction of employment growth in the economy (Haltiwanger *et al.*, 2016) and are the most cyclical (Fort *et al.*, 2013). If that is the case, one would expect these firms to show a different cyclicality pattern in skewness relative to large, well-established firms. Similarly, some sectors might be more responsive than others to economic fluctuations, perhaps driving the aggregate changes in the skewness of firms' growth rates that we find. To answer these questions, we start by exploiting the large LBD sample size to divide firms into narrow population groups. Perhaps surprisingly, we find that distribution of firm growth shows similarly cyclical patterns, irrespective of the industry, size, age, or other characteristics of the firm.

The top-left panel of Figure 3 shows that the skewness of employment growth is procyclical within firm-size groups.[10] Quantitatively, the skewness of employment growth

[10] To avoid contemporaneous correlation between growth and firm-size classification we classify firms

declines almost the same during recessions, whether we look at small and medium size firms of less than 50 or if we look at large firms with 1,000 workers or more. We also find that skewness is similarly procyclical between young and old firms, as shown in the top right panel, within different industries or regions, indicating that this phenomenon is wide spread and perhaps independent of firm fixed characteristics.

Alternatively, one might expect that the response of firms to shocks might be state-dependent, with more vulnerable firms being more responsive to changes in business conditions. For instance, financially constrained firms might be more exposed to large declines in employment or sales growth during recessions, hence accounting for the changes we observe in the data. The explore this possibility, we use data from Compustat (balance sheet data is not available for the population of firms in LBD) to evaluate whether firms that are more financially constrained display larger procyclical fluctuations in skewness of firms growth relative to firms that are less constrained. We measure how financially constrained a firm is in two ways: (i) by lagged average debt-to-asset ratio and by the lagged average interest to EBIT ratio.[11] Then within each year, we separate firms into two groups—above and below median—of the lagged measure of financial constraint and calculate the within-group skewness of sales and employment growth. The results are shown in the top panels of Figure 4. Although there is some heterogeneity across firms, the skewness of sales growth is procyclical for both types of firms, regardless of how constrained they are. We conclude that differences in access to credit across firms is not likely to be the main driver of the cyclical patterns observed in the skewness of firm-level growth.

Another possibility is that firms with poorer past performance are more likely to experience large negative drops in employment and sales once there is an aggregate shock (e.g., brick-and-mortar retailers doing poorly before the Covid pandemic might have experienced even larger declines in sales during the recession), hence explaining the negative change in skewness observed during recessions. To see if this is the case, we sort firms by their lagged average growth and calculate the skewness of sales growth within firms above and below the median of (past) sales growth. Although there are some differences in the *levels* of skewness between high- and low-growth firms, the bottom

by lagged employment since firms' growth is calculated between periods t and $t+1$. Results for sales growth using LBD data are shown in Appendix Figure **??** albeit for shorter sample period.

[11] More precisely, we calculate the leverage of firm j in period t as long-term debt plus current liabilities divided by the total value of assets and the interest to EBIT ratio as total interest expenses divided by EBIT. For each of these measures, we calculate the lagged average value as $\overline{x}_{jt} = 0.5 \times (x_{j,t-1} + x_{j,t-2})$. We use a lagged value of leverage to reduce concerns about endogeneity between the measure of financial conditions and firms' growth.

panel of Figure 4 shows that the skewness is similarly procyclical, dropping in recessions in a very similar fashion for both groups.[12] These results indicate that the changes in the distribution of firm growth rates that are observed during a typical recession are not associated with a particular firm characteristic, such as size, age, leverage, or recent growth rates. As we show in the following section, these results are also robust across different industries and countries.

3.2 US Industry Evidence

We also examine within-industry business cycles and skewness. This analysis both provides more variation in our core US data and also confirms that our aggregate growth-skewness relationships are not driven entirely by macro-factors like monetary or fiscal conditions. To do this, we take our US Census data and divide it into about 280, 4-digit NAICS sectors, and within each sector generate the annual Kelley skewness of firm growth rates and the average firm-level sales growth rates, so as to measure the aggregate conditions within the sector.

This is plotted in Figure 5. We see a strong upward slope: industries with higher-than-average mean sales growth rates also have significantly more positively skewed sales and employment growth rates. In terms of magnitudes, the top left panel of Figure 5 shows that when the average industry sales growth is –0.08, the Kelley skewness is around –0.1, indicating that 55% of the total dispersion in sales growth within an industry is accounted for by the left tail of the distribution. In contrast, when the average sales growth is 0.08, Kelley skewness is 0.10, so now it is the right tail that accounts for about 55% of the total dispersion. The effects for employment growth are even stronger, as shown in the right panel.

Sales and employment growth, however, depend on the shocks firms experience and their responses to these shocks. Industry-level information, however, allows us to look more closely to variations in productivity. In particular, we use data for a sample of manufacturing establishments in the United States that combines records from the Census of Manufacturing and the Annual Survey of Manufacturing from 1976 to 2019. The Census Bureau also provides a readily available measure of establishment-level productivity, which we use in our analysis (Foster *et al.*, 2016; Cunningham *et al.*, 2021).[13] It is well known, however, that standard measures of productivity (such as the one provided

[12] We find the same results using Census LBD data for employment and revenue growth.

[13] Since we do not have separated data on prices and quantities, our measure of productivity contain variation in physical productivity and demand, i.e., we measure revenue total factor productivity as in Foster *et al.* (2008).

by Census) might be affected by changes in capacity utilization (Basu, 1996). Intuitively, after a negative aggregate shock, firms might reduce the number of hours worked or the intensity of their equipment use, which might give the impression of a decline in productivity if not properly accounted for. If this response is heterogenous across firms, it might also lead to changes in the measured variance and skewness of firm-level growth.

To control for such changes, we regress firm productivity on the number of hours worked in the firm and electricity use—common capacity measures—and use the residual as our firm-level productivity cleansed from capacity effects.[14] We then obtain a measure of firms' productivity shocks, denoted by $\varepsilon_{i,t}$, from the residual of the following firm-level panel regression,

$$z_{i,t} = \beta_0 + \beta_1 z_{i,t-1} + \mu_i + \delta_t + \varepsilon_{i,t},$$

where $z_{i,t}$ is the log-productivity of establishment i in year t, μ_i is a firm fixed effect, and δ_t is a year fixed effect. We then calculate different moments of the distribution of $\hat{\varepsilon}_{i,t}$ within an industry-year bin. Because Census data only contains information about manufacturing establishments, here we divide our sample into 4-digit NAICS cells within a year, and we calculate the mean and the Kelley skewness of the productivity shock within each bin. As the bottom-left panel of Figure 5 shows, the skewness of firms' shocks is negative in industries experiencing average sales declines.

Second, we examine data on stock returns, which like productivity, is another measure proxying the productivity and demand shocks hitting firms. The bottom right panel plots the stock returns at the NAICS 2-digit level for Compustat firms against their average sales growth rates. We see that in industries with positive sales growth rates that stock returns have right-skewed stock returns and in industries with negative growth rates stock returns have a left-skewed distribution.

These industry level results are also confirmed in Table 2, which display a series of industry panel regressions in which the dependent variable is the Kelley skewness of the growth of employment, sales, productivity, and stock returns within an industry-year cell, and the explanatory variable is industry-level sales growth rates. The results in this case are based on a sample of large publicly traded firms from Compustat, which allows us to cover a longer time span. In all cases, we find that periods of high sales growth are periods in which the skewness of firm growth is significantly positive. Confirming the results in Figure 5, sales and employment skewness are more responsive to within-industry business conditions and productivity (as measure by revenue per worker or TFP

[14] Our skewness results are not sensitive to this cleaning: the previous version of this paper (Salgado *et al.*, 2019) reports similar results which are not cleansed on capacity measures.

growth) or returns. Importantly, as shown in the bottom rows of Table 2, the average skewness of firms' employment and sales growth is positive and becomes negative in industry recessions, defined here as years in which the within-industry growth is negative. The results are qualitatively similar for stock returns.

3.3 Cross-Country Evidence

The second contribution of our paper is to investigate firm skewness in 46 other countries that are geographically and economically diverse, spreading over five continents including high-income countries (such as Germany, Japan, or France) and middle-income countries (such as Peru, Egypt, or Thailand).

Figure 5 shows bin scatters for four different country-by-year firm-level skewness measures against a within-country measure of the business cycle.[15] The top panels show the Kelley skewness of the firm sales and employment growth against country GDP growth rates, revealing a strongly positive relationship similar to the one we find across industries. As with other firm-level growth measures, we also find that the skewness of TFP shocks is procyclical across different countries. In this case, we use firm-level data for a sample of European countries obtained from the Amadeus dataset collected by the BvD for which we have rich enough information to measure firm-level (revenue) TFP shocks, again indicating a positive association between firm growth a measure of the underlying propcess affecting firm profitability.[16] We complete our analysis by looking the variation of the skewness of annual returns across different countries using a sample of publicly traded firms. Although the coverage of the sock market varies significantly across countries, it is clear that in periods where the economy is growing fast, the distribution of stock returns is more positively skewed, whereas periods of economic downturns, are also periods in which returns skew negative.

These results, together with the procyclical skewness of firms' stock returns reported in Section 3.1, show that the skewness of firms' growth is explained, at least in part, by shocks that are also left-skewed. This procyclical skewness could be driven, for instance, by rising bankruptcy during recessions, which would generate left-skewed demand shocks

[15] To construct these figures, we have controlled for country- and time-fixed effects, so these results are not driven by fixed characteristics of the countries considered in the sample or by global shocks—such as the Great Recession—that can affect all countries at the same time.

[16] Our firm-level data from BvD Amadeus comprises information of small and large firms, both publicly traded and privately held from seventeen European countries, namely, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Island, Italy, Netherlands, Norway, Poland, Portugal, Sweden, and Ukraine. For ten of these countries (Germany, Spain, Finland, France, Italy, Norway, Poland, Portugal, Sweden, and Ukraine) we have enough information to estimate firm-level TFP. Appendix B.5 describes in full detail the sample selection and estimation procedure.

(e.g., if a major customer or supplier goes bankrupt, this will generate a large left-tail shock). The underlying driving process itself could also heterogeneously impact firms—that is, some firms lose badly in recessions and some firms gain heavily in booms.

Table 3, we repeat the cyclicality regression discussed above for the United States but this time exploiting the panel dimension of the cross-country dataset to assess the cyclicality of skewness in international data. The dependent variable is the skewness of employment growth, sales growth, productivity growth, or stock returns within a given country/year cell. The business cycle is captured by the log GDP per capita growth in the respective country, which we have rescaled to have a unit variance to facilitate the comparison with the rest of the results. The regressions also include a full set of time and country fixed effects to control for aggregate economic conditions that might affect all countries simultaneously or for fixed differences across countries. The results confirm our previous findings of procyclical skewness for all three variables with similar levels of statistical significance. Compared with the United States, the estimated coefficients is slightly lower across countries than for the US alone.

4 A Quantitative Exploration

The goal of the model is to highlight the importance of using the first, second and third moment of four measures - output, labor TFP and value growth - for business cycle analysis. We show these 12 metrics can identify the underlying driving process over the business cycle. We illustrate this with a standard quantitative model of firm dynamics.

This highlights three key results. First, to generate negative cross-sectional skewness in output, employment, TFP and value growth returns there needs to be a negative cross-sectional skewness shock to the driving process. Second, TFP and value growth moments have a tight connection to the moments of the underlying driving process. Third, output and employment growth moments do not have a tight connection to the moments of the underlying driving process, because they are sensitive to adjustment costs.

4.1 The Model

We consider an economy populated by a large number of firms. To keep the model simple, we assume firms only use labor in their production function, $y = zl^{\alpha}$ with fixed wages and prices. Firms are hit by idiosyncratic shocks to the driving process, z_{it}, where following Bertola and Caballero (1994) this combines shocks to demand and productivity. This shock has (potentially) time varying first, second and third moments. Denote the vector of moments of z as $\Theta = \omega(\mu, \sigma, \gamma)$. Then, we can write the problem of the firm

as

$$V\left(l_{-1},z,\Theta\right)=\max_{l}\left\{zl^{\alpha}-wl-\psi\left(l,l_{-1}\right)+\frac{1}{1+r}\mathbb{E}\left[V\left(l,z,\Theta'\right)\right]\right\},$$

$$\text{where hiring is defined as, } h=l-\left(1-\delta_h\right)l_{-1},$$

$$\text{and adjustment costs are } \psi\left(l,l_{-1}\right)=\psi_1 w\left|h\right|\mathbb{I}_{h>0}+\psi_2 w\left|h\right|\mathbb{I}_{h<0}+\psi_3 y\mathbb{I}_{|h|>0}+\psi_4 l\left(\frac{h}{l}\right)^2.$$

The parameter δ_h is the labor attrition rate, while the function $\psi\left(l,l_{-1}\right)$ spans the different adjustment costs that have been typically used in the literature: ψ_1 captures a hiring linear cost, ψ_2 is a firing linear cost, ψ_3 is a fixed disruption cost that is active when the firm adjusts labor and ψ_4 scales a quadratic labor adjustment cost.

Calibration. We use standard parameters in the literature. We set the discount rate $r=5\%$, the annual labor quit rate to 15%, and $\alpha=2/3$. We assume that the economy moves across two states, expansions and recessions, with transition matrix π^A. This has a (recession, recession) value of 0.79 from the NBER quarterly data, so recessions last on average 3 quarters. Adjustment costs come from Bloom (2009).

To define the distribution of the driving process for z we directly use the data for output growth in expansions in Figure 1. That is, for every point on our grid N_z the transition probabilities for z growth rates are taken directly from the empirical density in Figure 1. So, for example, in Figure 1 the probability of a growth rate of 10% is 0.078 and of 14% is 0.056, so that value is used in the baseline transition matrix T. This approach ensures we do not restrict our baseline stochastic process, for example assuming an first-order autoregressive process as it is common in the literature (e.g. Khan and Thomas (2008); Bloom *et al.* (2018)), but instead use the empirical process.

Recession shocks. We evaluate the impact on our simulation when we hit this economy with three different types of shocks. The first is a first-moment shock, in which the transition matrix T is shifted down by 2.5% across all points. This reduces the mean of the driving process but keeps the second and third moments unchanged. The second is a second moment shock, akin to the standard uncertainty shock. We take the baseline transition matrix T and symmetrically expand it so the mean and skewness are the same but the dispersion of driving process shocks has increased by 50%. Finally, we have the empirical recession shock, which uses the recession distribution of output growth from Figure 1 for T. As in the data, this recession shock involves a negative mean, a positive variance and a negative skewness shock.

Outcomes. We report four outcomes, all measured using the same approach as in our empirical data. The growth rates of output and employment using arc-percentage changes. The growth rate of TFP is the arc-percentage change of real revenues less factor-share weighted log inputs, $log(y) - \alpha log(l)$. Finally value growth is defined as capital gains plus dividends over lagged stock value, $(V' - V)/V$.

Optimal Policy To provide intuition before showing the simulation results, Figure 7 plots the optimal labor policy (left panel) and value function (right panel) for different types of adjustment costs across different levels of productivity, z_t.

The left panel shows a key result: The shape of the optimal policy choice of l_t depends on the adjustment cost. In the no-adjustment-cost case, optimal labor l_t is a smoothly increasing function of z_t so that the hiring rate $=\frac{(l_t - l_{t-1})}{0.5 \times (l_t + l_{t-1})}$ is continuously increasing in z_t. Hence, there is a one-to-one mapping from the hiring rate to productivity growth. Similarly, for quadratic adjustment costs there is a smoothly increasing relationship between l_t and z_t, again yielding a one-to-one mapping from hiring to productivity growth.

But this one-to-one mapping is not present for linear or fixed adjustment costs. Fixed adjustment costs in particular have large jumps in activity. Over a central region of z_t we see that $l_t = l_{t-1}$ so there is no hiring, as fixed costs make inaction optimal. At a higher threshold level of z_t the hiring rate jumps up, in this simulation to a level of about 50%, and continues to increase.[17] At a lower z_t threshold level, the hiring rate drops to approximately -40% and continues to fall. This is classic Ss behavior of hiring in response to fixed costs (e.g. Arrow *et al.* (1951)). Since firms tend to be clustered near this hiring threshold in models with labor attrition, these jumps in the labor policy can generate very lumpy firm changes (e.g. Caballero and Engel (1993)). Output growth, which inherits the dynamics of hiring growth through the production function $y = zl^{\alpha}$, will also display lumpy behavior with fixed adjustment costs.

In contrast, the right panel shows for all variants of adjustment costs that the value function has a smoothly monotonic relationship to z_t. The reason for this is due to "smooth pasting" (e.g. Dixit (1993), Dixit and Pindyck (1994)). This "smooth pasting" result arises from the optimality of the value function, which maximizes over any underlying non-convexities in adjustment costs. This means changes in the value function (stock returns in empirical data) provide a one-to-one mapping to the underlying driving process. Similarly, productivity growth, which is a primitive not influenced by labor

[17] Note our hiring rate is $\frac{(l_t - l_{t-1})}{(0.5 * l_t + 0.5 * l_{t-1})}$ so at the positive hiring jump this is approximately (5-3)/4=50%

inputs, also has a one-to-one mapping to the driving process.[18] Hence, productivity and value growth moments provide better indicators of the moments of the distribution of underlying shocks affecting firms.

4.2 Results

We study the evolution of 10,000 firms in our simulation, running this 1,000 times and taking the average. The simulation is first run for 100 periods to start from the ergodic steady state. Then in period 0 the economy is kicked into the recession state - defined by one of our shocks above - and then left to evolve naturally. Hence, from period 1 onwards the economy follows the transition matrix π^A.

To characterize the impact of these shocks we compute three moments of the cross-sectional distribution: the first moment (mean), the second moment (P90-P10 differential), and third moment (Kelley Skewness). As with our empirical data we use robust measures to limit the impact of outliers.

The impact of a mean shock. Figure 8 shows the impact of a first-moment shock that reduces the average driving process, z, by 2.5%. We plot four lines in every figure showing the results with for each type of adjustment costs. "No AC" refers to no adjustment costs, "Linear" implies $\psi_1 = \psi_2 > 0$, "Fixed" cost implies $\psi_3 > 0$, and "Quadratic" implies $\psi_4 > 0$.

In the left column we see as expected, average firm growth drops after a negative driving process shock, independent of adjustment costs. In particular, in the first plot in the row denoted by First Moment, we show the change in output growth after the first moment shock, showing that for all types of adjustment costs output growth drops by about 5% in the first quarter and then slowly returns to baseline over the next six quarters. In the second column, we show the change in employment growth after the first moment shock, displaying a very similar result. Employment growth drops by around 5% for all four types of adjustment costs in the first quarter, and then slowly recovers to its baseline level. In the third column, we show TFP growth, which drops and then slowly recovers. Finally, in the fourth column, we see a drop in returns on the impact of the shock - the negative driving process shock reduces the firm value on impact - but then then returns are unchanged from period 2 onward.

[18] This is true so long as adjustment costs are monetary - for example hiring and firing $ costs - rather than lost output. If adjustment costs show up as lost output, lumpiness in hiring or investment can translate into lumpiness in measured productivity growth. This is one reason why empirically we also use returns to analyze the underlying driving process.

