Large Firms and the Cyclicality of US Labour Productivity

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Abstract

We present novel stylized facts on the declining cyclicality of labour productivity for large firms. Changes in their output-labour productivity correlations are close to those observed in the aggregate data, unlike small firms. We show that, given their size and higher than average volatility, large firms can plausibly account for nearly 2/3 of aggregate labour productivity cyclicality. The decline in the procyclicality of labour productivity since the mid-1980s is driven by a rise in the relative volatility of employment. We provide evidence that the rise in volatility is driven by large firms' increased use of extensive margin adjustments in response to changes in firm-level output. In response to a 1% increase in real output, large firms hire an additional 75 workers in the pre-1985 period, compared to an additional 90 workers in the post-1985 period. Our findings are of direct relevance to the growing literature on the role of large firms in driving US business cycles.

Key words: Large Firms, Labour Productivity, Business Cycles

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1 Introduction

The role of large firms in determining both short- and long-run economic outcomes has been the subject of increased scrutiny in recent years. For example, Carvalho and Grassi (2019) propose a model of the business cycle in which idiosyncratic shocks can drive the cycle due to the presence of large firms. They find that the largest firms can account for roughly 30% of aggregate fluctuations. Daniele and Stüber (2020) examine local labour markets in Germany and find that higher local concentration is associated with more persistent local employment and higher conditional volatility; facts which are consistent with the large firm model proposed by Carvalho and Grassi (2019). Crouzet and Mehrotra (2020) examine the cyclicality of small and large firms and provide evidence that small firms are more sensitive to movements in GDP than large firms and suggest that small firms likely have a negligible effect on aggregate fluctuations. di Giovanni, Levchenko and Mejean (2018) study the 100 largest firms in France and find that they play an important role in generating international business cycle comovement, primarily through trade. Autor, Dorn, Katz, Patterson and Van Reenen (2020) provide a new interpretation of the fall in the labour share based on the rise of 'superstar firms'.[1] Gutiérrez and Philippon (2019, 2020) examine the economic footprint of these firms in the US and internationally, and find that contrary to popular wisdom, superstar firms have not become larger by shares of employees or sales, and that their contribution to productivity growth has fallen by more than 1/3 since 2000. However, little is known about the labour productivity dynamics of large-firms. In contrast to the literature above, we focus on this aspect as well as how the labour productivity dynamics have evolved over time.

One motivating factor for studying large-firm labour productivity is that at the aggregate level labour productivity dynamics have experienced significant changes over the business cycle. Labour productivity used to be strongly procyclical, moving together with output over the business cycle. However, since the onset of the Great Moderation this relationship has entirely disappeared. It is now nearly acyclical when labour productivity is defined as output per worker or moderately countercyclical when labour productivity is defined as output per hour. Explaining this change in contemporaneous cyclicality – the *labour productivity puzzle* – has attracted a large amount of research in the business cycle literature (Galí and Gambetti (2009), Stiroh (2009), Barnichon (2010), Fernald and Wang (2016), Garin, Pries and Sims (2018), Galí and van Rens (2020), vom Lehn and Winberry (2022)).[2] At the same time aggregate labour productivity also lost its positive leading economic indicator property and now negatively lags the business cycle (Brault and Khan 2020). While several explanations have been proposed for the labour productivity puzzle, none have explicitly considered the role of firm size. Specifically, we ask the following question: Does the cyclical behaviour of labour productivity among large firms resemble the cyclicality observed at the aggregate level?

To answer this question we compute firm specific measures of labour productivity using the Compustat database. We then construct a weighted-average of labour productivity conditional on firm size and compare the cyclicality of this measure with aggregate output. This comparison allows us to determine how closely large firms' labour productivity resembles aggregate labour productivity dynamics. Our measure of firm-level productivity is a value added measure defined as real sales less cost of goods sold over employment. We define 'large firms' as those with more than 1,000 employees, which is the same cutoff used in De Loecker, Eeckhout and Mongey (2021). We label 'small firms' as those with 1,000 or less employees. Our results, however, are robust to a range of definitions for large firms. Notably, as we discuss below, large firms account for the bulk of employment and sales in Compustat.

Our contribution to the literature is threefolds. First, we present novel stylized facts on the cyclical behaviour of labour productivity by firm size and compare them to those observed in aggregate labour productivity. Second, we decompose aggregate labour productivity dynamics into contributions from Compustat and non-Compustat firms. Compustat aggregates are dominated by large firms, and since they are on average more volatile than non-Compustat firms, we show that they account for a significant share of aggregate labour productivity cyclicality. Third, using our firm-level data set we find evidence that the observed decline in the procyclicality of aggregate labour productivity since the onset of the Great Moderation is driven by increased labour market flexibility among large firms, which has raised the relative volatility of employment. Fourth, our findings can serve as a useful benchmark to evaluate the properties of theoretical models in which large firms play an essential role.

Our main results on cyclicality of labour productivity are as follows: First, during the pre-1985 period, large firm labour productivity was strongly procyclical with a correlation coefficient of 0.68. In the post-1985 period large firm labour productivity declines significantly to a correlation of 0.28. In contrast, small firm labour productivity cyclicality is not statistically different from zero in either the pre- or the post-1985 period. The patterns of large firm labour productivity cyclicality are close to those observed at the aggregate level, where aggregate labour productivity has a correlation coefficient of 0.77 in the pre-1985 period and 0.17 in the post-1985 period.

Second, we find remarkably similar lead-lag patterns (i.e., correlations between labour productivity and output at different leads and lags) between large firms and the aggregate. In the pre-1985 period both aggregate and large firm labour productivity were strongly positively correlated with future output.[3] In contrast, small firm labour productivity is negatively correlated with future output movements over this period. In the post-1985 period, both aggregate and large firm labour productivity were strongly negatively correlated with past output. Over the same period, small firm labour productivity correlations with past output are not statistically different from zero.

Third, using our decomposition of aggregate labour productivity cyclicality into contributions from Compustat and non-Compustat firms, we find that Compustat firms can plausibly account for about 60% of aggregate labour productivity cyclicality in the post-1985 period, even though their shares of value added and employment are only about 30%.

Finally, given our firm-level data we evaluate several competing hypotheses regarding the decline in the procyclicality of labour productivity. We show that the decline in procyclicality is driven by a rise in the relative volatility of employment since the onset of the Great Moderation. Our evidence suggests that this rise is driven by large firms' increasing use of extensive margin adjustments in response to changes in firm-level output. In the pre-1985 period, large firms hired an additional 75 employees for a 1% increase in real output, and an additional 90 employees in the post-1985 period. In contrast, small firms have relied less on changing employment levels in response to changes in firm-level output in the post-1985 period.

The patterns of large firm labour productivity and aggregate labour productivity we have documented suggest that large firm behaviour prior to and after the Great Moderation could shed light on the labour productivity puzzle and the phase-shift observed in aggregate labour productivity since the mid-1980s.

2 Data & Results

Our analysis is based on annual data. We obtain the aggregate annual data from the Federal Reserve Bank of St. Louis (FRED). Our measure of aggregate output of the economy is the Nonfarm Business Sector: Real Output (FRED code: `OUTNFB`) and our measure of employment is the Nonfarm Business Sector: Employment (FRED code: `PRS85006013`). We define aggregate labour productivity as real output divided by the level of employment (output per person). We take logs and detrend output and productivity using the Hodrick-Prescott (HP) filter with a smoothing parameter of 6.25.[4]

For labour productivity measures conditional on firm size, we use the Compustat database. The database provides sales, cost of goods sold, and employment information at an annual frequency, and we use data from the years 1963 to 2018. It is worth noting that the database covers exclusively public US firms and thus may not be representative of private firms. For example, Davis, Haltiwanger, Jarmin, Miranda, Foote and Nagypál (2006) document opposing trends in employment volatility when comparing the Longitudinal Business Database (LBD) to Compustat. Employment volatility has been declining in the LBD, while it has been rising in Compustat. However, Compustat has an advantage over databases, such as the LBD, in that it allows us to make comparisons of labour productivity prior to and after the Great Moderation. Since our measure of the aggregate business cycle is for the non-farm business sector, we exclude all firms with NAICS codes below 20 (agriculture, forestry, fishing and hunting) and above 90 (government). Compustat filings do reflect global operations of firms and thus potentially introduces measurement error into our employment statistics. Since discrepancies are likely to be larger for foreign firms with US operations, we focus exclusively on firms headquartered in the US. Additionally, we drop firms with zero or negative sales/employment.[5]

To compute real sales and cost of goods sold measures we use the BEA GDP by Industry accounts price indices. Industry accounts roughly correspond to NAICS 3 digit codes. In cases where we cannot identify a firm based on NAICS 3 digit codes, we use a NAICS 2 digit code.[6] We define labour productivity for firm i in industry j in year t by

$$z_{i,t} = \frac{\text{value added}_{i,t}}{p_{j,t} n_{i,t}}, \tag{1}$$

where value added$_{i,t}$ is nominal sales less cost of goods sold in Compustat, $p_{j,t}$ is industry j's BEA price deflator, and $n_{i,t}$ in the number of employees reported in Compustat. After obtaining firm specific measures of labour productivity we construct an aggregate measure conditional on firm size according to

$$\text{Labour Productivity}_{t|size} = \sum_{i=1}^{K} \omega_{i,t} z_{i,t}, \tag{2}$$

where K is the number of firms conditional on size and $\omega_{i,t}$ is a firm weighting based on a firm's employment size relative to total employment in that size bin (i.e., $\omega_{i,t} \equiv \frac{n_{i,t}}{\sum_{i=1}^{K} n_{i,t}}$).[7] After computing the above productivity measure, we detrend the log of the time series with the HP filter. In the following sections we use these measures to discuss some long-run facts about small and large firms, and the behaviour of their labour productivity relative to aggregate productivity.

2.1 Long-run facts

While our main focus is on the cyclicality of large firm labour productivity and how it compares to aggregate labour productivity over the cycle, there are several long-run trends which are worthy of discussion, some of which have generated substantial discussion in the recent literature. Table 3 reports the average large firm shares of total firms, Compustat employment and real sales, and aggregate employment.

First, and perhaps unsurprisingly, large firms account for nearly all of employment and real sales in Compustat. While large firms account for about 60% of total firms in the pre-1985 period and 40% of total firms in the post-1985 period, they account for nearly all of employment and real sales in both periods. It is also noteworthy that large firms as a share of total firms (in Compustat) has fallen in the post-1985 period, yet their share of employment and real sales has remained relatively stable. This suggest that the firm size distribution in Compustat has become more skewed in the post-1985 period.

Second, it is not *a priori* obvious that large firms will drive aggregate outcomes. In the pre-1985 period, large firms account for 27% of total nonfarm US employment. This share rises to 29% in the post-1985 period.[8]

Third, when comparing the growth rates of labour productivity across small, large, and all firms in Compustat to the aggregate, we find substantial differences. Figure 1 plots average labour productivity growth for small and large firms in the left panel, and for all firms in Compustat and the aggregate in the right panel. Two noteworthy patterns are evident: First, is that small firms labour productivity is much more volatile than large firms and the aggregate; Second, small firms have on average higher labour productivity growth compared to large firms and the aggregate. Over the entire sample, small firms average labour productivity growth is 2.83%, compared to 1.48% for large firms and 1.67% in the aggregate.

Fourth, all firms in the Compustat database have average labour productivity growth close to the aggregate. Average labour productivity growth for all Compustat firms is 1.51%, compared to 1.67% in the aggregate. Additionally, Compustat productivity growth is positively correlated with aggregate productivity growth with a correlation coefficient of 0.49.

The above long-run facts show significant differences between small and large firms in terms of labour productivity, particularly in their growth rates and their contributions to the composition of the aggregate. In the following section we show that these differences also extend to their respective short-run behaviour of labour productivity.

2.2 Cyclicality: Contemporaneous correlations

Table 4 reports the correlations between aggregate output, Y_t^{agg}, and aggregate labour productivity, and between aggregate output and labour productivity for small and large firms. In the bottom row of the table, the number of firm-year observations used in computing the size-specific labour productivity measure are reported.

Under the aggregate column we can see the *labour productivity puzzle* – the sharp drop in the procyclicality of productivity after the mid-1980s. In the pre-1985 data, labour productivity was strongly procyclical over the business cycle. In the post-1985 period, however, this correlation fell dramatically to the point where it is only mildly procyclical and not statistically different from zero. Based on all firms in our Compustat data we find a very similar pattern to the aggregate, labour productivity was strongly procyclical during pre-1985 period and mildly procyclical afterwards.

The first novel stylized fact is that large firms exhibit similar labour productivity dynamics in the pre-1985 and post-1985 periods when compared to the aggregate. In the pre-1985 period, large firm labour productivity was strongly procyclical with a correlation coefficient of 0.67. In the post-1985 period this procyclicality declines significantly to 0.28. The magnitude of these correlations are close to those observed at the aggregate level. Small firms exhibit a decline in the point estimate of labour productivity procyclicality, but this correlation is not statistically different from zero in either the pre- or the post-1985 period.