In the middle row, denoted by Second Moment, we examine the cross-sectional dispersion of firm growth, where the results are more interesting. In the left panel, we see that for all types of adjustment costs *except* for fixed costs, there is no change in the second moment from a first-moment shock. However, the cross-sectional spread of sales growth falls with fixed-adjustment costs. This is because a negative mean shock pushes firms that would otherwise expand down down into their Ss inaction region. This reduces the P90-P10 percentiles by reducing the P90-P50 spread. In the second row of the middle column we see a very similar result for employment growth - with fixed costs of adjustment the P90-P10 spread falls, while for all other adjustment costs it is not materially changed.

This highlights an important result: the moments of output and employment growth are sensitive the to choice of adjustment costs, as discussed above in Section 4.1. Since employment is a control variable of the firm, the nature of adjustment costs impacts its evolution, and that in turn impacts output. This explains why output growth and employment growth, despite being widely available and well measured in micro data sets (such as Compustat or LBD), are less informative variables on the underlying nature of the driving process behind business cycles.

In the third and fourth columns of the middle row we see the TFP growth dispersion and stock-returns dispersion are not materially changed. The reasons for this is these outcomes have a strictly monotonic and almost linear mapping to the underlying driving process as noted in section (4.1). Since this underlying driving process has no change in its second moment, the TFP and stock-returns outcomes do not either.

Finally, in the bottom left plot in Figure 8—the row denoted by Third Moment—we see that sales growth shows a significant drop in skewness with fixed adjust costs, a smaller drop for linear adjustment costs, and no change for quadratic or no adjustment costs. The reason is these non-convex adjustments reduce hiring so much after a negative driving process shock that the right tail compresses—a decline in the P90-50 spread—reducing skewness. We see a similar result for employment growth, but no change for TFP or firm value growth.

In summary, different adjustment costs can generate skewness in employment and sales growth even if the driving process is not skewed. In contrast, the distribution of TFP and value growth have a close connection to the underlying driving process.

The impact of an uncertainty shock. In Figure 9, we examine the change of our twelve sets of moments in response to a second-moment shock that increases the dis-

persion of the driving process by 50%. In the first row, we see that the first moment of output growth and employment growth decline after a second moment (uncertainty) shock for fixed adjustment costs. For linear and quadratic costs however, average growth increases, driven by the Oi-Harman-Abel effect, which reflects the value of greater variance in the driving process when firms can expand to exploit good shocks and contract to insure against bad shocks.[19] This also raises the average firm value growth, as shown the last column if Figure 9.

In the second row we examine the second moment of the growth rates of our four measures, showing they rise when the underlying driving process has its dispersion increased. So, there is a clear pass-through from a higher variance in the driving process to a higher variance in all outcome measures.

Finally, in the third row we examine the third moment of the growth rates of our four measures. We see again that for non-convex adjustment costs (fixed and linear) there is a reduction in skewness for output and employment growth, specially for fixed adjustment costs. This is because the rise in uncertainty expands the Ss zone of inaction which reduces positive. However, with our uncertainty shock we see no material change in TFP or value growth skewness across any of the adjustment cost specifications.

Hence, it is not possible to get a robust pattern of falling cross-sectional skewness for output, employment, TFP and value growth with a second moment micro driving process. Fixed-costs can generate drops in the third moment of output and employment growth during recessions, but not TFP and value growth.[20]

The impact of an empirical recession shock. Finally, in Figure 10 we examine the impact of the empirical recessions shock to the driving process. As described in Section 2, this combines a negative first moment shock, a positive second moment shock and importantly a negative third-moment shock.

First, in the top row we see a significant drop in average output, employment, TFP and output growth across all adjustment costs. This is driven by the negative first moment shock in the empirical recessionary process. In the middle row we see for all adjustment costs except fixed an increase in spread driven by the second moment shock. The variance of employment and output growth for fixed-costs of adjustment drops,

[19] See the summary of the papers by Oi (1961), Hartman (1972), and Abel (1983) in Bloom (2014).

[20] Another inconsistency with first or second moment shocks generating skewness in output growth and employment growth is the level of skewness is *positive* even in recessions.With fixed-costs of adjustment the level of skewness does drop in recessions, but remains strongly positive. The reason is with fixed-costs there is almost no firing, generating highly right skewed growth rates.

however. This occurs because there is an average decline in productivity, pushing firms that would otherwise expand down further down into their Ss inaction region. Finally, in the bottom row we see how this negative skewness shock delivers a drop in skewness for output, TFP and value growth for all adjustment costs, and for employment growth for all adjustment costs except for fixed-costs.

This highlights two key findings. First, a negative skewness shock in the driving process maps into a negative shock in the growth rates of productivity growth and stock returns growth. This highlights the importance of these measures for analyzing the drivers of business cycles. Second, the moments of employment growth and output growth are sensitive to the types of adjustment cost, making them less reliable for evaluating the dynamics of shocks over the business cycle.

5 Conclusions

This paper studies how the distribution of the growth rate of firm-level variables changes over the business cycle. Using firm-level panel data for the United States from Census and non-Census datasets and firm-level panel data for almost forty other countries, we reach three main conclusions. First, recessions are characterized by a large drop in the skewness of firm-level employment, sales and productivity growth. Expansions, in contrast, are characterized by positive skewness in firm employment, sales and productivity growth. Second, the decline in the skewness of firms' outcomes is a phenomenon observed not only in the United States but also in other countries, both developed and developing, and within industries. Third, empirical and model-based estimates indicate that that shocks to the skewness of firm-level innovations predict future declines in macroeconomic activity. Taken together, these results suggest that the increase in firm-level disaster risk observed during the typical recession can play a major role in accounting for business cycles fluctuations.

References

Abel, A. B. (1983). Optimal investment under uncertainty. *The American Economic Review*, **73** (1), 228–233.

Ackerberg, D. A., Caves, K. and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, **83** (6), 2411–2451.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E. *et al.* (2020). Economic uncertainty before and during the covid-19 pandemic. *Journal of Public Economics*, **191**, 104274.

—, Barrero, J. M., Bloom, N., Davis, S. J., Meyer, B., Parker, N. *et al.* (2022). Surveying business uncertainty. *Journal of Econometrics*, **231** (1), 282–303.

Arellano, C., Bai, Y. and Kehoe, P. (2018). Financial markets and fluctuations in uncertainty. *Federal Reserve Bank of Minneapolis Staff Report*.

Arrow, K. J., Harris, T. and Marschak, J. (1951). Optimal inventory policy. *Econometrica: Journal of the Econometric Society*, pp. 250–272.

Bachmann, R. and Bayer, C. (2014). Investment Dispersion and the Business Cycle. *American Economic Review*, **104** (4), 1392–1416.

—, Elstner, S. and Hristov, A. (2017). Surprise, surprise–measuring firm-level investment innovations. *Journal of Economic Dynamics and Control*, **83**, 107–148.

—, — and Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, **5** (2), 217–249.

Barrero, J. M. (2022). The micro and macro of managerial beliefs. *Journal of Financial Economics*, **143** (2), 640–667.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, **121** (3), 823–866.

Basu, S. (1996). Procyclical productivity: increasing returns or cyclical utilization? *The Quarterly Journal of Economics*, **111** (3), 719–751.

— and Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, **85** (3), 937–958.

Berger, D., Dew-Becker, I. and Giglio, S. (2017). *Uncertainty shocks as second-moment news shocks*. Working Paper 23796, National Bureau of Economic Research.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, **77** (3), 623–685.

— (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, **28** (2), 153–76.

—, Floetotto, M., Jaimovich, N., Saporta-Eksten, I. and Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, **86** (3), 1031–1065.

—, Sadun, R. and Reenen, J. V. (2012). Americans do it better: Us multinationals and the productivity miracle. *American Economic Review*, **102** (1), 167–201.

— and Van Reenen, J. (2007). Measuring and explaining management practices across firms

and countries. *The quarterly journal of Economics*, **122** (4), 1351–1408.

Bollerslev, T. and Todorov, V. (2011). Tails, fears, and risk premia. *The Journal of Finance*, **66** (6), 2165–2211.

Busch, C., Domeij, D., Guvenen, F. and Madeira, R. (2022). Skewed Idiosyncratic Income Risk over the Business Cycle: Sources and Insurance. *American Economic Journal: Macroeconomics*, **14** (2), 207–242.

Caballero, R. J. and Engel, E. M. (1993). Microeconomic rigidities and aggregate price dynamics. *European Economic Review*, **37** (4), 697–711.

Colacito, R., Ghysels, E., Meng, J. and Siwasarit, W. (2016). Skewness in expected macro fundamentals and the predictability of equity returns: Evidence and theory. *The Review of Financial Studies*, **29** (8), 2069–2109.

Conrad, J., Dittmar, R. F. and Ghysels, E. (2013). Ex ante skewness and expected stock returns. *The Journal of Finance*, **68** (1), 85–124.

Cunningham, C., Foster, L., Grim, C., Haltiwanger, J., Pabilonia, S. W., Stewart, J. and Wolf, Z. (2021). Dispersion in dispersion: Measuring establishment-level differences in productivity.

Davis, S. J. and Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *Quarterly Journal of Economics*, **107** (3), 819–863.

—, —, Jarmin, R., Miranda, J., Foote, C. and Nagypal, E. (2006). Volatility and dispersion in business growth rates: Publicly traded versus privately held firms. *NBER Macroeconomics Annual*, **21**, 107–179.

Decker, R., Haltiwanger, J., Jarmin, R. and Miranda, J. (2015). *Where has all the skewness gone? The decline in highgrowth (young) firms in the US*. Working Paper 21776, National Bureau of Economic Research.

Dew-Becker, I. (2022). *Real-time forward-looking skewness over the business cycle*. Tech. rep., National Bureau of Economic Research.

Dixit, A. (1993). Choosing among alternative discrete investment projects under uncertainty. *Economics letters*, **41** (3), 265–268.

Dixit, A. K. and Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton university press.

Döpke, J., Funke, M., Holly, S. and Weber, S. (2005). *The cross-sectional dynamics of German business cycles: a bird's eye view*. Tech. rep., Discussion Paper Series 1.

Fernandez-Villaverde, J., Guerron-Quintana, P., Rubio-Ramirez, J. F. and Uribe, M. (2011). Risk Matters: The Real Effects of Volatility Shocks. *American Economic Review*, **101** (6), 2530–2561.

Fernández-Villaverde, J. and Guerrón-Quintana, P. A. (2020). Uncertainty shocks and business cycle research. *Review of economic dynamics*, **37**, S118–S146.

Ferreira, T. (2018). Stock market cross-sectional skewness and business cycle fluctuations.

Fort, T. C., Haltiwanger, J., Jarmin, R. S. and Miranda, J. (2013). How firms respond to business cycles: The role of firm age and firm size. *IMF Economic Review*, **61** (3), 520–559.

Foster, L., Grim, C., Haltiwanger, J. and Wolf, Z. (2016). Firm-level dispersion in productivity: is the devil in the details? *American Economic Review*, **106** (5), 95–98.

—, Haltiwanger, J. and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: selection on productivity or profitability? *American Economic Review*, **98** (1), 394–425.

Gabaix, X. (2008). Variable Rare Disasters: A Tractable Theory of Ten Puzzles in Macro-finance. *American Economic Review*, **98** (2), 64–67.

— (2012). Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *Quarterly Journal of Economics*, **127** (2), 645–700.

Gilchrist, S., Sim, J. W. and Zakrajšek, E. (2014). *Uncertainty, financial frictions, and investment dynamics*. Tech. Rep. 20038, National Bureau of Economic Research.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L. and Villegas-Sanchez, C. (2017). Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, **132** (4), 1915–1967.

Gourio, F. (2008). Disasters and recoveries. *American Economic Review*, **98** (2), 68–73.

— (2012). Disaster risk and business cycles. *American Economic Review*, **102** (6), 2734–2766.

— (2013). Credit risk and disaster risk. *American Economic Journal: Macroeconomics*, **5** (3), 1–34.

Guvenen, F., Ozkan, S. and Song, J. (2014). The nature of countercyclical income risk. *Journal of Political Economy*, **122** (2), 612–660.

Haltiwanger, J., Jarmin, R., Kulick, R., Miranda, J., Penciakova, V., Tello-Trillo, C. *et al.* (2019). *Firm-level Revenue Dataset*. Tech. rep., Center for Economic Studies, US Census Bureau.

—, Jarmin, R. S., Kulick, R. and Miranda, J. (2016). High growth young firms: contribution to job, output, and productivity growth. In *Measuring entrepreneurial businesses: current knowledge and challenges*, University of Chicago Press, pp. 11–62.

Harmenberg, K. and Sievertsen, H. H. (2017). *The Labor-Market Origins of Cyclical Income Risk*. Working paper, Institute for International Economic Studies.

Hartman, R. (1972). The effects of price and cost uncertainty on investment. *Journal of Economic Theory*, **5** (2), 258–266.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *Journal of Finance*, **55** (3), 1263–1295.

Higson, C., Holly, S. and Kattuman, P. (2002). The cross-sectional dynamics of the us business cycle: 1950–1999. *Journal of Economic Dynamics and Control*, **26** (9-10), 1539–1555.

—, —, — and Platis, S. (2004). The business cycle, macroeconomic shocks and the cross-section: the growth of uk quoted companies. *Economica*, **71** (282), 299–318.

Ilut, C., Kehrig, M. and Schneider, M. (2018). Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news. *Journal of Political Economy*, **126** (5), 2011–2071.

Jordà, Ò., Schularick, M. and Taylor, A. M. (2020). *Disasters everywhere: The costs of business cycles reconsidered*. Tech. rep., National Bureau of Economic Research.

Jurado, K., Ludvigson, S. C. and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, **105** (3), 1177–1216.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V. and Yesiltas, S. (2015). *How to construct nationally representative firm level data from the Orbis global database: New facts and aggregate implications*. Tech. rep., National Bureau of Economic Research.

Kehrig, M. (2011). *The Cyclicality of Productivity Dispersion*. Working Paper 11-15, Center for Economic Studies, U.S. Census Bureau.

Kelley, T. L. (1947). *Fundamentals of Statistics*. Harvard University Press.

Khan, A. and Thomas, J. K. (2008). Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics. *Econometrica*, **76** (2), 395–436.

Kilic, M. and Wachter, J. A. (2015). *Risk, Unemployment, and the Stock Market: A Rare-Event-Based Explanation of Labor Market Volatility*. NBER Working Paper 21575.

Kozeniauskas, N., Orlik, A. and Veldkamp, L. (2018). What are uncertainty shocks? *Journal of Monetary Economics*, **100**, 1–15.

Kozlowski, J., Veldkamp, L. and Venkateswaran, V. (2016). The tail that wags the economy: Belief-driven business cycles and persistent stagnation.

—, — and — (2018). *The tail that keeps the riskless rate low*. Tech. rep., National Bureau of Economic Research.

Leduc, S. and Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, **82**, 20–35.

Ludvigson, S. C., Ma, S. and Ng, S. (2021). Uncertainty and business cycles: exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, **13** (4), 369–410.

McKay, A. and Reis, R. (2008). The brevity and violence of contractions and expansions. *Journal of Monetary Economics*, **55** (4), 738–751.

Oh, S. and Wachter, J. A. (2018). *Cross-sectional Skewness*. Working paper, Wharton School at University of Pennsylvania.

Oi, W. Y. (1961). The desirability of price instability under perfect competition. *Econometrica*, **29** (1), 58–64.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment. *Econometrica*, **64** (6), 1263–1297.

Rietz, T. A. (1988). The equity risk premium: a solution. *Journal of Monetary Economics*,

22 (1), 117–131.

Salgado, S., Guvenen, F. and Bloom, N. (2019). *Skewed business cycles*. Tech. rep., National Bureau of Economic Research.

Schaal, E. (2017). Uncertainty and unemployment. *Econometrica*, **85** (6), 1675–1721.

Segal, G., Shaliastovich, I. and Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, **117** (2), 369–397.

Summers, L. H. *et al.* (1986). *Some skeptical observations on real business cycle theory*. Harvard Institute of Economic Research.

Syverson, C. (2011). What determines productivity? *Journal of Economic literature*, **49** (2), 326–65.

Veldkamp, L. L. (2005). Slow boom, sudden crash. *Journal of Economic Theory*, **124** (2), 230–257.

Venkateswaran, V., Veldkamp, L. and Kozlowski, J. (2015). *The Tail that Wags the Economy: Belief-Driven Business Cycles and Persistent Stagnation*. 2015 Meeting Papers 800, Society for Economic Dynamics.

Wachter, J. A. (2013). Can time-varying risk of rare disasters explain aggregate stock market volatility? *Journal of Finance*, **68** (3), 987–1035.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, **104** (3), 112–114.

Yasar, M., Raciborski, R. and Poi, B. (2008). Production function estimation in stata using the olley and pakes method. *The Stata Journal*, **8** (2), 221–231.

Supplementary Online Appendix

A Appendix: Robustness Results

Table A.1 – Data Sources and Sample Characteristics

Variable		Compustat	LBD	Census LBD-Rev	ASM/CM	BvD Osiris	BvD Amadeus
Employment	Mean	9,364	23	-	89	6,257	25
	P10	36	1	-	12	35	1
	P50	1,078	4	-	70	631	4
	P90	17,900	24	-	334	10,650	29
	P99	145,000	177	-	-	108,256	302
Sales (000s)	Mean	2,912	-	5,059	1,100	1.08	9.14
	P10	8	-	75	0.0	0.14	0.08
	P50	325	-	426	6.05	0.72	0.44
	P90	5,384	-	3,425	229	1.40	6.86
	P99	49,686	-	36,940	-	16.90	9.89
Frequency		Annual	Annual	Annual	Annual	Annual	Annual
Period		1970-2020	1978-2019	1998-2018	1976-2018	1991-2015	1996-2018
Obs. (M)		0.23	4.6	4.5	0.25	0.60	39.7
Unit. of Obs.		Firm	Firm	Firm	Estab.	Firm	Firm
Firm Type		Pub.	Pub./Priv.	Pub./Priv.	Pub./Priv.	Pub.	Pub./Priv.
Countries		US	US	US	US	Multiple	Multiple
Sectors		All	Non Farm	Non Farm	Manuf.	All	All

Note: Table A.1 shows the list of datasets and time-frames used in the analysis. Sample statistics correspond to 2010 for comparability. All monetary values are expressed in US dollars of 2010. We omit data from Global Compustat since it does not contain information on employment or sales. LBD sample statistics are aggregated at the firm-level. The 99th percentile is not reported to avoid disclosure of sensitive information. Total observations correspond to all sales observations across all years in the sample with valid observations of sales and employment. ASM results are calculated using sample weights. The 99th percentile of establishments sales and employment are not reported to avoid disclosure of sensitive information. See Table B.2 in the Appendix for a complete list.

B Appendix: Data Description

This appendix describes the data sources, the sample selection, and the calculations of the moments we use for our empirical analysis. In Section B.2 we describe the firm- and establishment-level data for the United States obtained from the Census Bureau's Longitudinal Business Database (LBD). Section B.3 describes our sample of Compustat firms. For our cross-country comparisons, we use firm-level data available in the Bureau van Dijk's Osiris database and Global Compustat which we describe in Section B.4. Finally, Section B.5 describes our sample and TFP estimation for our sample of firms from the BvD Amadeus dataset and the establishment-level data for the US Census of Manufacturing and the Annual Survey of Manufacturing. The online appendix and replication packet—on the authors' websites—contains further details and corresponding do-files for most of our calculations.

B.1 Firm-Level Survey Data

Firm-level information on expected and realized sales growth is obtained from the Survey of Business Uncertainty (SBU) developed by the Atlanta Fed in conjunction with Chicago Booth and Stanford. The goal of the survey is to elicit subjective probability distributions of from business executives and decisions makes about the macroeconomy and their own-firm outcomes such as sales, employment, or investment. The SBU began collecting data in 2014 and as of 2023, contains information from more than 2000 firms, across all 50 states in the United States, in every major non-farm sector, and across different segments of the firm-size distribution.

Every month, firm decision makers are asked, among other information, about their subjective expectations by means of a five-point subjective probability distribution over each firms' own four or twelve months future growth depending of the outcome variable (sales, employment, or capital expenditure). This flexible approach allows the responded to describe periods with different degree of growth, uncertainty, or more importantly for our purpose, if they expect positive or negative skewness of future outcomes. Importantly, since SBU also ask respondents about past realizations of the same variables, we are able to compare the skewness of expected and realized growth. Barrero (2022) documents additional properties of the subjective expectation probabilities and Altig *et al.* (2020) documents the significant changes observed in business uncertainty during the COVID pandemic. For our purpose, we can use the subjective probability across firms to construct percentiles of the *expected* sales growth distribution by weighting the expected sales growth with the support points probabilities provided by the responded. Additional details of the calculations can be found in Altig *et al.* (2022).

B.2 United States: Longitudinal Business Database

We construct measures of employment growth at the firm-level using the Census Bureau's Longitudinal Business Database (LBD). The LBD covers the universe of establishment in the non-farm private sector in the United States from 1976 to 2019. It provides detailed establishment and firm-level information on employment, payroll, establishment location, firm age, industry, legal form of organization, and others. Crucially, firm and establishment identifiers in the LBD allow us to construct measures of employment growth at different time horizons. From the LBD, we select a sample of establishments that, in a given year, have nonnegative, non-missing employment and payroll and have valid industry data. We then sum up the employment within the same firm across all establishments to construct an annual measure of

employment. Starting in 1998, the LBD also contains information on firm-level revenue (the so called LBDR). The coverage from the LBD to the LBDR is not complete. There is at least 30 percent of firms that have employment information (in LBD) but do not have revenue information (LBDR). A significant fraction of these firms (about 25%) are in the Other Services (except Public Administration) sector (NAICS 81). Importantly, the cross sectional moments for the employment growth distribution do not change when we focus in the sample of firms that have employment and revenue data. See Haltiwanger *et al.* (2016) for additional details on this data. We deflate nominal revenue measures to 2012 prices using the CPI (FRED series CPIAUCSL).

We measure the growth rate of employment of firm j in period t as the log-difference between periods t and $t+1$, $g^e_{j,t} = \log E_{j,t+1} - \log E_{j,t}$. In order to capture the entry and exit of firms, we replace by a 0 the level of employment in the period before the first establishment is observed for the first time and the period after the last establishment of the firm is observed for the last time in the sample. We then calculate the growth rate of employment using the arc-percentage change between periods t and $t+1$ which is given by $g^{arc}_{j,t} = \frac{E_{j,t+1}-E_{j,t}}{0.5\times(E_{j,t+1}+E_{j,t})}$. We take the arc-percent change as our baseline measure. We proceed in the same way for revenue growth.

To calculate the Kelley skewness we require the computation of specific percentiles of the distribution of employment growth. Notice that a percentile provides information about *one* particular firm, which violates the disclosure criteria imposed by the US Census Bureau. Hence, to avoid the disclosure of any sensitive information, we calculate the *pth* percentile of the employment growth distribution as the employment-weighted average on a band of +1 and -1 percent around percentile *pth*. For instance, the 90th percentile of the distribution is the weighted average of the employment growth across all observations between the 89th and 91st percentiles of the distribution, both ends included. We proceed in the same way to construct the 10th and 50th percentiles of the distribution and use these values to calculate the Kelley skewness, the 90th-to-10th log percentiles differential and the rest of the measures of dispersion. The massive sample size of the LBD (more than 4.6 million observations per year on average) ensures that the sample used to calculate each of the percentiles is large enough to have an accurate approximation to the actual quantiles of the distribution. All moments of the employment growth distribution are weighted by the average employment of the firm (or establishment in the case of establishment level results) between periods t and $t+k$, that is, $\overline{E}_{j,t} = 0.5 \times (E_{j,t+k} + E_{i,t})$. Similarly, we weight revenue growth measures by the average real revenue between periods t and $t+k$.

We also use the LBD to compare the empirical distribution of employment and revenue growth between recession and expansion years using a kernel density estimation. The sample selection is the same used in the rest of our results with a few exceptions. First, the densities are calculated using a pooled sample of firms for recession years (2001 and 2008) or expansion years (2003 to 2006 and 2010 to 2014). Second, we select a sample of firms that have at least 20 workers or more in year t. And third, the Census Bureau requires to drop the bottom and top 5% of the distribution when estimating empirical densities. The kernel densities presented in Figures 1 and 2 of the were calculated using the remaining sample.

B.3 United States: Compustat

We construct time series of the cross-sectional dispersion and skewness of the sales growth distribution, the employment growth distribution, the stock returns distribution, and others

using data of publicly traded firms from Compustat and CRSP accessed through the Wharton Research Data Services (WRDS).

For our results at the annual frequency, we obtain firm-level data from 1970 to 2020. The raw annual dataset contains 500,004 year/firm observations. We drop all observations with negative sales (Compustat variable sale), duplicated entries, and firms incorporated outside the United States (Compustat variable fic equal to "USA"). We also drop all observations that do not have a SIC classification or with a classification above 90. We deflate nominal variables using CPI (FRED series CPIAUCSL) and we calculate the growth rate of sales and employment (Compustat variable emp) as the log change between year t and $t+k$ with $k \in \{1, 3, 5\}$. This leaves us with 266,192 firm/year observation (sales growth) between 1970 and 2019, with an average of 5,663 firms per year. Our main sample considers firms with at least 10 years of data (not necessarily continuous) but our results remain robust if we drop this restriction or if we consider firms with at least 25 years of data. When accounting for entry and exit of firms using the arc-percentage change, for each firm we add an observation upon entry (equal to 2) and one additional observation upon exit (equal -2) under the assumption that before and after exit, the firm has a value of sales or employment equal to 0. We consider entry firms as newly listed firms, while exiting firms are those delisted in a particular period, independent of the reason (M&A, bankruptcy, or any other).

To measure the degree of financially constraints, we use two measures i) by lagged average leverage and ii) by the lagged average interest coverage ratio. The first is calculated as the ratio between short and long term debt (sum of DLTT and DLC) and total value of assets. We then calculate the lagged level of leverage as the average value of the leverage between periods $t-1$ and $t-2$. Finally, we winsorise this measure at the value of 2. To calculate the interest coverage ratio we take EBIT divided by total interest expenses (TIE). If TIE is equal to 0, then the coverage ratio is set to a large number (coverage ratio of infinity). We then calculate the lagged level coverage ratio as the average value of the leverage between periods $t-1$ and $t-2$.

For our results based on quarterly data, we begin by retrieving firm-level data of net sales and stock prices at the annual and quarterly frequency, and employment at the annual frequency, from 1964q1 to 2020q4. The raw dataset of sales (Compustat variable saleq) and stock prices (Compustat variable prccq) contains more than 1.7 million quarter-firm observations with an average of approximately 4,660 firms per quarter. We drop all observations with negative sales, duplicated observations, and firms incorporated outside the United States (Compustat variable fic equal to "USA"). We also drop all observations that do not have a SIC classification or with a classification above 90. Then, we deflate nominal sales by the CPI (FRED series CPIAUCSL), and we calculate the growth rate of sales as the log-difference and the arc percentage change between quarter t and $t+k$ with $k \in \{4, 12, 20\}$. This leaves us with around 1 million sales growth (log-difference) observations. For our main results, we consider firms with at least 10 years of data on quarterly sales (40 quarters, not necessarily continuous), which further reduces the sample to 819,977 observations between 1970q4 and 2017q2, with an average of 5,359 firms per quarter. Finally, in each quarter we calculate different cross-sectional moments discussed in the main body of this document. Our main sample considers firms with at least 10 years of data (40 quarters), although our results remain robust if we drop this restriction or if we consider firms with 25 years of data (more than 100 quarters). When accounting for entry and exit of firms using the arc-percentage change, for each firm we add an observation upon entry (equal

to 2) and one additional observation upon exit (equal to -2) under the assumption that before entering and after exit, the firm has a value of sales or employment equal to 0. We consider entry firms as newly listed firms while exiting firms are those delisted in a particular period, independent of the reason (M&A, bankruptcy, or any other).

B.4 Cross-Country: BvD Osiris and Global Compustat

Cross-country firm-level panel data on sales and employment come from the Bureau van Dijk's Osiris database.[21] Osiris is a database of listed public companies, commodity-producing firms, banks, and insurance companies from over 190 countries. The combined industrial company dataset which we use in our analysis contains financial information for up to 20 years and 80,000 companies.

The raw dataset contains 977,412 country/firm/year observations from 1982 to 2018. We drop all observations with missing or negative sales, all duplicated entries, and all firms with missing NAICS classification. We transform all observations into US dollars using the exchange rate reported in the same database. Then, we deflate nominal sales using US annual CPI and calculate the growth rate of real sales as the log change and arc percentage change between years t and $t+k$ with $k \in \{1, 3\}$. This leaves us with 748,574 observations (log change of sales). We further restrict the sample to firms with more than 10 years of data; country/year cells with more than 100 observations; countries with more than 10 years of data; and years with more than 5 countries. This sample selection reduces the dataset to an unbalanced panel of 678,563 observations in 45 countries between 1989 and 2015. We complement this data with real GDP in US dollars from the World Bank's World Development Indicators database.

The cross-country data on daily stock prices come from the Global Compustat database (GCSTAT), which provides standardized information on publicly traded firms for several countries at annual, quarterly, and daily frequencies. The raw data contain firm-level observations of daily stock prices between 1985 and 2018 for 48 countries. We drop all duplicated observations and drop all firms with less than 2000 observations (firms with approximately 10 years of data). Then we calculate daily price returns as the log-difference of the stock price between two consecutive trading days. We apply a similar sample selection, keeping firms with at least 10 years of daily price data. The total sample contains an unbalanced panel of 44 countries from 1985 to 2017 from which we drop all country quarters with less than 100 firms. The final data contains a total of 29 countries from 1985 to 2017. Then, within each quarter, we calculate the cross-sectional moments of the daily stock price distribution. We complement this dataset with per capita GDP growth from the World Bank's World Development Indicators and quarterly GDP growth from the OECD Stats. Table B.2 shows the list of countries available in our dataset and the data available for each country.

[21] See Kalemli-Ozcan *et al.* (2015) for additional details on the Orbis dataset.

TABLE B.2 – DATA AVAILABILITY BY COUNTRY

Source:	BvD Osiris		Global Compustat	BvD Amadeus				BvD Osiris		Global Compustat	BvD Amadeus		
	Sales	Emp	Returns	Sales	Emp	TFP		Sales	Emp	Returns	Sales	Emp	TFP
ARG	x	x					IRN	x	x				
AUS	x	x	x				ISL				x	x	
AUT				x	x		ISR	x	x	x			
BEL	x	x	x	x	x		ITA	x	x	x	x	x	x
BLR				x	x		JPN	x	x	x			
BMU	x	x					KOR	x	x	x			
BRA	x	x	x				MEX	x	x				
CAN	x	x					MYS	x	x				
CHE	x	x	x	x	x		NLD	x	x	x	x	x	
CHL	x	x	x				NOR	x	x	x	x	x	x
CHN	x	x					NZL			x			
DEU	x	x	x	x	x	x	PAK	x	x				
DNK	x	x	x	x	x		PER	x	x				
EGY	x	x					PHL	x	x				
ESP	x	x	x	x	x	x	POL			x	x	x	x
FIN	x	x	x	x	x	x	PRT				x	x	x
FRA	x	x	x	x	x	x	RUS	x	x	x			
GBR	x	x	x	x	x		SGP	x	x				
GRC	x	x	x	x	x		SWE	x	x	x	x	x	x
HKG	x	x					THA	x	x				
HUN				x	x		TUR	x	x	x			
IDN	x	x	x				UKR				x	x	x
IND	x	x	x				ZAF	x	x	x			
IRL			x	x	x								

Note: Table B.2 shows data available for each country (identified by its isocode). US data sources are omitted.

B.5 TFP Estimation

B.5.1 Cross-Country: BvD Amadeus

In this appendix, we describe in detail the construction of our measure of firm-level TFP using data from BvD Amadeus. This dataset has been used for several other researchers. For instance, Bloom and Van Reenen (2007) uses this dataset to evaluate management practices in the UK, French and German sampling frames. Bloom *et al.* (2012) discusses extensively the coverage of Amadeus. Some other paper have also calculated productivity using this data, more prominently Gopinath *et al.* (2017) in their analysis of misallocation in Spain and other European countries. We provide an extensive comparison of our data and results to those presented by these authors in subsection B.5.4. See also Kalemli-Ozcan *et al.* (2015) for details about constructing a representative dataset using BvD Amadeus data.

We consider a set of countries, namely, Germany, Spain, Finland, France, Hungary, Italy, Netherlands, Norway, Poland, Portugal, Sweden, and Ukraine, for which firm-level information is available for enough industries and sectors. For each country in the sample, we retrieve firm-level panel data from Amadeus trough WRDS. Our data contains a large range of firms, from small to very large firms (V+L+M+S: plus Small Companies dataset), both publicly traded and privately held. The main variables we use in our analysis are the following (Amadeus names of variables in parenthesis):

- Sales (TURN),
- Operating revenues (OPRE),
- Employment (EMPL),
- Cost of Employees (STAF),
- Cost of Material (MATE),
- Total Fixed Assets (FIAS),
- Industry (NAICS and SIC codes),
- Exchange rate from local currency to Euros (EXCHANGE2).

In order to estimate firm-level productivity for a large number of firms within each country, we perform a simple sample selection. For each country, we drop duplicates, observations without information on industry (NAICS), and firms with discrepancies between the country identifier and the firm identifier (INDR).[22] We also drop all observations with missing, zero, or negative values in either of the following variables: OPRE, MATE, FIAS, and STAF. We also drop all observation with zero or negative value of VA = OPRE – MATE which is our measure of value added. We deflate all monetary values by the country-specific CPI (obtained from the World Bank). All monetary values are transformed to Euros using the exchange rate supplied by BvD.

[22] The first two characters in the firm identifier in Amadeus refer to the country.

B.5.2 Estimating TFP

The literature has considered several different methods to measure TFP at the firm-level (Syverson, 2011) and in this section we consider few standard methods. If we assume that the firm's production function is Cobb-Douglas, we can estimate the firm-level productivity, $z_{i,j,t}$, as the residual of the following equation,

$$\log y_{i,j,k,t} = \alpha_K \log K_{i,j,k,t} + \alpha_L \log E_{i,j,k,t} + z_{i,j,k,t}, \tag{2}$$

where $y_{i,j,k,t}$ is the value added of firm i, in industry j, in country k, in year t; $K_{i,j,k,t}$ is the deflated measure of fixed assets and $E_{i,j,k,t}$ is a measure of labor input (employees or wage bill).

We use four different methods to estimate $z_{i,j,t}$. The first method—which we use in our main empirical results—uses country-industry factor shares to estimate α_L and α_K. In particular, we calculate the total wage bill and total value added at the country-industry-year level. Industries are defined by two-digit NAICS. To ensure our measure of factor shares is calculated with enough firms, we restrict our estimates to years in which the country-industry-cell contains more than one hundred observations and periods with more than five sectors within a country-year. We then obtain the labor share as

$$\alpha_{L,j,k,t} = \frac{\sum_{i \in I_{j,k,t}} w_{i,j,k,t}}{\sum_{i \in I_{j,k,t}} y_{i,j,k,t}},$$

where $I_{j,k,t}$ is the set of firms in the industry-sector-year cell and $w_{i,j,k,t}$ is the cost of employees at the firm-level (STAF). Then, we calculate the capital share as $\alpha_{K,j,k,t} = 1 - \alpha_{L,j,k,t}$.[23] We then apply these factor shares in equation (2) to obtain our first measure of productivity as the difference between $\log y_{i,j,k,t}$ and

$$\left((1 - \alpha_{L,j,k,t}) \log K_{i,j,k,t} + \alpha_{L,j,k,t} \log E_{i,j,k,t}\right).$$

In the second method, we obtain $z_{i,j,t}$ as the residuals of a firm-level OLS panel regression. In order to control for differences in labor quality across firms, we use the wage bill (STAF) at the firm level as a measure of labor input. We then run, an OLS panel regression to obtain $\hat{z}_{i,j,k,t}$ for each firm.

The third approach—which is our baseline method—uses the methodology developed by Olley and Pakes (1996) to estimate $\hat{z}_{i,j,k,t}$. This method has stricter data requirements and therefore, we further restrict our within-country sample to firms with information about investment expenditure (change in the value of total fixed assets, FIAS), and firms with at least 5 years of data. Furthermore, because the data available in BvD Amadeus was increasingly populated until 2005, we consider information only after that year. To obtain the Olley and Pakes (1996) estimates we use the Stata command OPREG as implemented by Yasar *et al.* (2008).

The fourth method abstracts from capital differences across firms and proxies a measure of labor productivity. In particular, we obtain labor productivity as the residual of the following

[23] In this calculation, we use the nominal values of value added and cost of employees.

equation estimated using OLS within each country

$$\log y_{i,j,k,t} = \tilde{\alpha}_L \log E_{i,j,k,t} + \mu_i + \tilde{z}_{i,j,k,t}. \tag{3}$$

The fifth and six methods estimate productivity using Ackerberg *et al.* (2015) and the method of Wooldridge (2009) respectively, again using the Stata command OPREG.

Then, for each productivity measure, we estimate firm level productivity shocks as the residual of the following OLS panel regression within each country

$$\hat{z}_{i,j,k,t} = \beta_{0,k} + \beta_{1,k}\hat{z}_{i,j,k,t-1} + \mu_i + \delta_t + \epsilon_{i,j,k,t}, \tag{4}$$

where μ_i and δ_t are firm and year fixed effects respectively. In order to reduce the impact of outliers that normally appear in micro data, for each country, we winsorize each measure of productivity shock at the top and bottom 1%. Additionally, we use the average of the real sales growth within a bin (defined by country, industry, or year) as a measure of business conditions. Then, for each measure of productivity shock, we calculate the average shock within a country-industry-year bin and different percentiles of the distribution. To further ensure our results are not driven by outliers at the country-industry level, after we have obtained these percentiles, we trim the measures of Kelley skewness and the average productivity shocks at the top and bottom 1% and we restrict our sample to country-industry-year bins with more than 100 firms. Our results, however, follow through is we relax these conditions.