2.3 Business cycle lead-lag properties

Our contemporaneous cyclicality results show that large firm labour productivity cyclicality resembles the aggregate in both the pre-1985 and post-1985 periods while small firms do not. A related, but arguably more informative check, is to explore not just contemporaneous comovement but also cyclicality at different leads and lags. In Figure 2 we report the correlations of small and large firm labour productivity correlations at different leads and lags, along with leads and lags of the aggregate. Leads and lags are annual (e.g., a correlation at -1 is the correlation between current aggregate output and labour productivity in the previous year).

Focusing on the aggregate labour productivity at different leads and lags, we see that since the onset of the Great Moderation it is not only contemporanous cyclicality which has changed dramatically, but also that labour productivity lags output over the cycle. In the pre-1985 period, aggregate labour productivity was strongly correlated with one year ahead output ($Corr(Y_t^{agg}, Prod_{t-1}^{agg}) = 0.62$).[9] In the post-1985 period the magnitude of the leading correlation is strongly diminished, and in fact labour productivity now features a negative lagging property over the business cycle where the largest correlation is given by $Corr(Y_t^{agg}, Prod_{t+1}^{agg}) = -0.67$ (Brault and Khan (2020)).

Our second novel stylized fact is that the large firm lead-lag pattern is remarkably similar when compared to the aggregate. In the pre-1985 period large firm labour productivity correlations with one year ahead and current aggregate output are 0.64 and 0.67, respectively, compared to 0.62 and 0.77 in the aggregate. Additionally, the largest correlation is contemporaneous as in the aggregate data. In the post-1985 period large firms' labour productivity is strongly negatively correlated with past output, as in the aggregate data. Large firms' labour productivity correlations with one and two year ago output are -0.39 and -0.48, respectively, compared to -0.67 and -0.41 in the aggregate.

By contrast, small firms' lead-lag behaviour looks quite different from both large firms and the aggregate. In the pre-1985 period small firm labour productivity is negatively correlated with output one and two years in the future and positively correlated with past output, both facts which are at odds with the aggregate data. In the post-1985 period small firm labour productivity correlations with future output (leads) are similar to the aggregate, but correlations with past output (lags) are quite different from the aggregate.

3 Robustness

In the following sections we discuss several additional considerations relative to our baseline results in Section 2. These are intended to highlight the robustness of our baseline results.

3.1 End of year filing date

One potential concern with labour productivity measures based on the annual Compustat data is that filing dates for some firms do not necessarily coincide with year end measures of our aggregate output variable. For example, some firms consider their fiscal year end in the month of June. This may have the unintended effect of distorting our cyclicality measures. To check whether this issue matters, we restrict our Compustat database to only those firms which file on the last day of December. This reduces our firm-year observations for large firms from 17,955 to 12,692. When doing so, we find little difference from our baseline results, and in fact our large firm properties appear closer to the aggregate. In the pre-1985 period large firm labour productivity has a correlation coefficient of 0.66, and in the post-1985 period this correlation declines to 0.17. Small firm correlations are nearly identical to those in Table 4. This suggests that the timing of filing dates is not an important factor in any of the results presented in Section 2.

3.2 First-difference filter

Our baseline considers cyclical fluctuations generated from the Hodrick-Prescott filter. We also consider cyclical fluctuations based on a first-difference filter, which corresponds to year-over-year growth rates. Cyclical fluctuations generated from a first-difference filter lead to some differences from our baseline results. First, aggregate and large firm labour productivity remain procyclical in the post-1985 period. Large firms have a correlation of 0.60 in the pre-1985 period and a correlation of 0.27 in the post-1985 period. In comparison, aggregate labour productivity has a correlation coefficient of 0.79 in the pre-1985 period and a correlation of 0.32 in the post-1985 period. Second, we find that small firms exhibit procyclical labour productivity in the pre-1985 period with a correlation coefficient of 0.43. However in the post-1985 period, and in contrast to large firms and the aggregate, small firm labour productivity is acyclical with a correlation coefficient of 0.04.

3.3 Manufacturing versus non-manufacturing

It is well documented that US output over this period underwent substantial composition changes, from a primarily manufacturing-based economy in the pre-1985 period to a primarily serviced-based economy in the post-1985 period (Fort, Pierce and Schott 2018). We explore labour productivity changes when we distinguish between manufacturing and non-manufacturing firms.[10]

In this case we find some heterogeneity across sectors. In the pre-1985 period both large manufacturing and non-manufacturing firms exhibit procyclical labour productivity with correlation coefficients of 0.60 and 0.58. In the post-1985 period large manufacturing firms labour productivity is not statistically different from zero. Large non-manufacturing firms labour productivity have mildly procyclical labour productivity. In the pre-1985 period, small manufacturing firms have procyclical labour productivity with a correlation coefficient of 0.63. In the post-1985 period these firms have acyclical labour productivity. Small non-manufacturing firms have acyclical labour productivity in both subsamples. Since large firms account for nearly all of employment and sales in Compustat, and both manufacturing and non-manufacturing large firms exhibit declines in the procyclicality of labour productivity, it is unlikely our results are driven by changes in the composition of output between manufacturing and non-manufacturing sectors.[11]

3.4 Alternative definition of large firms

Our baseline results are based on a definition of large firms being firms with over 1,000 employees, which is the same definition used in De Loecker, Eeckhout and Mongey (2021). However, the literature has used a range of cutoffs to define large firms. In Table 8, we recompute our cyclical correlations using definitions of large firms as those with over 10,000 and 20,000 employees, which are the lower and upper cutoffs for large firms used in Carvalho and Grassi (2019). A cutoff of 10,000 employees to define large captures the top 10-25% of firms in Compustat (based on employment size) in any given year, while a cutoff of 20,000 employees captures the top 5-10% of firms in any given year.

In both cases, allowing the lower bound of the definition of 'large firms' to rise does not alter our baseline conclusions. In fact, defining large firms as those with over 20,000 employees brings about a much larger decline in the procyclicality of labour productivity, consistent with the aggregate in the post-1985 period. At the same time, allowing the upper bound to define 'small firms' to rise leads to results which are more consistent with the aggregate and baseline large firm results. This suggests that the decline in the procyclicality of labour productivity from the pre-1985 to post-1985 period is not driven exclusively by the largest firms, but a property of many firms over a given size. However the largest decline in procyclicality does appear for the largest firms.

4 Large Firms in the Aggregate

Sections 2 and 3 documented that the decline in the procyclicality of labour productivity since the onset of the Great Moderation is a robust feature for large firms, with declines quite close to the decline observed in the aggregate. In the following section we provide some context to the importance of large firms for aggregate outcomes. To do so, we provide a decomposition of the aggregate output labour productivity correlation into contributions from Compustat and non-Compustat firms. But as the previous sections have highlighted, *all firms* results in Compustat are dominated by large firms due to their size. Then in our decomposition, contributions from Compustat can be thought of primarily as contributions from large firms.