B.5.3 Additional Evidence on the Skewness of Productivity Shocks

As we discussed in Section 3.2, the skewness of productivity shocks is robustly negative during periods of low economic activity within a country or an industry. Here we show some additional robustness results. Figure B.1 shows that the positive relation between the skewness of the productivity shocks and the business conditions is robustly positive, independently of the estimation method one uses to calculate firm-level productivity. For comparison, the top left panel repeats our main results shown in Figure B.1. Table B.3 shows a series of panel regressions in which the independent variable is the skewness of TFP shocks for each of the four methods described in Section B.5.2 and the main regressor is the average of the real sales growth (log change of operative revenues) within a country-industry-year cell. The coefficient associated to the average sales growth is positive and statistically significant at the 1% in all cases and of the same order of magnitude. This indicates that in periods in which industries experience a decline in sales, the skewness of the productivity shocks affecting the firms in that industry is negative as well.

Finally, Table B.4 shows that the skewness of firm's shocks is procyclical at the country level. In particular, we show the results of an industry-panel regression for each country in our sample using the average TFP shock as our measure of business condition. The results are indicative that the procyclicality of the skewness of firm shocks is not driven by any particular country in our sample and it is stronger in countries such as Germany and France.

B.5.4 Comparing Sample with Gopinath *et al.* (2017)

High quality data is crucial to determine the business cycle variation of higher order moments of firms growth. more so when the goal is to analyze firm-level TFP. In our analysis, we use

TABLE B.3 – POSITIVE CORRELATION OF SALES GROWTH AND SKEWNESS OF FIRM'S SHOCKS

	(1)	(2)	(3)	(4)
Estimation Method:	Factor Shares	Panel Regression	Olley and Pakes	Labor Productivity
Ave. Sales Growth	1.21***	1.10***	1.18***	1.256***
	(0.40)	(0.31)	(0.40)	(0.37)
R^2	0.18	0.14	0.31	0.17
N	3,873	3,873	3,873	3,873

Note: Table B.3 shows a set of country-industry panel regressions in which the dependent variable is the Kelley skewness of firm productivity shocks calculated using the four different methods described in Section B.5.2. In all regressions, the explanatory variable is the average sales growth within the same bin. All regressions control for country, industry, and year fixed effects. Standard errors (below the point estimates) are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

data from BvD Amadeus, which has been used before to calculate firm level productivity by other researchers. Hence, to further validate our analysis, we compare our sample to that of Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez (2017) (GKKV thereafter) that used the same data to study the effects of misallocation in Spain and other europeans countries using BvD Amadeus.

In what follows, we provide a step-by-step comparison of our analysis to that in GKKV. Performing this analysis was very useful to validate our construction, clean a few inconsistencies in the data, and improve in our estimation. The main difference between our results and theirs is that GKKV focuses mostly on manufacturing firms in Spain whereas we calculate productivity across all sectors available in our dataset. Having said that, we can follow their sample selection as close as possible and show, first, that the resulting cross-sectional statistics are qualitatively similar, and second, that our results (i.e., that the skewness of firms' productivity shocks is procyclical) are robust the sample restriction used by GKKV.

Beyond comparing our sample to GKKV, we perform a few additional robustness checks that further validate our analysis. In particular,

- We analyzed the relation between sector growth and the skewness of firms TFP shocks by firm characteristics (i.e., large and small firms and young and old firms)
- We further restricted our sample to firms with at least 5 years of data so as to control for the exit of firms that can affect the left tail of the firm growth distribution.
- Following the recommendation of Referee 3, we further orthogonalized firms productivity shocks from aggregate effects controlling for a flexible polynomial.

In all cases (showed in Appendix B.5 of the paper), we find our results to be robust to these changes. We decided, however, to keep our baseline data in the main text and relegate the comparison and results based on the GKKV sample selection to the Appendix B.5 of the paper. We would be happy to include these new results in the main text or expand in the comparison between our sample and the results from GKKV if you think that is necessary. Below, we expand on these results in more detail. Thanks again for pushing us in this direction.

TABLE B.4 – SKEWNESS OF FIRMS' SHOCKS IS PROCYCLICAL AT THE COUNTRY LEVEL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ISO	DEU	DNK	ESP	FIN	FRA	GBR	GRC	HUN	IRL
Sales Growth	5.27***	4.47***	1.69***	2.27***	3.24***	2.25***	1.27***	0.87***	1.70***
	(0.70)	(1.02)	(0.32)	(0.14)	(0.45)	(0.14)	(0.24)	(0.24)	(0.19)
R^2	0.66	0.63	0.60	0.64	0.56	0.74	0.47	0.76	0.66
N	208	73	392	245	334	275	179	271	186

Continuation

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
ISO	ISL	ITA	NLD	NOR	POL	PRT	SWE	UKR
Sales Growth	2.56***	1.29***	2.12***	2.04***	1.87***	1.74***	2.86***	1.56***
	(0.31)	(0.19)	(0.21)	(0.35)	(0.36)	(0.17)	(0.228)	(0.209)
R^2	0.84	0.55	0.72	0.51	0.52	0.61	0.65	0.55
N	102	306	152	208	264	234	228	229

Note: Table B.4 shows a set of industry panel regressions in which the dependent variable is the Kelley skewness of firm productivity shocks. Firm-level productivity was calculated as the residuals of a firm-level panel regression (the second method described in section B.5.2). In each column, the independent variable is the average TFP shock within an industry. Each regression includes a set of industry and time fixed effects. Standard errors (below the point estimates) are clustered at the industry level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Sample Selection. Following GKKV, we clean our data in five steps within each country. First, we control for potential reporting errors. Second, we verify the internal consistency of the data we use in the analysis. Third, we implement additional controls on the specific variables we use in the TFP estimation step. Fourth, we winsorize the variables used in the analysis. We then drop duplicated observations in the dataset. We compare the resulting sample statistics with that presented in the published version of GKKV and their online appendix. Finally, we use the resulting dataset to calculate productivity using the same methods we use in our baseline analysis to show that our results are robust the sample selection used by GKKV. In what follows, we list this cleaning in detail following the same order they are applied to the data. The variable names available in BvD Amadeus are provided in parenthesis when appropriate.

- Step 1: Correcting reporting mistakes
  - We drop year-firm observations with missing in all the following variables at the same time: total value of assets (FIAS), operating revenues (OPRE), sales (TURN), and employment (EMP)
  - We drop firms with negative value of FIAS in any year; firms with negative EMP or EMP above 2 million workers in any year; firms with negative TURN in any year; firms with negative value of fixed assets (TFAS) in any year.
  - We drop firm-year observations with missing value of materials (MATE) or non-positive value of MATE; firm year observations with missing value of OPRE or non-positive value of OPRE; firm year observations with missing value of FIAS or non-positive value of FIAS

- Step 2: Internal consistency
  - We drop firm-year observations with a ratio of the sum of TFAS, intangible assets (IFAS), and other assets (OFAS) to FIAS greater than 1.
- Step 3: Variable specific controls
  - We drop firms-year with negative value of age, where age is constructed as the calendar year minus the date of incorporation of the firm plus one.
  - We drop firm-year observations with missing value of wage bill (STAF) or non-positive value of STAF; Firm-year observations with negative value of IFAS; Firm-year observations with a ratio of TFAS to IFAS greater than 1; Firm-year observations with TFAS plus IFAS equal to 0.
  - We drop firm-year observation with missing industry classification and with NAICS in the public sector (Four digit NAICS above 9000).
  - We drop firm-year observations in the top and bottom 0.1% of the capital stock-to-wage bill distribution, where capital stock is defined as TFAS plus IFAS.
  - We drop firm-year observations with negative value added (VA) where VA is calculated as OPRE minus MATE. We then drop firm-year observations with STAF-to-VA ratio at the top and bottom 0.1% of the distribution or with STAF-to-VA ratio above 1.1.
- Step 4: Winsorization
  - We winsorize OPRE, STAF, TURN, and VA at the bottom 1% and to 0.5%.
- Step 5: Repeated variables
  - Some firm-year records are repeated in the sample, we drop these repeated firm-year observations.

We save the resulting database for each country.

Calculating Productivity. Using this new dataset and our baseline dataset, we recalculate firm-level TFP and evaluate whether the skewness of firm-level productivity shocks remains procyclical. In particular, as we further discuss Appendix B.5, in the new version of the draft we include new results based on six different productivity estimation methods: factor shares, revenue per worker, the method of Olley and Pakes (1996), the method of Ackerberg *et al.* (2015), and the one proposed by Wooldridge (2009).

To calculate productivity, we apply each of the previous methods and we obtain a measure of productivity level z_{jt}^k for firm j in country k in period t. We then regress within each country

$$\log z_{jt}^k = \rho z_{jt-1}^k + \lambda_j + \delta_t + \epsilon_{jt}^k,$$

where λ_j and δ_t are a firm and a year fixed effect. Our measure of shocks is then given by $\hat{\epsilon}_{jt}^k$. To further control for outliers we,

- Step 1: Trim $\hat{\epsilon}_{jt}^{k}$ at the top and bottom 0.1%.
- Step 2: Calculate cross-sectional moments of the firm sales growth and TFP shock distribution only for year-country-sector bins with more than 100 firms.
- Step 3: Winsorize the distribution of mean sales growth and Kelley Skewness at the top and bottom 5%.

None of these changes have major consequences in our results. We use the resulting data to evaluate the relation between firm growth and skewness. The results based on the baseline built of the data are shown in Figure B.1 whereas the results based applying the sample selection of GKKV are shown in Figure B.2. The two main take aways from comparing these figures is, first, that in all cases, we find that the skewness of firm-level productivity shocks is procyclical, and second, that our results are robust to applying the sample selection of GKKV.

Database Comparison and Results. Finally, we compare different cross-sectional moments available in GKKV and their appendix, to similar cross-sectional moments coming from our dataset set under the GKKV sample selection. This serve as a further validation that our dataset is suitable for the analysis we perform. Across our analysis, we compare our data to the aggregates reported by Eurostats through its Structural Business Statistics database (SBS). In particular, we obtain information for aggregate level employment (SBS table tin00148), aggregate level gross output (SBS table tin00146), sector level wages (SBS table tin00154), sector level employment (SBS table tin00151), and sector level gross output (tin00149). All variables are expressed in Euros of corresponding year.

First, we compare the share of employment, wage bill, and gross output in manufacturing available in GKKV to the results coming from our dataset for the years in which our data overlaps with in GKKV's sample. This is shown in Table B.5. Relative GKKV, our sample on manufacturing covers a smaller fraction of the wage bill and gross output. Coverage of employment, however, is closer although still below that of GKKV. This is to be expected since we only use the data available through WRDS whereas GKKV use data of different vintages and discs that increase the their sample size. When we consider the whole economy, that is, including all firms and sectors after sample cleaning, the coverage of our dataset is still significant: across different variables and years, our sample accounts for between 40% and 54% of aggregate economic activity in Spain. This is also true across the rest of the countries we use in our dataset, as shown in Table B.6.

We then calculate cross-sectional moments of the distribution of five key variables: value added, employment, wage bill, total value of assets, and sales. The results in our data are shown in Table B.7 for the whole economy and manufacturing. Relative to GKKV, that show similar results in their online appendix, our firms are smaller across different dimensions, but qualitatively, the cross sectional moments are comparable. We conclude that, despite difference, our data captures a significant fraction of economic activity across the countries in our sample, and therefore, can be used to draw conclusions about the relation between aggregate economic activity and firms' growth

TABLE B.5 – SHARE OF EMPLOYMENT, WAGE BILL, AND GROSS OUTPUT AVAILABLE IN SAMPLE

	Gopinath et al. 2017 Spain Manufacturing			Salgado et al. (2023) Spain Manufacturing			Spain Economy		
	Emp.	Wage Bill	Gross Output	Emp.	Wage Bill	Gross Output	Emp.	Wage Bill	Gross Output
2009	0.71	0.72	0.75	0.54	0.44	0.39	0.45	0.43	N/A
2010	0.68	0.73	0.74	0.56	0.45	0.40	0.48	0.38	0.40
2011	0.69	0.74	0.75	0.60	0.48	0.40	0.52	0.40	0.41
2012	0.65	0.71	0.72	0.63	0.50	0.41	0.54	0.42	0.42

Note: This table shows the share of employment, wage bill, and gross output available in the dataset of manufacturing firms in GKKV (left panel), in our dataset (center panel), and across the entire economy (right panel) for Spain. Firm level data coming from BvD Amadeus database whereas country- and industry-level data from Structural Business Statistics database. The center panel uses a total sample of 632,948 firm-years observations. The right panel uses a total sample of 3,947,773 firm-years observations across all years available.

TABLE B.6 – SHARE OF EMPLOYMENT, WAGE BILL, AND GROSS OUTPUT AVAILABLE IN SAMPLE

	Year 2012			Year 2016		
Country	Emp.	Wage Bill	Gross Output	Emp.	Wage Bill	Gross Output
Germany	0.36	0.37	0.36	0.34	0.34	0.34
Spain	0.54	0.42	0.42	0.65	0.65	0.65
Finland	0.53	0.46	0.38	0.57	0.57	0.57
France	0.36	0.36	0.36	0.44	0.44	0.44
Hungary	0.40	0.48	0.50	0.40	0.40	0.40
Italy	0.48	0.41	0.45	0.59	0.59	0.59
Norway	N/A	0.69	0.49	0.96	0.96	0.96
Poland	0.12	0.31	0.33	0.13	0.13	0.13
Portugal	0.57	0.48	0.50	0.71	0.71	0.71
Sweden	0.37	0.26	0.26	0.47	0.47	0.47

Note: This table shows the share of employment, wage bill, and gross output available in the dataset relative to the economy-wide levels for two years across all countries in the Amadeus sample. Firm level data coming from BvD Amadeus database whereas country- and industry-level data from Structural Business Statistics database.

TABLE B.7 – CROSS-SECTIONAL STATISTICS

		Economy Wide		Manufacturing				Economy Wide		Manufacturing	
		Mean	Std. Dev.	Mean	Std. Dev.			Mean	Std. Dev.	Mean	Std. Dev.
Spain	Value Added	0.8	3.2	1.3	4.2	Hungary	Value Added	4.5	4365.7	6.8	5647.1
	Employment	19.1	373.9	20.9	173.3		Employment	91.9	402.7	168.9	457.1
	Wage Bill	0.4	1.3	0.6	1.6		Wage Bill	1.1	983.5	2.0	1321.4
	Total Assets	2.2	78.9	2.3	41.8		Total Assets	6.3	27922.2	10.9	44051.1
	Sales	2.0	8.2	3.1	10.9		Sales	10.3	11415.6	17.6	15712.2
Italy	Value Added	1.6	5.9	2.4	6.8	Poland	Value Added	2.2	27.6	3.1	35.2
	Employment	19.9	239.1	25.6	153.2		Employment	82.6	412.8	127.7	307.6
	Wage Bill	0.5	1.7	0.8	2.1		Wage Bill	0.6	6.9	0.9	8.3
	Total Assets	2.2	98.9	2.3	43.2		Total Assets	2.9	120.6	3.8	97.4
	Sales	3.0	12.0	4.8	14.5		Sales	5.1	66.0	8.2	92.0
Portugal	Value Added	0.5	2.0	0.8	2.4	Sweden	Value Added	1.0	35.2	1.4	41.9
	Employment	13.6	136.5	19.9	62.1		Employment	13.0	148.2	15.4	66.3
	Wage Bill	0.2	0.6	0.3	0.7		Wage Bill	0.5	14.7	0.7	17.3
	Total Assets	1.3	58.7	0.9	8.5		Total Assets	1.5	497.6	1.4	206.2
	Sales	1.1	4.4	1.6	5.4		Sales	2.2	83.8	2.9	98.8
Germany	Value Added	39.3	116.1	37.8	106.8	Ukraine	Value Added	43.7	106.6	42.6	112.8
	Employment	499.6	3440.3	415.8	3217.1		Employment	200.4	1564.1	257.5	967.8
	Wage Bill	14.3	39.7	14.4	37.7		Wage Bill	6.0	12.2	8.0	15.7
	Total Assets	53.7	732.7	61.8	957.2		Total Assets	71.0	1350.9	58.9	540.8
	Sales	81.9	256.8	78.7	231.0		Sales	56.7	128.6	74.0	163.2
France	Value Added	2.1	8.0	3.9	11.6	Finland	Value Added	1.3	6.1	2.3	9.0
	Employment	41.3	1095.4	58.0	555.7		Employment	22.8	249.6	38.3	355.9
	Wage Bill	0.8	2.8	1.5	4.0		Wage Bill	0.5	2.2	0.9	3.2
	Total Assets	3.8	246.5	4.7	104.8		Total Assets	1.5	71.3	2.4	32.4
	Sales	4.0	15.3	7.2	22.3		Sales	2.6	13.3	4.6	19.2
Norway	Value Added	2.1	71.8	3.9	107.0		Value Added	97.8	158.7	65.3	77.6
	Employment	11.1	78.1	16.2	60.4		Employment	1307.0	2534.0	1296.3	2155.4
	Wage Bill	1.0	29.9	1.8	44.0		Wage Bill	38.2	58.8	19.8	24.0
	Total Assets	4.4	1013.9	8.6	1522.7		Total Assets	95.4	213.4	125.5	274.1
	Sales	4.5	160.9	8.6	244.5		Sales	313.1	451.3	217.1	253.0

Note: This table shows cross-sectional moments of the distribution of key firm-level variables used in the calculation of firm-level productivity. All values are expressed in millions of euros. We deflate nominal values by country-level CPI. Moments are first calculated within each year and then averaged across all years within a country. Firm level data coming from BvD Amadeus database.

B.5.5 Controlling for non-linear responses

Although our results robustly suggest that firm skewness is procyclical, it is possible that this relation is explained by non linear responses of firms's TFP to aggregate shocks that are not week capture by fixed average differences across years—i.e., they are not stripped out by the time fixed effect in Equation 4). One way to evaluate whether firms revenue TFP is differentially exposed to aggregate fluctuations is to strip out the covariance with respect to aggregate GDP. As a reminder, in our baseline results, we measure TFP shocks as the residuals of the following panel regression, which we run for each country in our sample,

$$\log z_{i,t} = \rho \log z_{i,t-1} + \lambda_i + \delta_t + \epsilon_{i,t}. \tag{5}$$

We can capture potential non-linear responses to a common aggregate shock by interacting $\log z_{i,t-1}$ with with a linear, quadratic, or cubic function of GDP growth, that is, for a quadratic case we estimate for each country

$$\log z_{i,t} = \rho \log z_{i,t-1} + \beta_1 \log z_{i,t-1} \times \Delta GDP_t + \beta_2 \log z_{i,t-1} \times \Delta GDP_t^2 + \delta_t + \lambda_i + \eta_{i,t}. \tag{6}$$

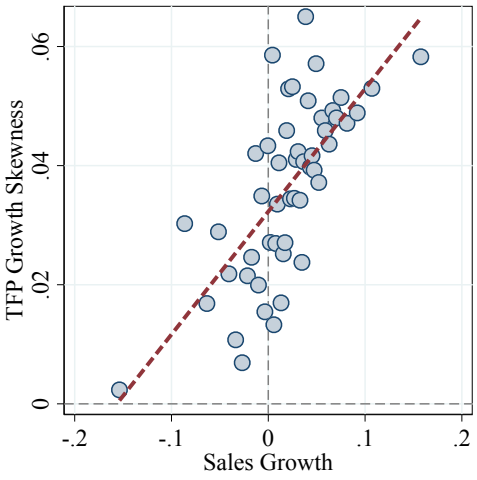
Alternative, it is possible that firms are differentially exposed to the business cycle so that β_1 for instance is sector or firm specific. To evaluate this case, we can estimate the following specification

$$\log z_{i,t} = \beta_{i,0} + \rho \log z_{i,t-1} + \beta_{i,1} \times \Delta GDP_t + \nu_{i,t}, \tag{7}$$

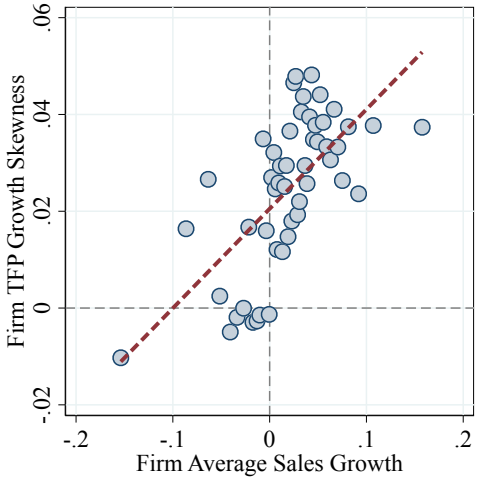
and then study whether different estimates of $\eta_{i,t}$ or $\nu_{i,t}$, change the cyclicality in the skewness that we observe in our baseline specification. We implement specifications 6 and 7 using our baseline TFP estimation results—which are based on the standard Olley and Pakes (1996) methods—using data from BvD Amadeus. Results based on US Census ASM are similar but not disclosed. The results, shown in Figure B.3, indicate that the skewness of TFP residuals is procyclical. We conclude that controlling for potential non linear responses might affect our results, the baseline conclusion remains unaltered.

FIGURE B.1 – BASELINE: SKEWNESS OF TFP SHOCKS IS PROCYCLICAL

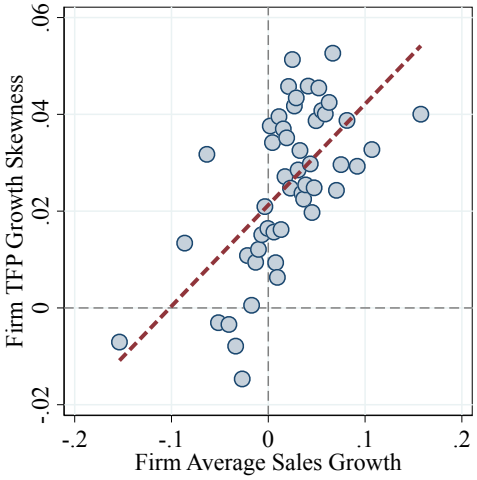
(A) Baseline (Olley Pakes)



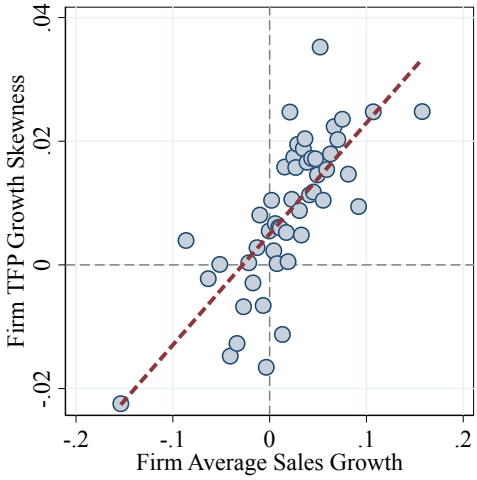
(B) Factor Share



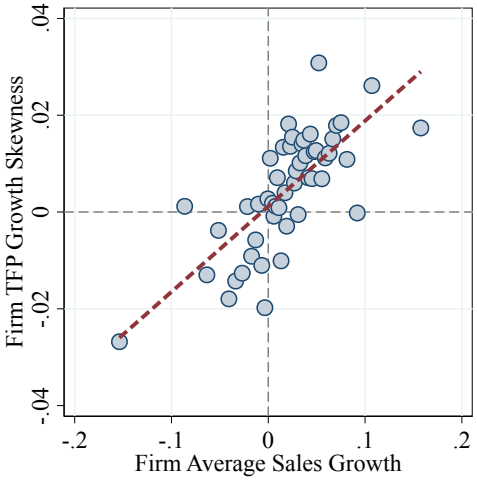
(C) Value Added per worker



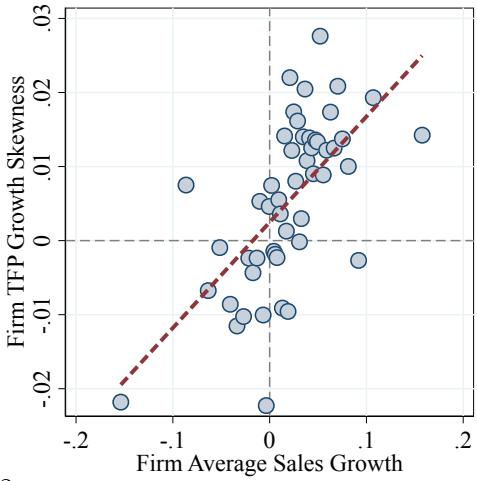
(D) OLS



(E) Ackerberg, Caves, and Frazer (2015)



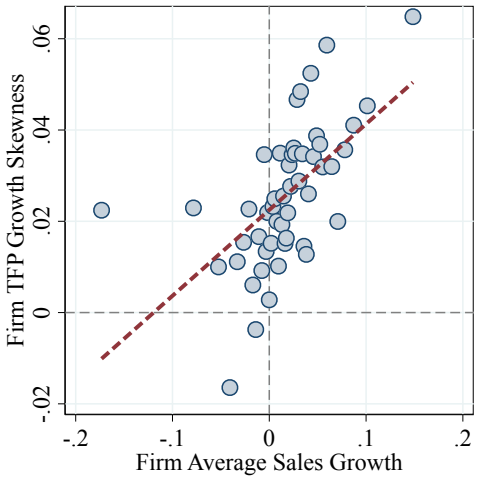
(F) Wooldridge (2009)



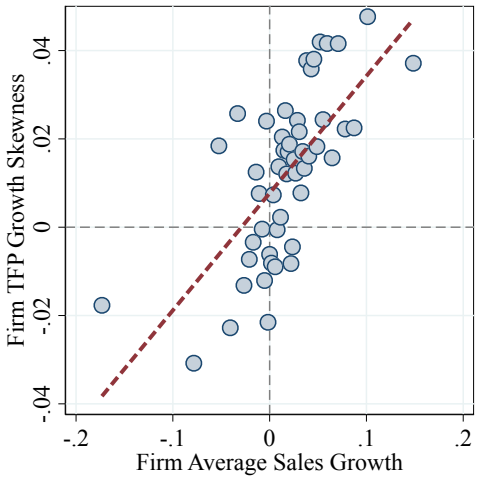
Note: This figure shows the relation between the average firm sales growth within a year-country-industry and the skewness of firm productivity shocks within the same bins calculated using different methods. Binscatters control for year, country, and industry fixed effects. Industries defined as two digit NAICS.

FIGURE B.2 – GKKV: SKEWNESS OF TFP SHOCKS IS PROCYCLICAL

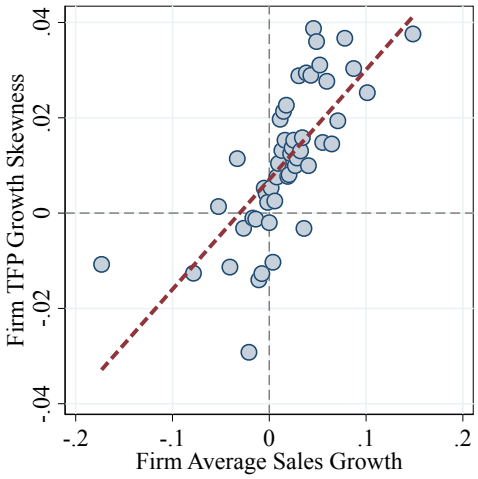
(A) Baseline (Olley Pakes)



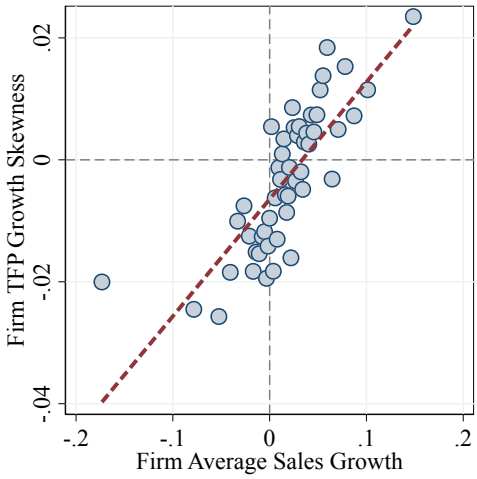
(B) Factor Share



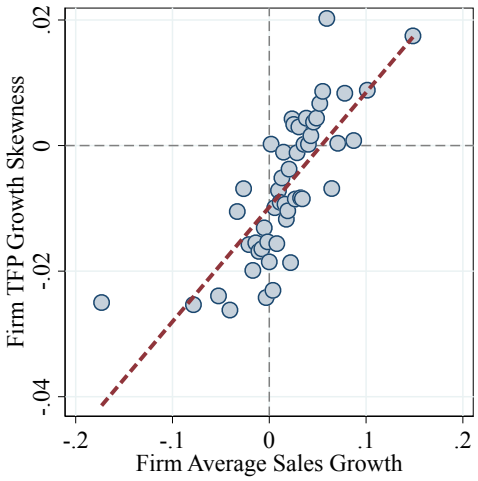
(C) Value Added per worker



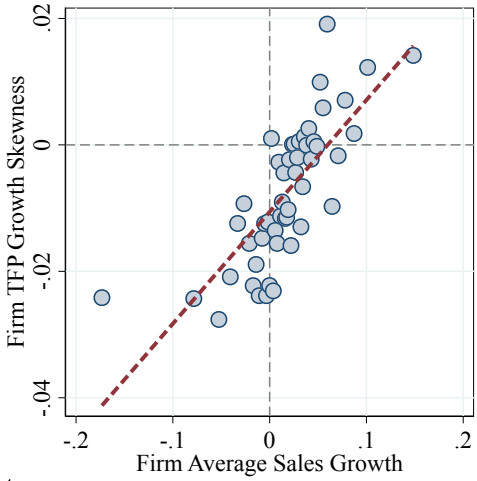
(D) OLS



(E) Ackerberg, Caves, and Frazer (2015)

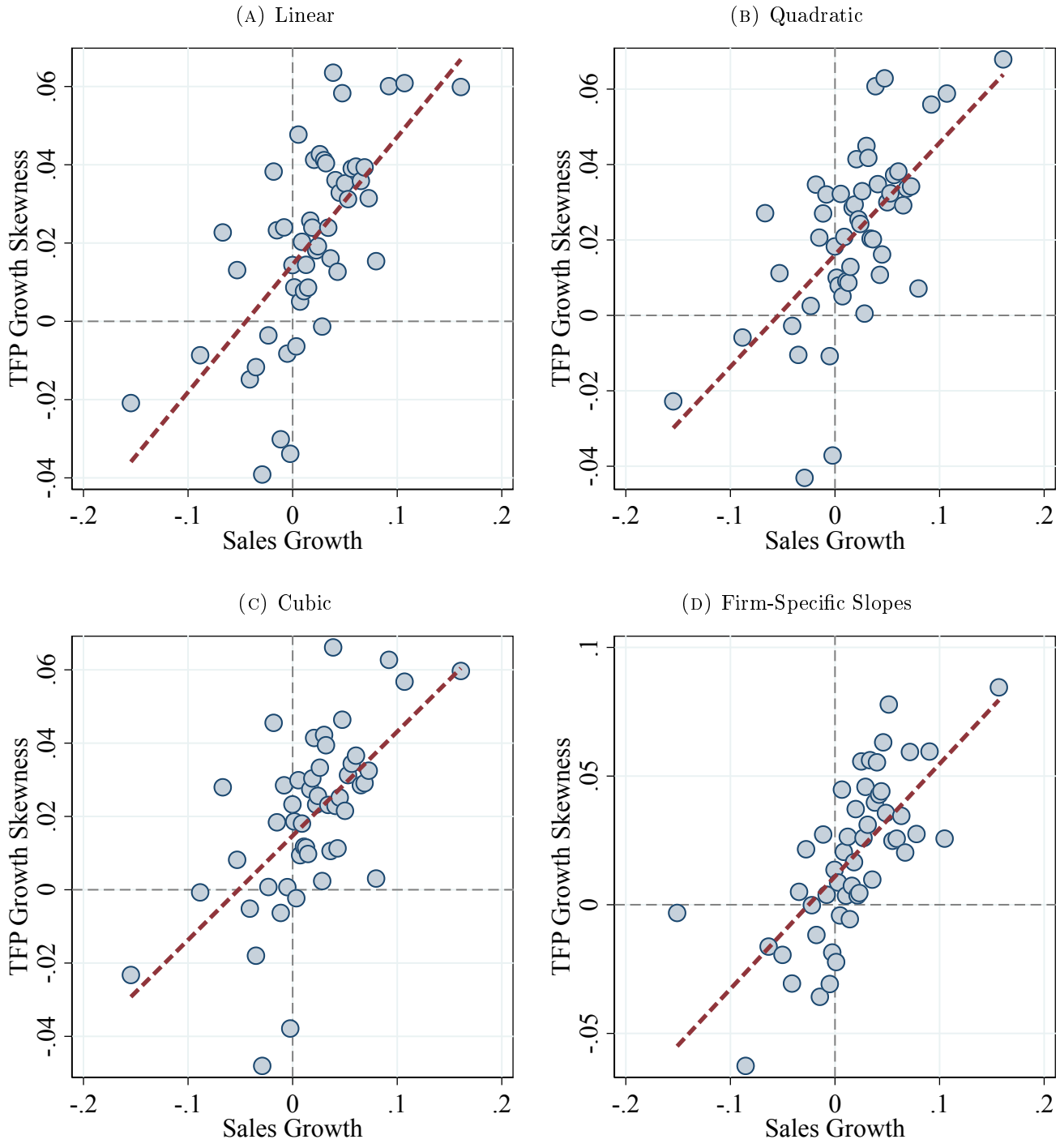


(F) Wooldridge (2009)



Note: This figure shows the relation between the average firm sales growth within a year-country-industry and the skewness of firm productivity shocks within the same bins calculated using different methods. Binscatters control for year, country, and industry fixed effects. Industries defined as two digit NAICS. The same is constructed using the sample cleaning of GKKV.

FIGURE B.3 – TFP MEASURES AND SKEWNESS CONTROLLING FOR AGGREGATE CONDITIONS



Note: This figure shows industry-country-year level binscatters of average sales growth (x-axis) and Kelley skewness of firms TFP innovations (y-axis). Bin scatters control for industry (2-digit NAIC), country, and year fixed effects. Panel A to C are based on Equation 6 for a linear, quadratic, and cubic interaction with country-level GDP growth. Panel D is based on Equation 7 considering firm-specific slopes. TFP estimation is based on the Olley and Pakes (1996) method.

B.5.6 United States: Productivity, US Census, Survey of Manufacturing, and Capacity Utilization

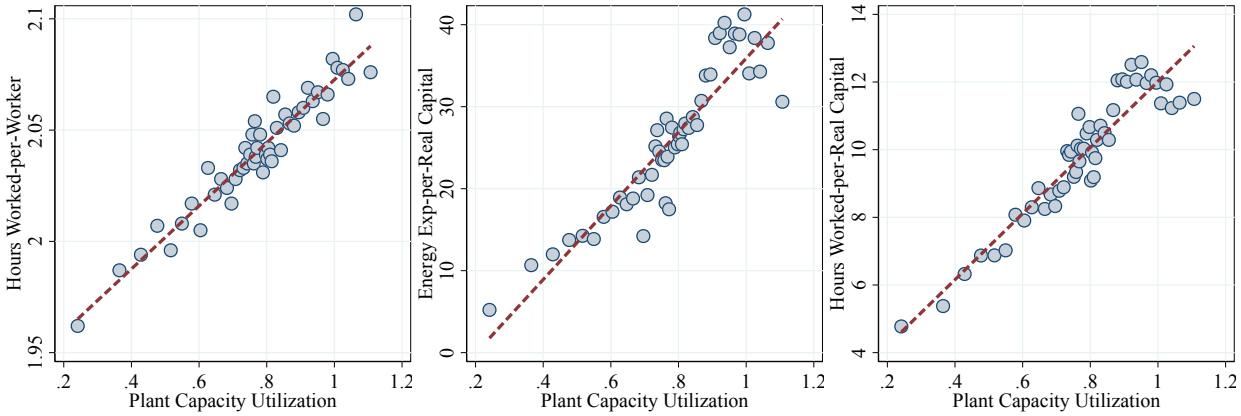
Here we describe the sample selection and moment construction using data from the US Census of Manufacturing (CM) and the Survey of Manufacturing firms (ASM). The CM, which is part of the Economic Census, is conducted every five years, in every year ended in 2 or 5 and was first implemented in 1963. It covers all establishments with at least one paid employee in the manufacturing sector (NAICS 31-33) for a total sample between 300,000 and 400,000 establishments per Census. Information is delivered by firms at the establishment level and Census provides a unique identifier (lbdnum) which we use to follow establishments over time. The Census Bureau complements the CM data with the ASM every year the Economic Census is not conducted since 1973. Relative to the CM, the ASM is skewed towards large firms as it covers all establishments of firms covered by the CM above a certain threshold and a smaller sample of small and medium size firms. The average sample of firms in our sample is around 30,000 establishments per year for a total of about 1.1 million establishment/year observations. The merged CM/ASM contains consistent data in industry, sales, employment, capital expenditures, materials, and others. Importantly, from 1976 to 2019, the data contains measures of log-productivity prepared by the Bureau of Labor Statistics which we directly use in our analysis. The data set and construction of the TFP measures are described in Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2021).

To keep a consistent sample selection across datasets, we consider establishments for ten or more years of data. Since the ASM sample is refreshed every Census year for small and medium firms, this sample selection criteria naturally select large and stable firms. Our results, however, are robust to the changes in this10-years threshold.

It is well known that failing to control for changes in capacity utilization can lead to wrong estimates on the cyclicality of firm and aggregate productivity (Basu, 1996). This might be even more important using firm-level data and when trying to measure higher order moments. To control for changes in firm-level utilization that might bias our results, we residualize the log of measured productivity for different measures of utilization available in the ASM, namely, average number of hours for productive workers and energy utilization. In particular, we have use firm-level capacity utilization administrative data from the Census' Quarterly Survey of Plan Capacity Utilization (QPC) and the Annual Survey of Manufacturing (ASM). We proceed in three steps which we describe below.