Our decomposition works with growth rates of aggregate output and labour productivity for simplicity.[12] At any time t, the level of aggregate labour productivity is a employment-weighted sum of labour productivity in Compustat and non-Compustat firms

$$LP_t = \left(\frac{N_t^c}{N_t}\right) LP_t^c + \left(\frac{N_t^{nc}}{N_t}\right) LP_t^{nc}, \tag{3}$$

where N^c and N^{nc} are the total number of employees in Compustat and non-Compustat firms, and the sum of these groups is total employment, N. Under the assumption that the employment and value added shares of Compustat firms in total employment and output are constant in each subsample, it can be shown that the aggregate output labour productivity correlation is a weighted sum of correlations between: (1) aggregate output and Compustat firms' labour productivity; and (2) aggregate output and non-Compustat firms' labour productivity. This decomposition is gives

$$\rho(\Delta Y_t, \Delta LP_t) \approx \left(\frac{\bar{Y}^c}{\bar{Y}}\right) \frac{\sigma_{LP^c}}{\sigma_{LP}} \rho(\Delta Y_t, \Delta LP_t^c) + \left(\frac{\bar{Y}^{nc}}{\bar{Y}}\right) \frac{\sigma_{LP^{nc}}}{\sigma_{LP}} \rho(\Delta Y_t, \Delta LP_t^{nc}), \tag{4}$$

where $\bar{Y}^c/\bar{Y}$ is the value added share of Compustat firms and $\sigma_{LP^c}/\sigma_{LP}$ is the standard deviation of Compustat firms' labour productivity divided by the standard deviation of aggregate labour productivity. Identical definitions apply for non-Compustat firm variables denoted by superscript nc. $\rho(\Delta Y_t, \Delta LP_t)$, $\rho(\Delta Y_t, \Delta LP_t^c)$, and $\rho(\Delta Y_t, \Delta LP_t^{nc})$ are the correlations between aggregate output and aggregate labour productivity, aggregate output and Compustat labour productivity, and aggregate output and non-Compustat labour productivity. The intermediate steps to derive (4) are provided in the Appendix.

Given (4), we can compute the weight associated with Compustat firms' labour productivity correlation, as well as provide a reasonable approximation to the weight for non-

Compustat firms. Table 9 reports the relevant variables for the post-1985 period.[13]

In the post-1985 period, the (average) value added share of Compustat firms is 0.28 and the standard deviation of labour productivity is 4.61. Together, these imply that the coefficient weight associated with Compustat firms' aggregate output labour productivity correlation is about 1.1. For non-Compustat firms, we do not know the standard deviation of labour productivity. However, given that the aggregate is lower than Compustat, this would suggest that non-Compustat firms' labour productivity standard deviation is below the aggregate. Suppose that $\sigma_{LP^{nc}} = 1$, then the weight associated with non-Compustat firms' labour productivity correlation is somewhere around 0.7. Thus, while Compustat firms' shares of output and employment are only around 1/3, their contribution to aggregate labour productivity dynamics is *substantial* due to the fact that they are much more volatile than non-Compustat firms. Our decomposition suggests that Compustat firms' labour productivity correlation is responsible for around 2/3 of aggregate labour productivity cyclicality in the post-1985 period.

This finding is consistent with the recent evidence in Aguilera-Bravo, Casares and Khan (2022), who study US business dynamism since the mid-1990s. They find that entering and exiting firms are on average much smaller terms of their job size than in the past. Consequently, most of the churn in job flows is done by incumbent firms. In our case, virtually all large firms are incumbent firms.

5 Large Firms and the Rising Relative Volatility of Employment

The previous sections have documented two facts: (1) that the decline in the procyclicality of labour productivity since the onset of the Great Moderation is a robust feature for large

US firms, with declines close to those observed in the aggregate; and (2) that large firms in Compustat matter disproportionately for aggregate labour productivity cyclicality due to their size and volatility over the business cycle.

In this section we explore possible sources for the decline in the procyclicality of labour productivity at the firm level. The driving factor behind the decline in the procyclicality of aggregate labour productivity is the rise in the *relative* volatility of aggregate employment since the 1980s. To see why this matters for the output-labour productivity correlation, note that this correlation can be rewritten in the following way

$$\rho(\tilde{Y}_t, \tilde{LP}_t) \equiv \frac{\sigma(\tilde{Y})}{\sigma(\tilde{LP})}\left(1 - \frac{\sigma(\tilde{N})}{\sigma(\tilde{Y})}\rho(\tilde{Y}_t, \tilde{N}_t)\right), \tag{5}$$

where $\tilde{Y}$ is detrended aggregate output, $\tilde{LP}$ is detrended aggregate labour productivity, and $\sigma(.)$ is the standard deviation of output, employment, and labour productivity.[14] In our HP-filtered data, the correlation between aggregate output and employment, $\rho(\tilde{Y}_t, \tilde{N}_t)$, is 0.83 in the pre-1985 period and 0.85 in the post-1985 period. Further, the ratio of the standard deviation of output to labour productivity, $\sigma(\tilde{Y})/\sigma(\tilde{LP})$, has remained nearly constant in the pre- and post-1985 periods. This implies that the primary factor responsible for a decline in the output labour productivity correlation is a rise in the relative volatility of aggregate employment, $\sigma(\tilde{N})/\sigma(\tilde{Y})$, which has risen from 0.67 in the pre-1985 period to 1.06 in the post-1985 period. Then explaining the decline in the procyclicality of labour productivity amounts to explaining the rise in the relative volatility of employment.

There are several competing explanations that could explain the decline in procyclicality of labour productivity and rising relative volatility of employment. For example, Galí and van Rens (2020) argue that the rising relative volatility of employment is due to improvements in job match quality, leading to a decline in labour market turnover. If firms face convex employment adjustment costs, then a reduction in the average number of job separations (due to better match quality) permits firms more adjustments along the extensive margin before adjustment costs become prohibitively expensive. Mitra (2020) proposes an alternative explanation where the rapid de-unionization which occurred during the 1980s lowered the costs of hiring and firing workers, causing firms to rely less on labour hoarding behaviour.[15] Garin, Pries and Sims (2018) argue that the decline in the procyclicality of labour productivity can be explained by a change in importance of aggregate and sectoral shocks in the presence of costly labour reallocation. They document a decline in the relative contribution of aggregate shocks and a corresponding rise in the relative contribution of sectoral shocks to the volatility of aggregate output after 1983.[16] vom Lehn and Winberry (2022) argue that the rising relative volatility of employment and decline in procyclicality of labour productivity is driven by a rise in sector-specific shocks to investment networks, which generate large employment responses. However, none of these explanations explicitly considers the role of firm size.

Alternatively, in a world where granularity matters for aggregate outcomes (e.g., Gabaix (2011)), large firms could drive the change in the aggregate relative volatility of employment. This could be related to, for example, changes in the shocks hitting large firms, or a change in how large firms respond to shocks. Barnichon (2010) shows that the volatility of aggregate technology shocks relative to non-technology (demand) shocks has risen since the mid-1980s. Giroud and Mueller (2019) emphasize that large firms are more exposed to undiversifiable aggregate risk, which may changed since the 1980s.[17]

In our view these competing explanations broadly fit into two non-mutually exclusive categories. The first concerns structural elements which may have changed how firms' employment responds to shocks. The second concerns shocks themselves, which may be different in the post-1985 period. Further, these changes may be different across small and large firms.

Using our firm-level data, we examine if firms' employment responses to changes in firm-level and aggregate conditions are different in the post-1985 period. To do so, we focus on the elasticity of firm-level employment to changes in firm-level and aggregate output.[18] We proxy firm-level output using real sales, an approach common in the literature following Gertler and Gilchrist (1994). We proxy aggregate conditions using aggregate output growth, following Crouzet and Mehrotra (2020). In this regard, our variables for firm-level and aggregate conditions are composite measures of supply and demand shocks.

The model we estimate is

$$\begin{aligned} \Delta\text{Emp}_{i,t} =& \alpha + \gamma_j + \alpha_1 \text{Age}_{i,t} + \delta_0 \text{Large}_{i,t} + \beta_1 \Delta\text{Output}_t + \beta_2 \Delta\text{Sales}_{i,t} \\ &+ \delta_1 \text{Large}_{i,t} \times \Delta\text{Output}_t + \delta_2 \text{Large}_{i,t} \times \Delta\text{Sales}_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where i identifies a firm, t a year, and j an industry. $\Delta\text{Emp}_{i,t}$ is the growth rate of employment in firm i in year t. γ_j are industry specific intercepts which are defined at the 2-digit NAICS level. We define *Age* using a proxy, which is the length of time that a firm is in the Compustat database.[19] Large is a binary variable indicating whether a firm has more than 1,000 employees. ΔOutput_t is the growth rate of non-farm US output which is common to all firms, and $\Delta\text{Sales}_{i,t}$ is the growth rate of firm-specific real sales. δ_1 and δ_2 capture any differential effects to changes in firm-level and aggregate conditions for large firms' employment growth.

Table 10 reports OLS estimates for equation (6) for the pre-1985 and post-1985 periods in columns (1) and (2). Column (3) reports a single regression for the entire sample with dummy variable interactions for the post-1985 period. This allows us to statistically test for changes in the responses of small and large firms to firm-level and aggregate conditions.

Our estimates for age, α_1, suggests that older firms have on average lower employment growth. The magnitude of this effect is sizable with one additional year being associated with between -0.15% and -0.34% lower employment growth. This finding is consistent with Haltiwanger, Jarmin and Miranda (2013), who find that firm age plays a significant role in firm growth. Estimates of average large firm employment growth relative to small firms, δ_0, vary quite dramatically between the pre-1985 and post-1985 periods. In the pre-1985 period large firms grew close to 2.5% more per year on average than smaller firms. In the post-1985 period this effect nearly doubles with large firms employment growth being on average 4.36% higher than smaller firms.

Estimates for β_1 suggest that firms' employment growth is sensitive to aggregate conditions, but this effect is larger for small firms ($\delta_1 < 0$).[20] This finding resonates quite closely with the evidence in Crouzet and Mehrotra (2020), who find that over the 1977-2014 period small firms' sales, inventory, and investment growth are significantly more sensitive to aggregate fluctuations than large firms. Our results also offer a pre- and post-1985 comparison of these effects for small and large firms. Interestingly, while small firms have become more sensitive to aggregate fluctuations in the post-1985 period, large firms sensitivity has remained relatively constant. Estimates for β_1 rise from 0.37 in the pre-1985 period to 0.99 in the post-1985 period. For large firms, $\beta_1 + \delta_1$ is 0.17 in the pre-1985 period and 0.2 in the post-1985 period.

Our estimates for the employment elasticity to firm-level conditions, β_2, also documents significant differences between small and large firms. In the pre-1985 period estimates of small firms' employment elasticity, β_2, find that for a 1% increase in real output, small firms increased employment by 0.34%. For large firms in the pre-1985 period this employment elasticity was 0.54%, suggesting that large firms are more sensitive to changes in firm-level conditions. In the post-1985 period, small and large firms diverge in terms of their employment elasticity to firm-level conditions. Small firms' employment elasticity falls to 0.27%, while large firms' employment elasticity rises to 0.60%. Estimates from column (3) indicate that this difference is statistically significant across the pre- and post-1985 period for small and large firms. In economic terms, our elasticities imply that large firms on average hired an additional 75 employees for a 1% change in real sales in the pre-1985 period (average large firm employment during this period is 13,973). In the post-1985 period, large firms on average hired roughly an additional 90 employees for a 1% change in real sales (average large firm employment during this period is 14,912).[21]

Our findings for the employment elasticity to firm-level conditions are related to Decker, Haltiwanger, Jarmin and Miranda (2020), who study the role of shocks and firm responsiveness in the decline of job reallocation. They find that shock dispersion has become higher since the 1980s and thus is an unlikely candidate to explain the decline in job reallocation. However, they find that firm responsiveness has fallen and is a more promising candidate to explain the decline in reallocation. Our findings are consistent with theirs, however they do not examine whether firm responsiveness is heterogeneous across firm size, as we do. If we instead focus on a homogeneous firm responsiveness coefficient, as they do, we find that firm responsiveness has fallen from 0.375 in the pre-1985 period to 0.298 in the post-1985 period, and that this difference is statistically significant at the 1% level (these results are reported in Table 2 column (A4) the Appendix).