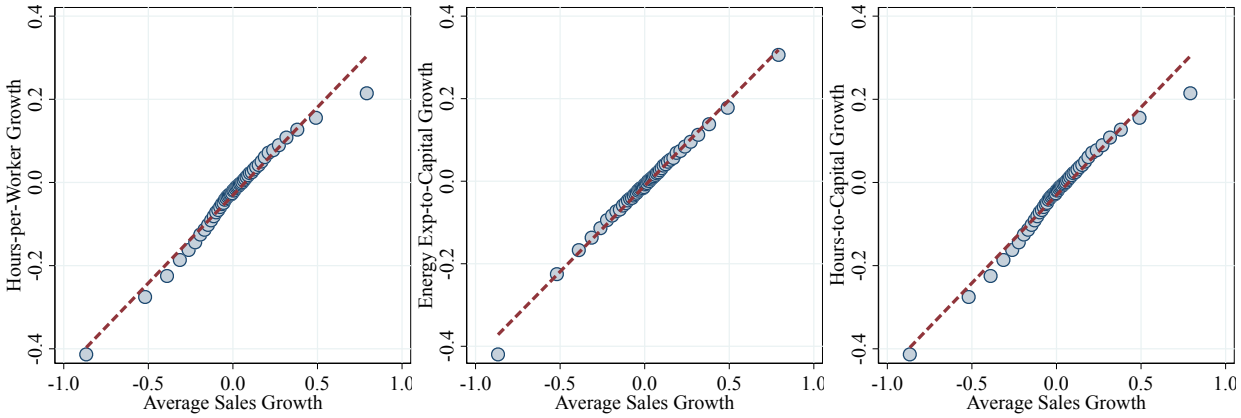
i. First, we use two questions from QPC to calculate what fraction of the total capacity that is used by a plant in any given time. This measure of capacity utilization is only available for those plants in the QPC. Therefore, we merge the QPC data with the ASM which contains information on output and inputs, including energy usage and hours worked. With these variables, we construct three measures of plant capacity utilization: i) average number of hours per worker ii) the ratio between real energy expenditure and real value of machinery and equipment, and iii) the ratio between total hours worked and the real value of machinery and equipment. Figure B.4 shows that all these measures are highly correlated with the QPC measure of capacity utilization, which we take as our benchmark. Hence, in our analysis, we use the ASM-based measures of capacity utilization given they appear to be tightly correlated with QPC data (but which is not available for our fuller

FIGURE B.4 – CORRELATION OF CAPACITY UTILIZATION IN CENSUS' QPC AND ASM



Note: Figure B.4 shows industry-year level bin-scatters the measure of plant capacity utilization from QPC (x-axis) and a proxy for capacity utilization from ASM (y-axis). Binscatters control for year and industry fixed effects. Industry are at the 3-digit NAIC level.

FIGURE B.5 – CAPACITY UTILIZATION IS PROCYCLICAL IN ASM



Note: Figure B.5 shows industry-year level bin-scatters the measure of plant capacity utilization growth (y-axis) and plant sales growth (log-change of total value of shipments) from ASM. Binscatters control for year and industry fixed effects. Industry are at the 3-digit NAIC level.

dataset). This delivers three credible measures of capacity utilization for the entire ASM data sample.

ii. Second, we check if the ASM-based measures of capacity utilization are procyclical, which is an important validation step. For this, we use plant-level data and correlate the growth rate of the three ASM-based measures of capacity utilization we described above with the growth rate of the real value of shipments (revenue growth). As expected, we find a positive and strong correlation between revenue growth and capacity utilization growth. These results are displayed in Figure B.5. Each figure shows mean sales growth at the industry level and the mean growth of capacity utilization for different measures controlling for year and industry fixed effects. The tight positive slope indicates that in periods in which the sales growth is above the industry average, utilization is also above its industry average.

iii. Third, using our capacity utilization measures, we regress the log-TFP measure avail-

able in Census on these measure of capacity utilization using a rich set of polynomials to account for potential non-linearities in the relation between plant capacity utilization and productivity. This should cleanse any impact of capacity utilization from our measurement of TFP given this flexible functional form. In particular, we use multiple specifications which span a linear term for capacity utilization to a third-degree polynomial. We use the residuals of these regressions as our utilization-adjusted measure of TFP and we analyze whether the skewness of this measure is procyclical. To do so, we calculate the mean and Kelley skewness of TFP growth within a year/3-digit NAIC code and we regress these two measures.

TABLE B.8 – SKEWNESS OF FIRM TFP GROWTH IS PROCYCLICAL

(A) TFP Growth

Specification	β	SE	*t-stat*	R^2
Baseline	1.158	0.061	18.75	0.131
Residual 1	1.164	0.062	18.75	0.129
Residual 2	1.164	0.062	18.74	0.129
Residual 3	1.167	0.062	18.78	0.129
Residual 4	1.168	0.062	18.8	0.129
Residual 5	1.164	0.062	18.91	0.133
Residual 6	1.151	0.062	18.68	0.130
Residual 7	1.168	0.062	18.8	0.129

(B) Sales Growth

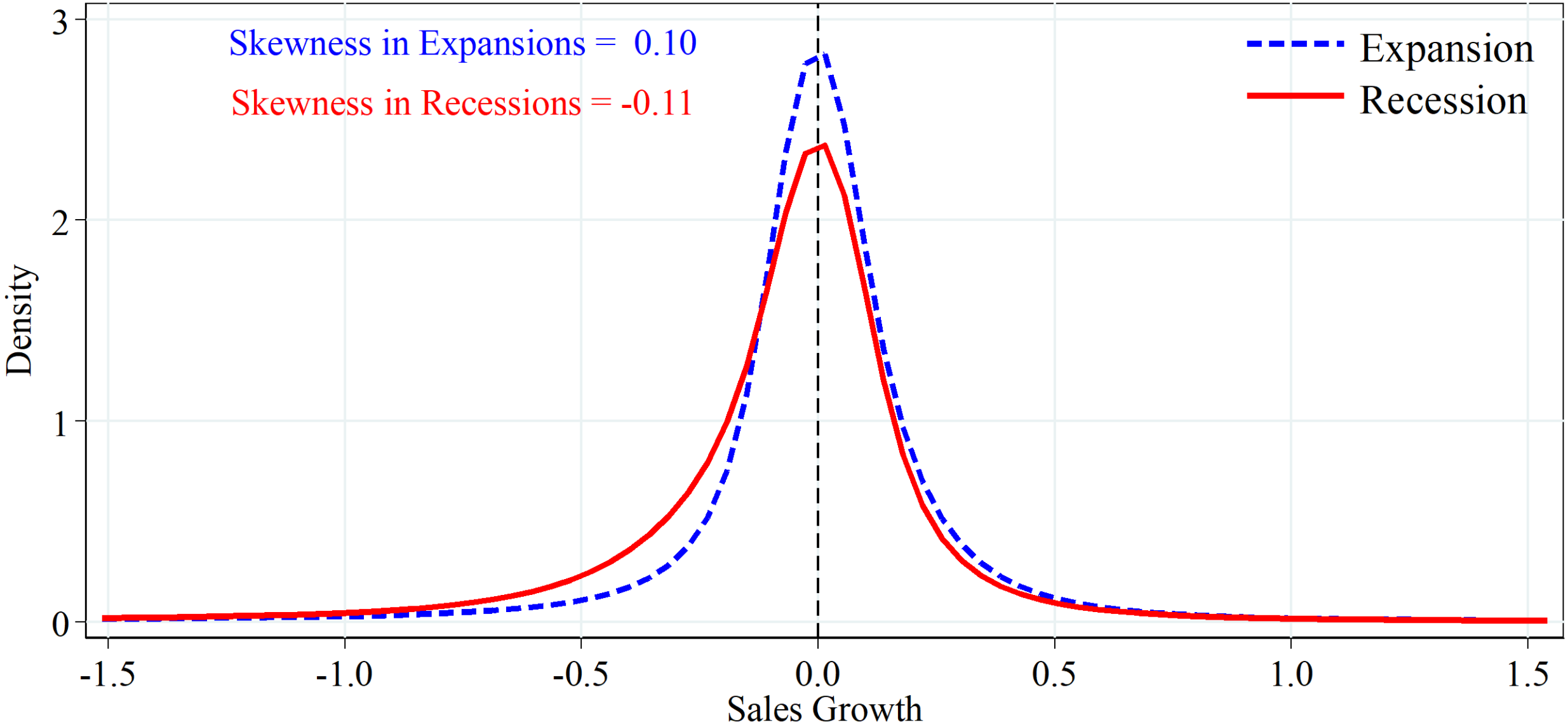
Specification	β	SE	*t-stat*	R^2
Baseline	0.564	0.050	11.52	0.080
Residual 1	0.587	0.050	11.95	0.080
Residual 2	0.587	0.050	11.95	0.081
Residual 3	0.589	0.050	11.99	0.081
Residual 4	0.590	0.050	12.01	0.081
Residual 5	0.576	0.050	11.75	0.083
Residual 6	0.569	0.050	11.66	0.081
Residual 7	0.590	0.050	12.01	0.081

Note: Figure B.8 shows industry panel regressions (3-digit NAIC) of the Kelley skewness of TFP growth on the average TFP growth and average sales growth within an industry using data from the Census Annual Survey of Manufacturing. All regressions weighted by sample weights and include a year and industry fixed effects. We use three measures of capacity utilization: Hours per worker, Energy Per Capital, and Hour Per Capital. Baseline is the correlation between TFP shocks skewness and mean TFP shock or mean sales growth without any adjustment for capacity utilization. Residual 1 refers to log-TFP residualized using a model in which the three measures of capacity utilization enter linearly; Residual 2 adds a quadratic term on each measure, Residual 3 adds a cubic term, and Residual 4 adds a quartic term. Residual 5 uses a quartic polynomial only on Hours per worker, Residual 6 a quartic on Energy per Capital, and Residual 7 uses Hours Per Capital unit.

Table B.8a shows the results of these regressions controlling for year and industry fixed effects. The first row (baseline) calculates the relation between TFP shocks skewness and mean TFP shocks or mean sales growth without any controls for capacity utilization. Residual 1 refers to log-TFP residualized using a model in which the three measures of capacity utilization enter linearly; Residual 2 adds a quadratic term on each measure, Residual 3 adds a cubic term, and Residual 4 adds a quartic term. Residual 5 uses a quartic polynomial only on Hours per worker, Residual 6 a quartic on Energy per Capital, and Residual 7 uses Hours Per Capital unit.

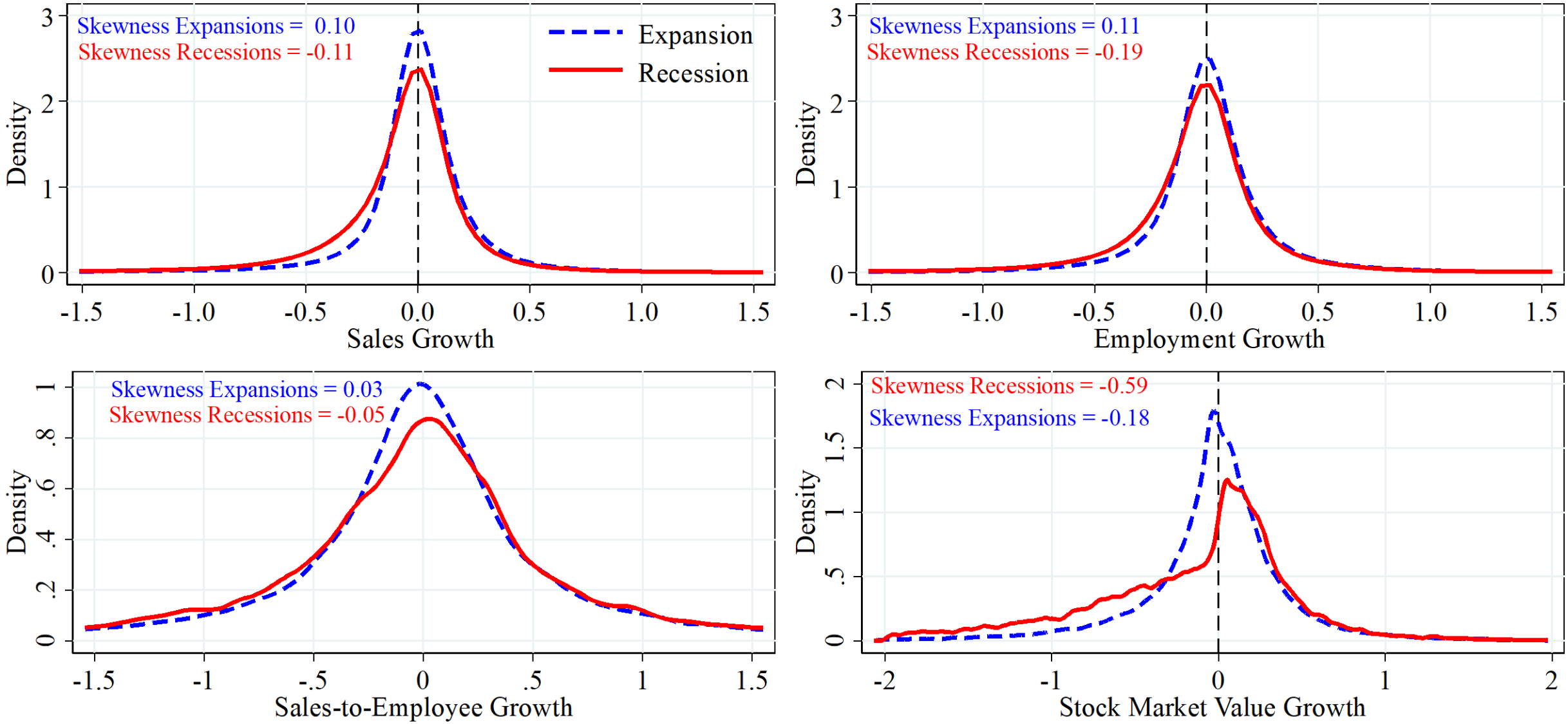
We repeat these regressions using the average sales growth within an industry instead of the average TFP growth. The results, shown in Table B.8b, indicate a positive relation between the skewness of TFP growth and the average sales growth at the industry level. We conclude that, although capacity utilization is an important contributor to the observed changes in measure productivity, controlling for its fluctuations does not materially affect the procyclical nature of the skewness of the distribution of firm shocks.

Figure 1: Firm Sales Growth has Procyclical Skewness



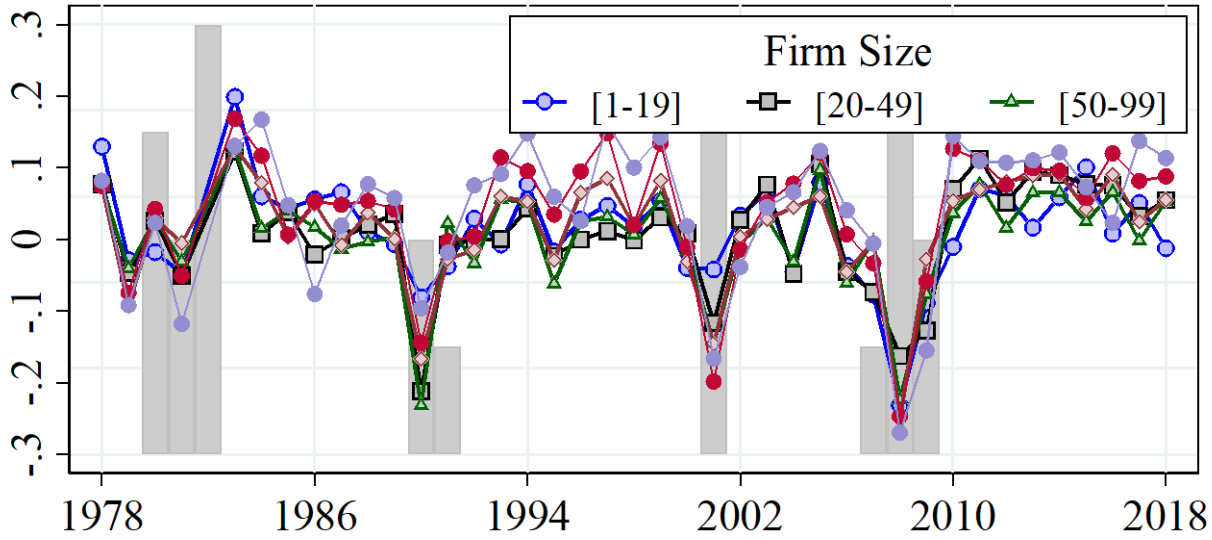
Note: Distribution of firm sales output growth from the US Census' Longitudinal Business Database for firms with 20 employees or more. Each density has been adjusted to have a median of zero. Blue-dashed line for expansion years (2003 to 2006 and 2010 to 2018, approximately 590,000 firm-year observations), red-solid line recession years (2001, 2008, and 2019, approximately 570,000 firm-year observations). Skewness is measured using Kelley Skewness.