Lastly, our firm-level and aggregate output variables are intended to capture idiosyncratic and aggregate shocks. However, vom Lehn and Winberry (2022) argue that the rise in the relative volatility of employment is due to a rise in the relative importance of sectoral shocks propagated through their investment network. Notably, the sectors which define their investment network contain the majority of the large firms in our data. Large firms in mining, utilities, construction,and manufacturing sectors alone comprise about 50% of all large firms in the pre- and post-1985 periods. These shares are shown in Figures 4 and 5. To see how large firms respond to sectoral shocks, and if the inclusion of these shocks changes our findings, we construct a measure of sector-level productivity using a Solow residual following vom Lehn and Winberry (2022).[22] The inclusion of sectoral-level TFP shocks does not change our baseline results, large firms are less sensitive to aggregate conditions and more sensitive to firm-level conditions. Changes in the pre- and post-1985 periods are consistent with our baseline results. These results are reported in (A6) and (A7) of Table 2. Further, we find that sectoral TFP shocks generate positive responses in employment growth for small firms, but the responses for large firms are not statistically different than zero. It is worth noting, however, that our exercise captures *within* sector employment responses to sectoral shocks, and not the propagation of these shocks throughout the investment network.[23]

Within the context of competing explanations above, our results suggest that large firms *and* structural changes are at the center of the rising relative volatility of employment and decline in procyclicality of labour productivity. This conclusion based on two findings: First, our evidence suggests that large firms play an outsized role in the cyclicality of labour productivity because they account for a significant share of output and employment, and these quantities are more volatile for large firms over the business cycle. Secondly, large firms exhibit a change in responsiveness to firm-level output consistent with a rising relative volatility of employment. While small firms have exhibited changes in responsiveness to aggregate activity, our findings suggest that they have a negligible impact on aggregate cyclical labour productivity changes because the fall in their labour productivity cyclicality is smaller than large firms, and they are small in size. This finding is with evidence in Crouzet and Mehrotra (2020). These two findings point towards a rising relative volatility of aggregate employment and a corresponding decline in the procyclicality of labour productivity.[24] Large firms have increasingly relied on labour input adjustments since the onset of the Great Moderation, driving up the relative volatility of employment and decreasing the procyclicality of labour productivity.

6 Conclusion

A significant research effort has gone into understanding the decline in the cyclicality of labour productivity in the US since the mid-1980s. At the same time, a major phase shift also occurred in that aggregate labour productivity negatively lags the business cycle. We studied whether large firm labour productivity dynamics also display the cyclical properties of aggregate labour productivity and presented a set of novel stylized facts. Cyclical changes in large firm labour productivity are quite close to the changes observed in the aggregate data. Large firm contemporaneous cyclicality declined significantly from the pre-1985 to the post-1985 period, and the correlations at different leads and lags are remarkably close to the aggregate data. By contrast, labour productivity dynamics of small firms do not resemble the aggregate patterns. Our evidence suggests that large firms account for a significant share of cyclical labour productivity movements due to their size and volatility.

Changes in large firm dynamics can, therefore, be a potential candidate to explain the labour productivity puzzle. Our evidence supports explanations that include structural transformations related to labour market flexibility since the mid-1980s. We documented that employment elasticity has risen for large firms in the post-1985 period, while small firm employment elasticity has fallen. In response to a 1% increase in real output, large firms on average hire an additional 75 employees in the pre-1985 period, and an additional 90 employees in the post-1985 period. More generally, our finding can serve as a useful benchmark to evaluate the properties of theoretical models of business cycles in which large firms play a central role.

Notes

[1] See, for example, Acemoglou (2020) and Vives (2020) on the role of market power of firms such as Google/Alphabet, Apple, Facebook, Amazon, and Microsoft (referred to with the acronym *GAFAM*).

[2]Biddle (2014) provides an overview on the history of ideas for the behaviour of labour productivity over the business cycle.

[3]Early work by Burnside and Eichenbaum (1993) emphasized the ability of factor-hoarding to explain lead-lag correlations in labour productivity. Factor-hoarding can cause labour productivity to lead the cycle due to the presence of unmeasured inputs such as labour effort or capital utilization which can be the first to respond to shocks, and only later will measured inputs like employment respond due to adjustment costs (Burnside 1998).

[4]The correlations are similar when using alternative filters, such as the one suggested by Hamilton (2018). These results are available upon request. In Section 3 we show results for a first-difference filter.

[5]Additional details on our Compustat data construction are available in the Online Appendix.

[6]This case represents a very small sample of our observations, roughly equal to 5% of our firm-year observations. Our NAICS mapping to industries is reported in the Online Appendix.

[7]For a sales based weighting scheme the qualitative pattern for large firms is similar to the aggregate. Small firms display a counterfactual pattern relative to the aggregate in the pre-1985 period. These results are available upon request.

[8]di Giovanni et al. (2018) report similar outcomes for France, where the top 100 firms account for roughly 20% of value added, exports, and imports.

[9]The largest correlation is contemporaneous which would indicate that the labour productivity is neither leading nor lagging. It is, however, important to point out that the leading indicator property documented in Brault and Khan (2020) during this period is based on quarterly data, so these results are not necessarily inconsistent since we are working with annual data.

[10]In earlier versions of this paper we also reported these changes for "*investment hubs*" as defined in vom Lehn and Winberry (2022). However, we found significant overlap between manufacturing and investment hubs results and for brevity have chosen to omit those results here. These results are available upon request.

[11]We also explored an alternative definition of value added which subtracted sales, general, and administrative (SGA) costs from sales. We found that small firms labour productivity was procyclical in the pre-1985 period and acyclical in the post-1985 period. However, the decline for small firms is smaller than the decline

for large firms and the aggregate.

[12]As Section 3.2. documented, the type of detrending method does not alter our conclusions about the similarities between changes in large firms' output labour productivity correlation and the aggregate.

[13]While one may be tempted to use the decomposition to assess the contribution of large firms to the change in labour productivity dynamics over the pre- and post-1985 periods, our assumption of constant employment and valued added shares is least plausible in the pre-1985 period, where employment and value added shares of Compustat firms did rise substantially. For this reason we focus on the post-1985 period. The shares are pictured in Figure 3.

[14]Appendix A.2 shows how to rewrite the output labour productivity correlation in this way.

[15]Dossche, Gazzani and Lewis (2022) show that OECD countries with lower employment volatility have more procyclical labour productivity in the 1984-2019 period. They argue that this finding can be explained by structural differences in the labour market.

[16]A similar finding is reported by Foerster, Sarte and Watson (2011).

[17]Another well documented fact is the rise in firms' market power since the 1980s (De Loecker, Eeckhout and Unger 2020). However, we view rising market power as unlikely to explain the change in the cyclicality of labour productivity. If rising markups leads to reduced pass-through of shocks to firms' employment, then this should reduce the relative volatility of employment and raise the output labour productivity correlation.

[18]While our baseline results focus on HP filtered output and labour productivity, here we consider growth rates for three reasons. First, we found little difference between our baseline results (HP filtered) and growth rates (see Section 3.2). Second, using growth rates allows us to avoid HP filtering firm-level variables for which we may have few observations for an individual firm. Third, growth rates provide a natural interpretation for us to evaluate changes in structural features.

[19]Fort, Haltiwanger, Jarmin and Miranda (2013) argue that firm age is an important factor in employment dynamics. Compustat, however, does not track firm age and as such we resort to a proxy using time in the database. Crouzet and Mehrotra (2020) take a similar approach.

[20]In the Appendix in Table 1, we report results for continuous firm size regressions instead of a large firm cutoff employment level. These results yield identical conclusions.

[21]In related work, Kudlyak and Sánchez (2017) find that short-term debt of large firms is more sensitive than small firms, and declined by more after the 2008 recession.

[22]We thank the authors for making this data available. We detrend sector-level TFP using a fourth order log-polynomial as they do in their paper.

[23]Brault and Khan (2022) examine employment responses of US firms to sectoral shocks in investment hubs.

[24]In line with this conclusion, Gordon (2010) uses aggregate data to decompose the response of output per hour to changes in the output gap before and after 1986. He finds that output per hour is no longer procyclical after 1986 and this is primarily driven by a larger response of the employment rate to output gap changes.

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A Appendix

A.1 Additional Results

Table 1: EMPLOYMENT ELASTICITY TO FIRM AND AGGREGATE DEMAND

	(A1) Pre-1985	(A2) Post-1985	(A3) Full sample
Age	−0.286***	−0.136***	−0.286***
	(0.022)	(0.008)	(0.028)
Employment	0.009	0.010**	0.009
	(0.005)	(0.004)	(0.007)
ΔOutput	0.352***	0.885***	0.352***
	(0.032)	(0.046)	(0.041)
ΔSales	0.369***	0.293***	0.369***
	(0.003)	(0.002)	(0.004)
Employment × ΔOutput	−0.006***	−0.007***	−0.006***
	(0.001)	(0.001)	(0.002)
Employment × ΔSales	0.004***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)
Post-1985 × Age	—	—	0.150***
			(0.029)
Post-1985 × Employment	—	—	0.002
			(0.008)
Post-1985 × ΔOutput	—	—	0.533***
			(0.060)
Post-1985 × ΔSales	—	—	−0.076***
			(0.005)
Post-1985 × Employment × ΔOutput	—	—	−0.002
			(0.002)
Post-1985 × Employment × ΔSales	—	—	0.004***
			(0.001)
Observations	53,968	181,209	235,177
Adjusted R^2	0.2147	0.1800	0.1851
Industry controls	2-digit NAICS	2-digit NAICS	2-digit NAICS

Notes: The dependent variable is firm-level employment growth. Instead of a discrete cutoff for large firms, the regressions here use employment size interactions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 2: ROBUSTNESS: EMPLOYMENT ELASTICITY TO FIRM AND AGGREGATE DEMAND

	(A4) Full sample	(A5) Full sample	(A6) Pre-1985	(A7) Post-1985
Age	−0.289***	−0.379***	−0.332***	−0.144***
	(0.028)	(0.037)	(0.026)	(0.008)
Large	—	2.790***	2.279***	4.066***
		(0.459)	(0.372)	(0.341)
ΔOutput	0.332***	1.223	0.329***	0.853***
	(0.040)	(1.11)	(0.051)	(0.062)
ΔSales	0.375***	0.337***	0.337***	0.319***
	(0.004)	(0.005)	(0.004)	(0.002)
Large × ΔOutput	—	−0.198**	−0.096	−0.628***
		(0.081)	(0.069)	(0.094)
Large × ΔSales	—	0.201***	0.184***	0.294***
		(0.011)	(0.009)	(0.006)
Sectoral TFP	—	—	0.357***	0.098***
			(0.032)	(0.029)
Large × Sectoral TFP	—	—	−0.412***	−0.169***
			(0.047)	(0.046)
Post-1985 × Age	0.155***	0.193***	—	—
	(0.028)	(0.037)		
Post-1985 × Large	—	1.150***	—	—
		(0.553)		
Post-1985 × ΔOutput	0.555***	—	—	—
	(0.058)			
Post-1985 × ΔSales	−0.077***	−0.071***	—	—
	(0.004)	(0.005)		
Post-1985 × Large × ΔOutput	—	−0.547***	—	—
		(0.117)		
Post-1985 × Large × ΔSales	—	0.133***	—	—
		(0.012)		
Observations	235,177	235,177	46,502	159,152
Adjusted R^2	0.1820	0.2038	0.2221	0.2262
Industry controls	2-digit NAICS	2-digit NAICS	2-digit NAICS	2-digit NAICS
Year fixed effects		✓		

Notes: The dependent variable is firm-level employment growth. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

A.2 Expressing the aggregate output labour productivity correlation in terms of standard deviations

The correlation between detrended output and detrended labour productivity is given by

$$\rho(\tilde{Y}_t, \tilde{LP}_t) = \frac{Cov(\tilde{Y}_t, \tilde{LP}_t)}{\sigma(\tilde{Y})\sigma(\tilde{LP})}, \tag{7}$$

where $\tilde{LP}_t = \tilde{Y}_t - \tilde{N}_t$. Then the above can be expanded as

$$\rho(\tilde{Y}_t, \tilde{LP}_t) = \frac{\sigma(\tilde{Y})^2}{\sigma(\tilde{Y})\sigma(\tilde{LP})} - \frac{Cov(\tilde{Y}_t, \tilde{N}_t)}{\sigma(\tilde{Y})\sigma(\tilde{LP})}. \tag{8}$$

Multiplying and dividing the latter term by $\sigma(\tilde{N})$

$$\rho(\tilde{Y}_t, \tilde{LP}_t) = \frac{\sigma(\tilde{Y})}{\sigma(\tilde{LP})} - \rho(\tilde{Y}_t, \tilde{N}_t)\frac{\sigma(\tilde{N})}{\sigma(\tilde{LP})}, \tag{9}$$

where $\rho(\tilde{Y}_t, \tilde{N}_t)$ is the correlation between output and employment. Finally, factoring yields

$$\rho(\tilde{Y}_t, \tilde{LP}_t) = \frac{\sigma(\tilde{Y})}{\sigma(\tilde{LP})}\left(1 - \rho(\tilde{Y}_t, \tilde{N}_t)\frac{\sigma(\tilde{N})}{\sigma(\tilde{Y})}\right). \tag{10}$$