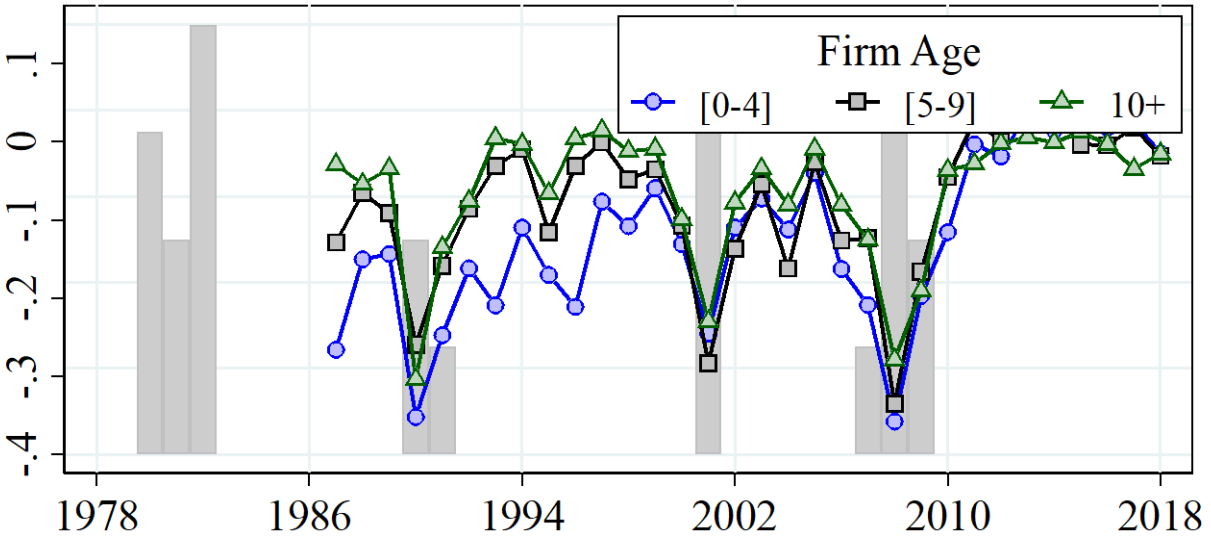
Figure 2: Firm Sales, Employment, Productivity and Stock Market Value Growth have Procyclical Skewness

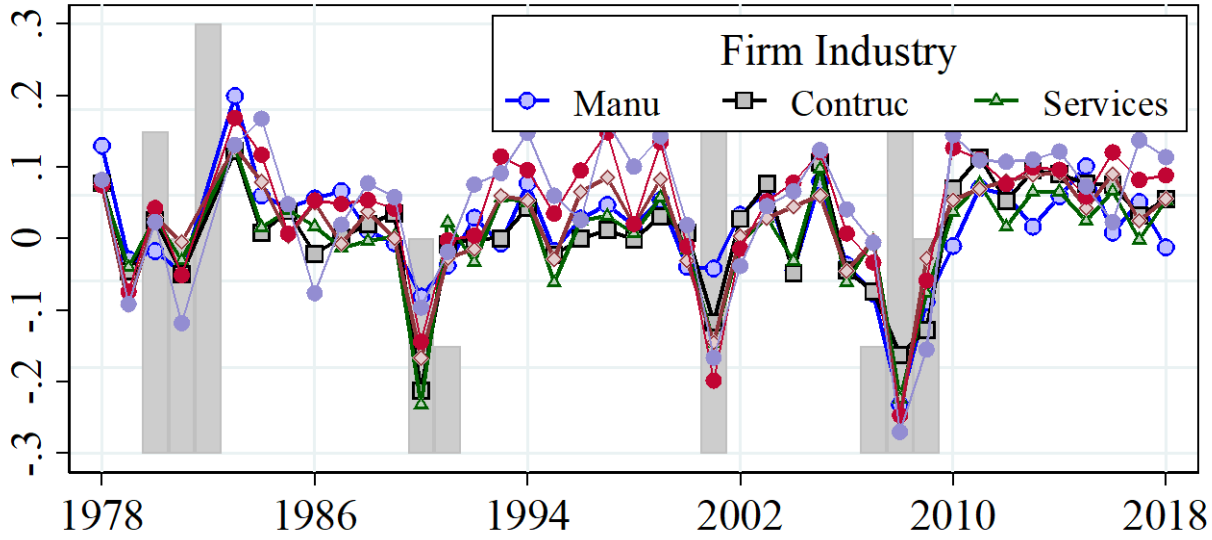


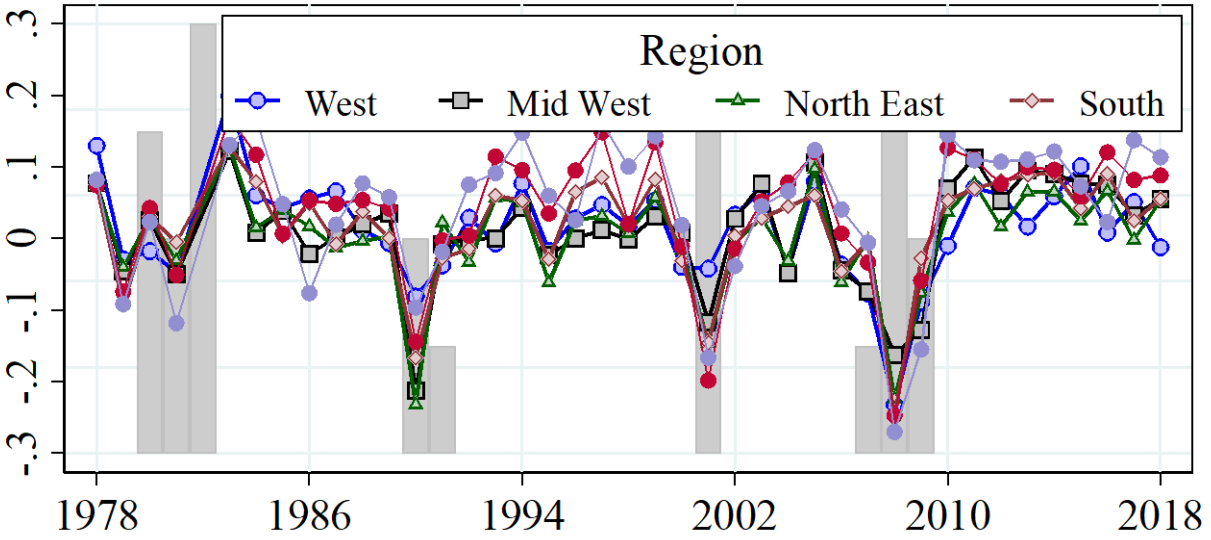
Note: Distribution of firm growth constructed from the US Census' LBD for firms with 20 employees or more for sales, employment, and sales-per-employee growth. Firm employment sums across all establishments. Stock Market Value Growth for publicly traded firms from CRSP. Each density has been 1st moment adjusted to a median of zero. Blue-dashed line sample of expansion years (2003 to 2006 and 2010 to 2019) red-solid line sample of recession years (2001, 2008, and 2020). Skewness is Kelley Skewness.

Figure 3: Firm Employment Growth Skewness is Cyclical for all Firm Size, Age, Industry and Region Splits



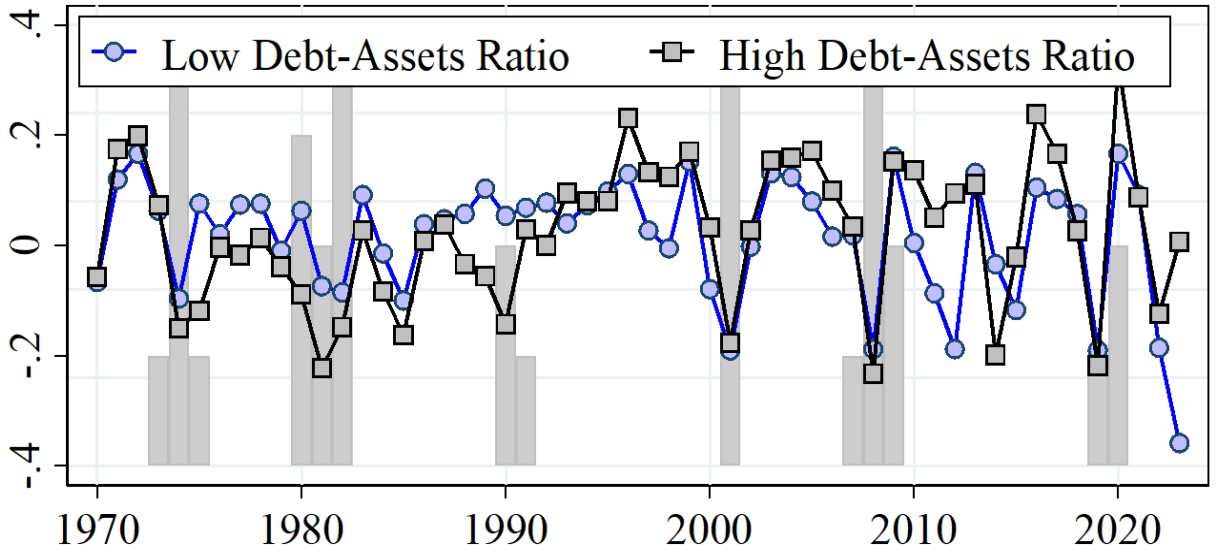


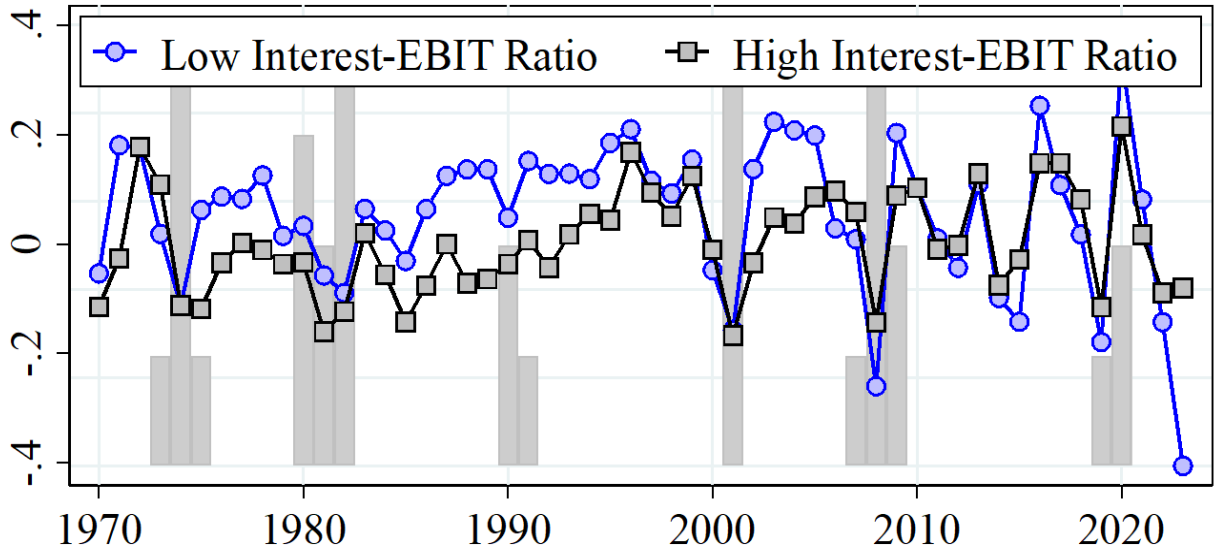


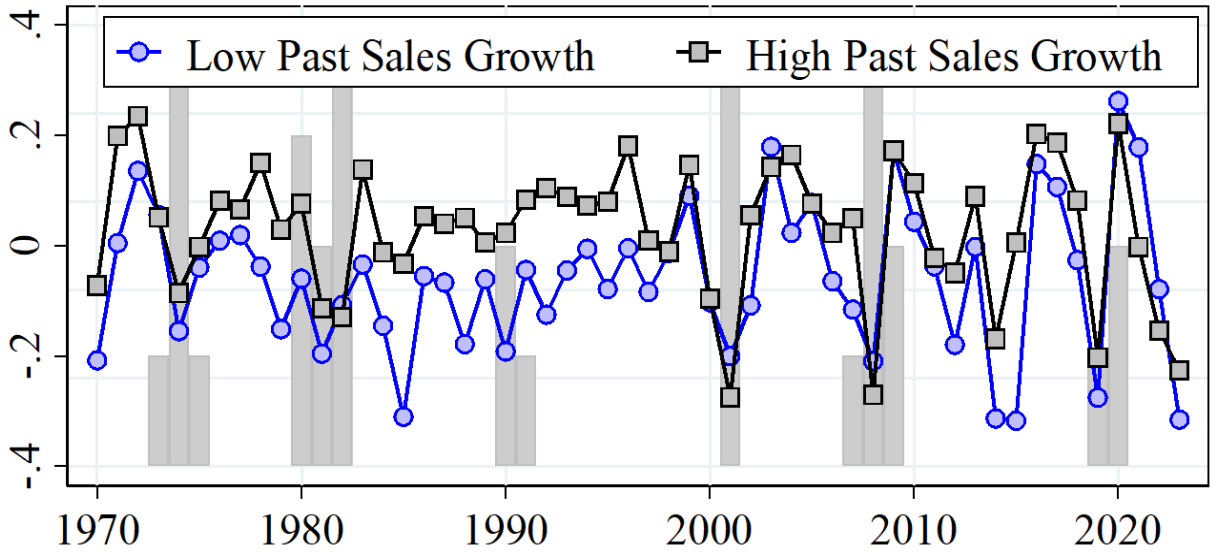


Note: This figure shows the time series of the cross-sectional Kelley skewness of the distribution of firm employment growth for different firm groups using data from the US Census' Longitudinal Business Database (LBD), containing an average of about 4.6 million firm observations per year. Shaded areas are the share NBER recession quarters within a year. Regions are the four Census Divisions.

Figure 4: Firm Sales Growth Skewness is Cyclical for all Financial Conditions Indicator splits

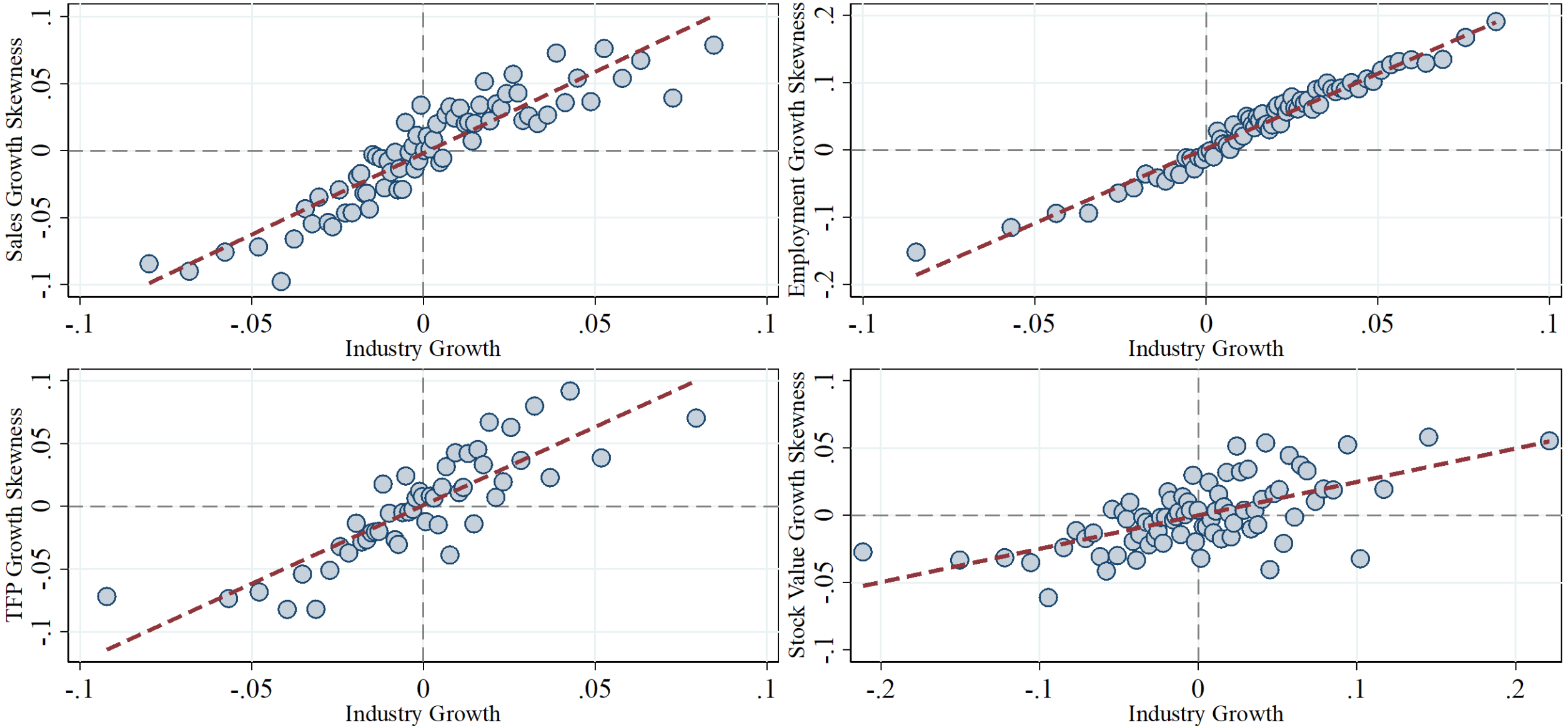






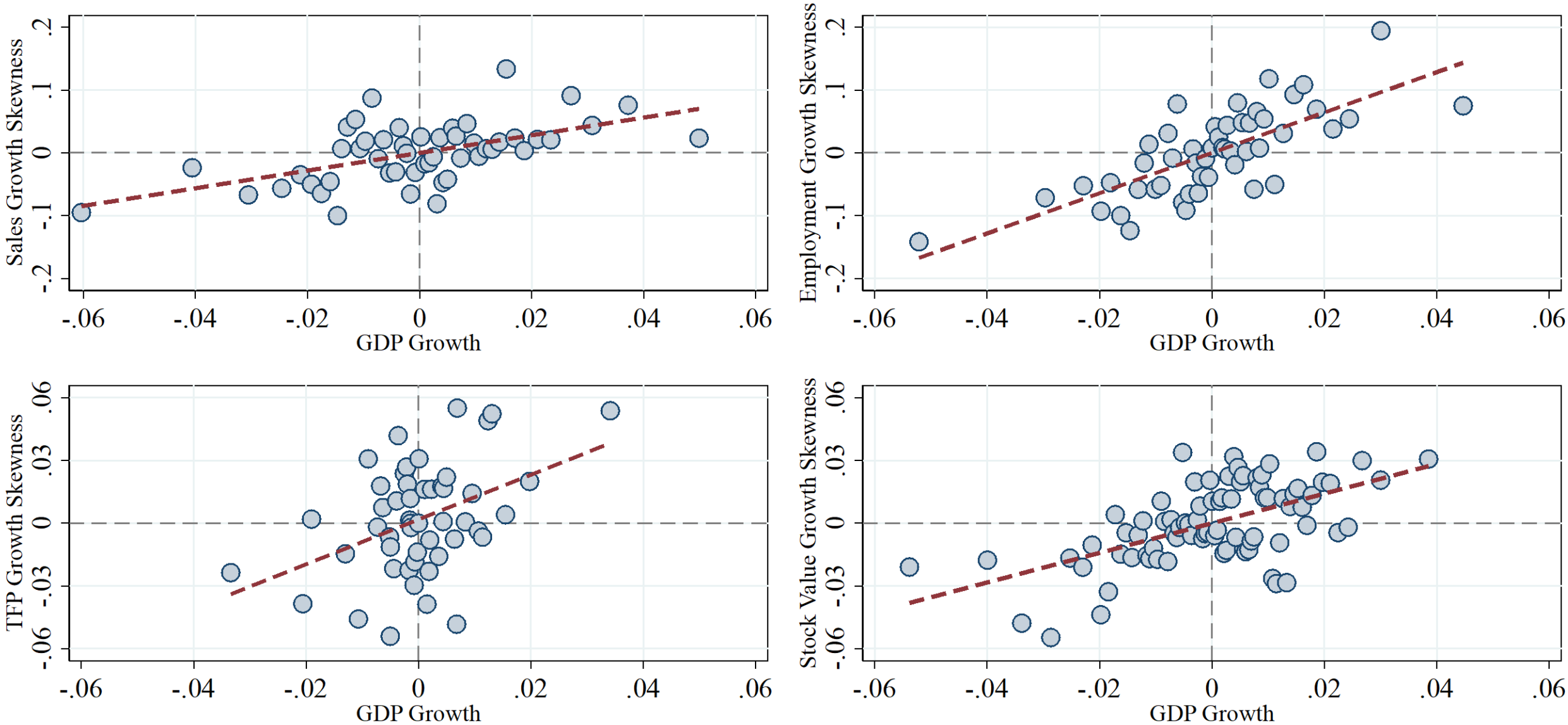
Note: This figure shows the time series of the cross-sectional Kelley skewness of the distribution of firm sales growth for different firm groups using data from the Compustat. Shaded areas are the share NBER recession quarters within a year. Debt-to-Asset ratio is defined as sum of short- and long-term debt divided market capitalization. Interest-to-EBIT ratio is defined as lagged interest expenses divided by earnings before interest and taxes. Past sales in period t is the average sales growth for periods t-1 and t-2.

Figure 5: Firm Sales, Employment, Productivity and Stock Value Growth have Industry Level Procyclical Skewness



Note: This figure shows bin-scatters of the Kelley skewness of firm employment growth (top left panel), firm sales growth (top right panel), establishment TFP growth (bottom left panel), and firm stock returns (bottom right panel) against the average sales growth within an industry-year. Top panels use data from the US Census' Longitudinal Business Database (LBD) aggregated across establishments to the firm level. Bottom two panels use Compustat and CRSP data respectively. "Industry growth" is average sales growth.

Figure 6: Firm Sales, Employment, Productivity and Stock Value Growth have Country Level Procyclical Skewness

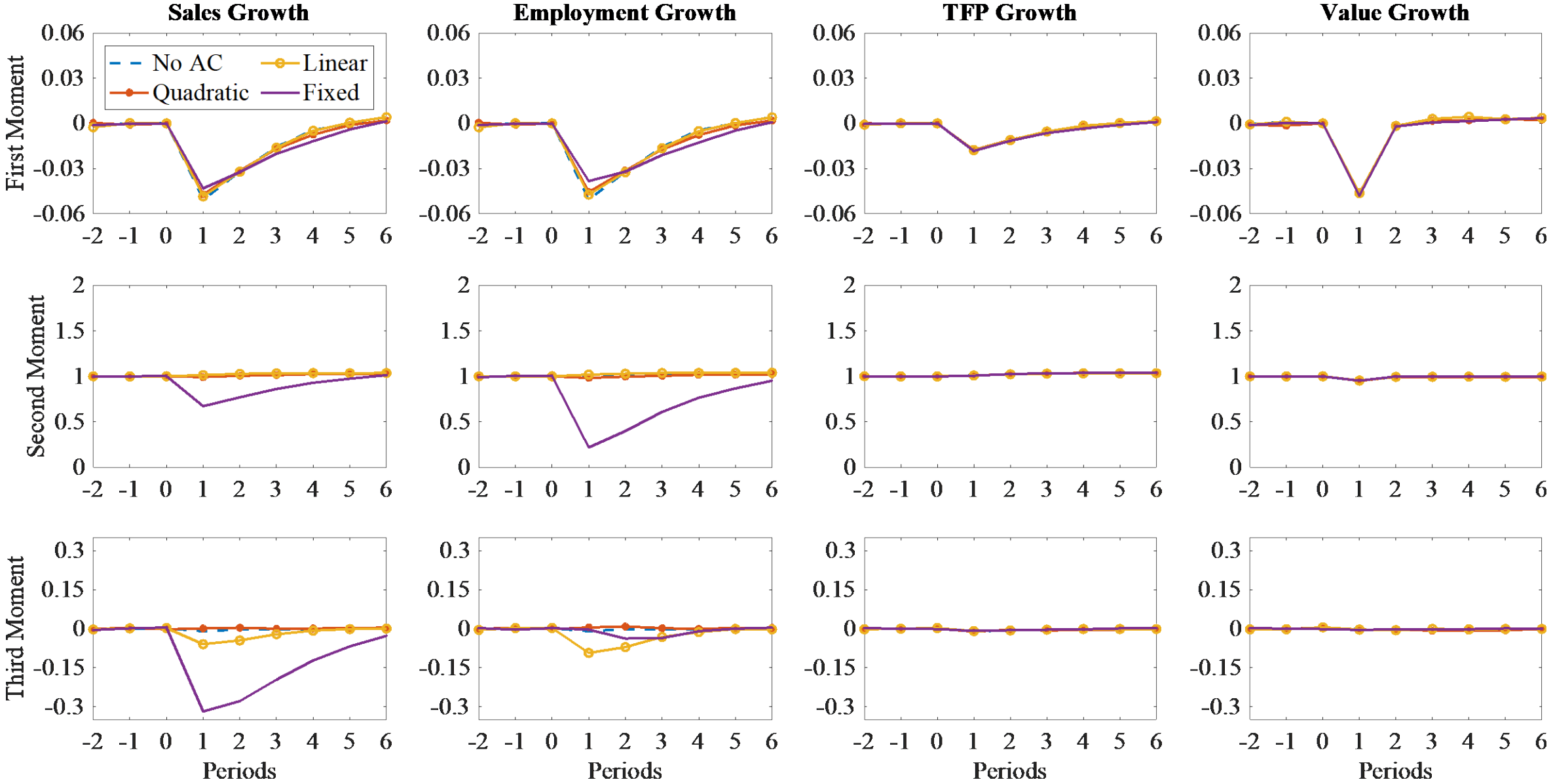


Note: This figure shows bin-scatters of the Kelley skewness firm of firm growth against GDP growth. Top panels use data from from Osiris for 42 countries covering years 1984 to 2018, for an average sample of about 11,700 firms per year. Bottom left panel uses data from Amadeus with 2-digit industries in 10 countries covering years 1999 to 2018, for a sample of about 320 thousand firms per year. Bottom right panel uses data from from Global Compustat for stock returns for 31 countries covering the years 1985 to 2020 for a sample of about 38 thousands firms per years. Bin-scatters control for country and year fixed effects.

Figure 7: Labor Policy Functions can Jump while Value Functions are Continuous

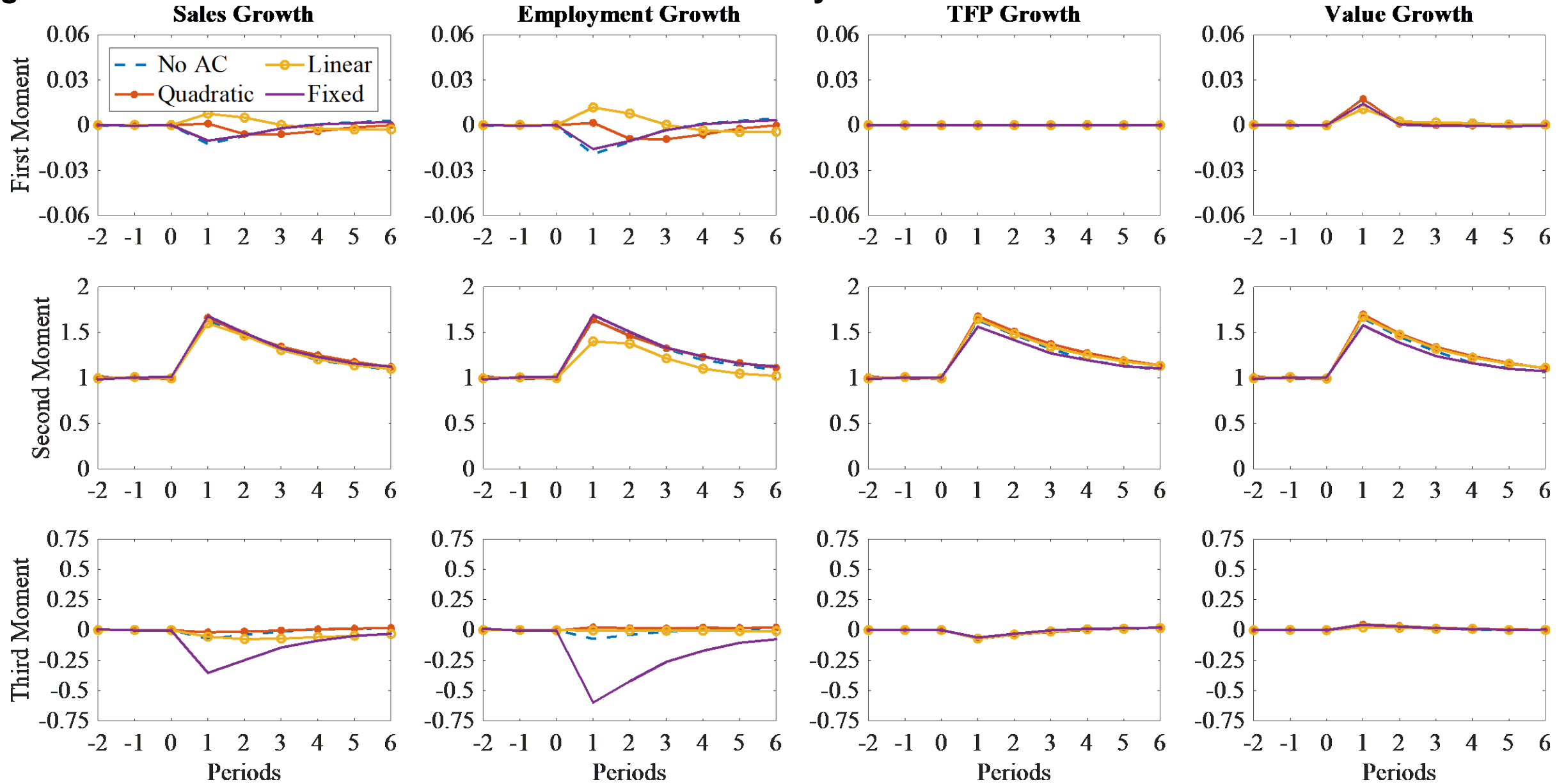
Note: Value and policy functions implied by the model under different adjustment costs for range of values of the firm-level business conditions at the baseline parameters and business conditions transition matrix. The lagged labor value is 3 in all simulations (the median grid point for labor).

Figure 8: Simulated Cross Sectional Moments in response to a First Moment Shock



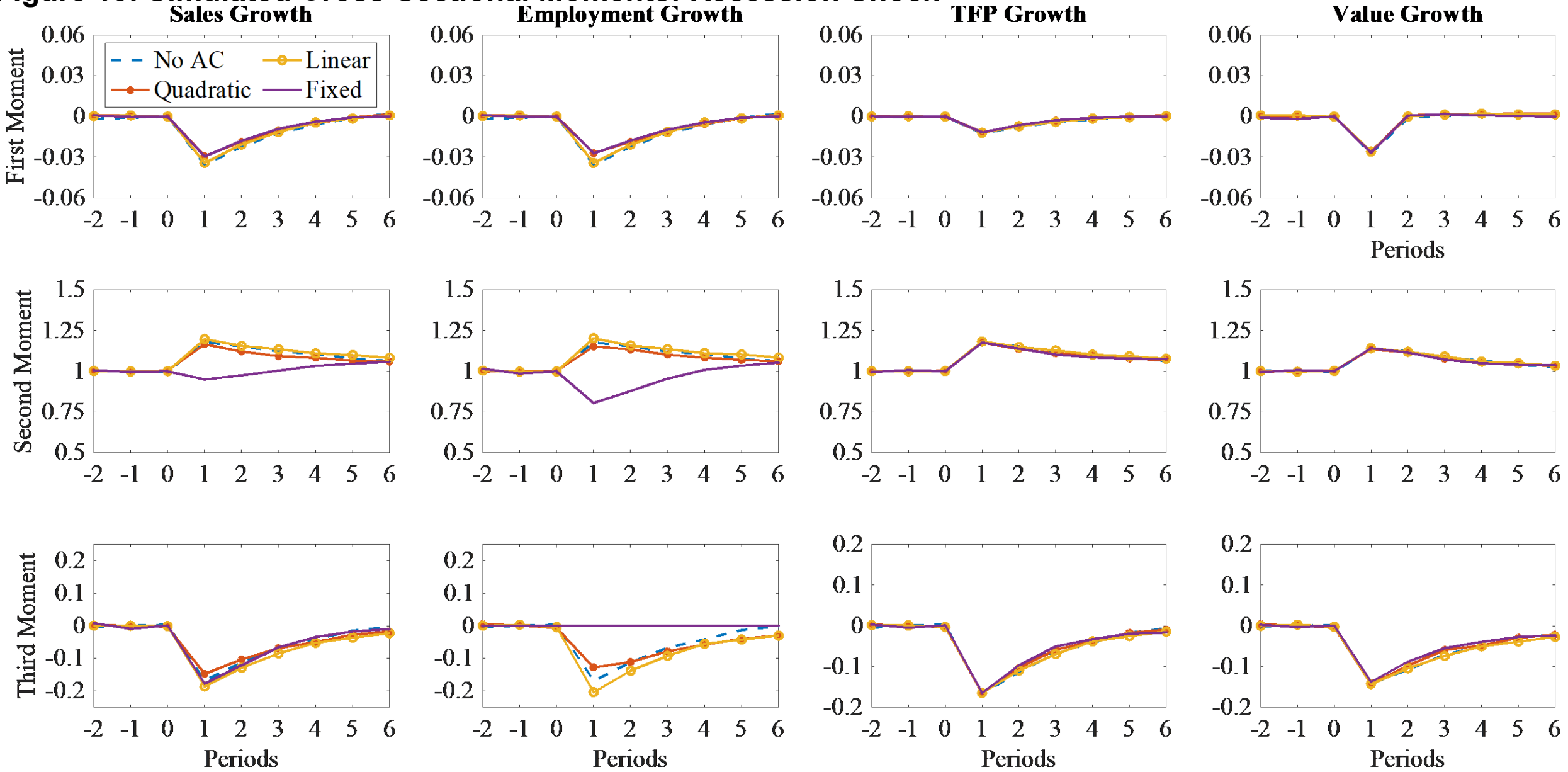
Note: Simulated cross-sectional moments of firm growth after a first-moment (mean) shock. From left to right: output growth, employment growth, TFP growth, and stock value returns. From top to bottom row: average growth, P90-P10 dispersion of growth, Kelley skewness of growth. For comparison, we normalize the first and third row to 0 and the second row to 1 in period 0. In each plot we show four cases: "No AC" refers to no adjustment costs, "Linear" implies a per unit cost to hire or fire labor, "Fixed" implies a lump-sum cost to adjust labor whatever the change, and "Quadratic" implies adjustment costs are quadratic in the rate of adjustment

Figure 9: Simulated Cross-Sectional Moments: Uncertainty Shock



Note: Simulated cross-sectional moments of firm growth after a first-moment (mean) shock. From left to right: output growth, employment growth, TFP growth, and stock value returns. From top to bottom row: average growth, P90-P10 dispersion of growth, Kelley skewness of growth. For comparison, we normalize the first and third row to 0 and the second row to 1 in period 0. In each plot we show four cases: "No AC" refers to no adjustment costs, "Linear" implies a per unit cost to hire or fire labor, "Fixed" implies a lump-sum cost to adjust labor whatever the change, and "Quadratic" implies adjustment costs are quadratic in the rate of adjustment

Figure 10: Simulated Cross-Sectional Moments: Recession Shock



Note: Simulated cross-sectional moments of firm growth after a first-moment (mean) shock. From left to right: output growth, employment growth, TFP growth, and stock value returns. From top to bottom row: average growth, P90-P10 dispersion of growth, Kelley skewness of growth. For comparison, we normalize the first and third row to 0 and the second row to 1 in period 0. In each plot we show four cases: "No AC" refers to no adjustment costs, "Linear" implies a per unit cost to hire or fire labor, "Fixed" implies a lump-sum cost to adjust labor whatever the change, and "Quadratic" implies adjustment costs are quadratic in the rate of adjustment

Table 1: The Skewness of Firm Growth is Procyclical, US Time Series

	(1) $Sales_t$	(2) $Emp._t$	(3) Rev/Emp_t	(4) $Returns_t$
ΔGDP_t	0.058***	0.062***	0.084***	0.035***
	(0.010)	(0.007)	(0.026)	(0.010)
R^2	0.50	0.61	0.15	0.11
Obs.	20	42	51	199
Period	98-19	76-21	98-19	70-23
Freq.	Yr	Yr	Yr	Qtr
Source	LBD	LBD	LBD	CRSP
Average	0.00	0.02	0.09	-0.09
Expansion	0.02	0.05	0.11	-0.05
Recession	-0.11	-0.10	-0.07	-0.12
Yr. Obs.	4.6M	4.6M	4.5M	4.0K

Note: Time-series regressions for the United States where the dependent variable is the Kelley skewness of the distribution of one-year firm employment growth, sales growth and sales/employment growth from the US Census' Longitudinal Business Database (LBD) (columns 1 to 3) and one-year stock returns from CRSP (column 4). Cross-sectional moments weighted by average employment. Newey-West standard errors below point estimates. Regressions include a linear trend. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: The Skewness of Firm Growth is Procyclical Across US Industries

	(1) $Sales_{j,t}$	(2) $Emp._{j,t}$	(3) $Rev/Emp._{j,t}$	(4) $TFP_{j,t}$	(5) $Returns_{j,t}$
$\Delta Sales_{j,t}$	0.610***	0.577***	0.113*	0.022***	0.020***
	(0.161)	(0.188)	(0.056)	0.010	(0.003)
R^2	0.62	0.66	0.14	0.26	0.41
Obs.	931	938	918	457	3,214
Period	70/24	70/24	70/24	76-19	70/24
Freq.	Yr	Yr	Yr	Yr	Qtr
F.E.	Yr/Ind	Yr/Ind	Yr/Ind	Yr/Ind	Qtr/Ind
Source	CSTAT	CSTAT	CSTAT	ASM	CSTAT
Average	0.09	0.06	0.06	0.00	-0.09
Expansion	0.13	0.11	0.11	0.03	-0.07
Recession	-0.04	-0.13	-0.13	-0.03	-0.15
Yr. Obs.	4.1K	4.1K	4.1K	30.0K	4.1K

Note: Industry-panel regressions. Dependent variable is the Kelley skewness of the within-industry distribution of firms-level outcomes from Compustat and the US Annual Survey of Manufacturing (ASM). Industry j at 2-digit NAICS level for all but column (4). ASM industry at 4 digit NAICS. Independent variable is average sales growth within an industry-year. Standard errors clustered at the industry level. Compustat sample consider firms with 10+ years of data. Regressions include a linear trend. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Skewness of Firm Growth is Procyclical Across Countries

	(1) $\text{Sales}_{j,t}$	(2) $\text{Emp.}_{j,t}$	(3) $\text{TFP}_{j,t}$	(4) $\text{Returns}_{j,t}$
$\Delta GDP_{j,t}$	0.034***	0.068***	0.018***	0.017***
	(0.009)	(0.012)	(0.004)	(0.002)
R^2	0.378	0.275	0.521	0.310
Obs.	989	957	2648	5418
Period	84-18	84-18	99-18	85-20
Freq.	Yr	Yr	Yr	Qtr
F.E.	Yr/Ctry	Yr/Ctry	Yr/Ctry	Qtr/Ctry
Source	BvD	BvD	Amadeus	GCSTAT
Average	0.11	0.05	0.02	-0.097
Expansion	0.14	0.07	0.03	-0.06
Recession	-0.02	-0.04	0.01	-0.14
Sample	12.3K	21.0K	411.0K	38,0K

Note: Country-level panel regressions in which the dependent variable is the Kelley skewness of different firm-level outcomes in country k in period t . Employment and sales data come from BvD Osiris dataset (42 countries), TFP shocks are estimated using data from the BvD Amadeus dataset (10 countries), and stock returns are from Global Compustat (GCSTAT, 37 countries). In each regression, the independent variable is the one-year GDP per capita growth. Standard errors are clustered at the country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.