A.3 The importance of Compustat firms for aggregate productivity dynamics

Following the notation used in Section 2, aggregate labour productivity at time t is defined as

$$LP_t = \sum_{i=1}^{K} \left(\frac{n_{i,t}}{\sum_{i=1}^{N} n_{i,t}} \right) \frac{y_{i,t}}{n_{i,t}} \qquad \equiv \frac{1}{N_t} \sum_{i=1}^{K} y_{i,t}, \tag{11}$$

where $y_{i,t}$ is real value added of firm i. N is the total numbers of employees in the economy (both private and public), and K is the total number of firms. Total value added can be decomposed into value added from Compustat firms (K_c) and non-Compustat firms (K_{nc})

$$LP_t = \frac{1}{N_t} \left(\sum_{i=1}^{K_c} y_{i,t} + \sum_{i=1}^{K_{nc}} y_{i,t} \right). \tag{12}$$

Next, let N_t^c and N_t^{nc} be the total employment levels of Compustat and non-Compustat firms in period t. Then total labour productivity can be rewritten as weighted shares of labour productivity from Compustat and non-Compustat firms

$$LP_t = \left(\frac{N_t^c}{N_t} \right) LP_t^c + \left(\frac{N_t^{nc}}{N_t} \right) LP_t^{nc}, \tag{13}$$

where N_t^c / N_t and N_t^{nc} / N_t are the shares of total employees in Compustat/non-Compustat firms. Let λ_t^c and λ_t^{nc} denote these shares at any time t so that the aggregate level of labour productivity is given by

$$LP_t = \lambda_t^c LP_t^c + \lambda_t^{nc} LP_t^{nc}. \tag{14}$$

Next, aggregate labour productivity growth is given by

$$\Delta LP_t = \frac{LP_t - LP_{t-1}}{LP_{t-1}}, \tag{15}$$

and substituting in expressions for the aggregate level of labour productivity as weighted shares of Compustat and non-Compustat labour productivity gives

$$\Delta LP_t = \frac{LP_{t-1}^c}{LP_{t-1}} \frac{\lambda_t^c LP_t^c - \lambda_{t-1}^c LP_{t-1}^c}{LP_{t-1}^c} + \frac{LP_{t-1}^{nc}}{LP_{t-1}} \frac{\lambda_t^{nc} LP_t^{nc} - \lambda_{t-1}^{nc} LP_{t-1}^{nc}}{LP_{t-1}^{nc}}. \tag{16}$$

Next, we make two simplifying assumptions that within each subsample the share of employment and real value added in Compustat firms are constant. This implies that $\lambda_t^c = \lambda_{t-1}^c = \lambda^c$ and $\lambda_t^{nc} = \lambda_{t-1}^{nc} = \lambda^{nc}$. It also implies that $LP_{t-1}^c / LP_{t-1} = LP_t^c / LP_t = LP^c / LP$ and $LP_{t-1}^{nc} / LP_{t-1} = LP_t^{nc} / LP_t = LP^{nc} / LP$. With these two assumptions, the expression for aggregate labour productivity growth simplifies to

$$\Delta LP_t \approx \left(\frac{\bar{Y}^c}{\bar{Y}} \right) \Delta LP_t^c + \left(\frac{\bar{Y}^{nc}}{\bar{Y}} \right) \Delta LP_t^{nc}, \tag{17}$$

which states that aggregate labour productivity growth is a real value added weighted share of labour productivity growth in Compustat and non-Compustat firms. Substituting this into the aggregate output labour productivity correlation gives

$$\rho(\Delta Y_t, \Delta LP_t) \approx \left(\frac{\bar{Y^c}}{\bar{Y}}\right)\frac{Cov(\Delta Y_t, \Delta LP_t^c)}{\sigma_Y \sigma_{LP}} + \left(\frac{\bar{Y^{nc}}}{\bar{Y}}\right)\frac{Cov(\Delta Y_t, \Delta LP_t^{nc})}{\sigma_Y \sigma_{LP}}. \tag{18}$$

Let σ_{LP^c} and $\sigma_{LP^{nc}}$ be the standard deviations of labour productivity for Compustat and non-Compustat firms. Then the aggregate output labour productivity correlation can be written as a weighted sum of the aggregate output Compustat/non-Compustat labour productivity correlations

$$\rho(\Delta Y_t, \Delta LP_t) \approx \left(\frac{\bar{Y}^c}{\bar{Y}}\right)\frac{\sigma_{LP^c}}{\sigma_{LP}}\rho(\Delta Y_t, \Delta LP_t^c) + \left(\frac{\bar{Y}^{nc}}{\bar{Y}}\right)\frac{\sigma_{LP^{nc}}}{\sigma_{LP}}\rho(\Delta Y_t, \Delta LP_t^{nc}). \tag{19}$$

Table 3: AVERAGE LARGE FIRM SHARES

		Compustat		Aggregate
Sample	Firms (%)	Employment (%)	Sales (%)	Employment (%)
1963-1984	62.49	98.34	98.18	27.67
1985-2018	42.53	97.66	96.74	29.16

Notes: Large firms are firms with greater than 1,000 employees. By definition the small firm share is one minus the large firm share. These shares are the averages over each sample period. Aggregate employment is the total number of nonfarm employees, which was retrieved from FRED (PAYEMS).

Table 4: CYCLICAL LABOUR PRODUCTIVITY: AGGREGATE, SMALL FIRMS, AND LARGE FIRMS

		$\rho(Y^{agg}, Prod_t^{size})$		
Sample	Aggregate	All firms	$<= 1k$	$> 1k$
1963-1984	0.77	0.68	0.28	0.67
	[0.046]	[0.092]	[0.180]	[0.093]
1985-2018	0.17	0.28	0.07	0.28
	[0.103]	[0.134]	[0.159]	[0.130]
Firm-year obs.		258,975	141,580	117,395

Notes: The table reports the correlations between labour productivity and aggregate output (Y^{agg}). All measures are logged and HP filtered. The 'Aggregate' column shows the correlation based on aggregate productivity. Numbers in square brackets are standard errors computed using the Delta method with a Newey-West estimator and 4 lags.

Table 5: CYCLICAL LABOUR PRODUCTIVITY: END OF YEAR FILING DATES

Sample	Aggregate	$\rho(Y^{agg}, Prod_t^{size})$ All firms	$<= 1k$	$> 1k$
1963-1984	0.77	0.67	0.26	0.66
	[0.046]	[0.098]	[0.150]	[0.099]
1985-2018	0.17	0.17	0.04	0.17
	[0.103]	[0.135]	[0.153]	[0.132]
Firm-year obs.		165,589	85,860	79,729

Notes: The table reports the correlations between labour productivity and aggregate output (Y^{agg}). The 'Aggregate' column shows the correlation based on aggregate productivity. Numbers in square brackets are standard errors computed using the Delta method with a Newey-West estimator and 4 lags.

Table 6: CYCLICAL LABOUR PRODUCTIVITY: FIRST-DIFFERENCE FILTER

Sample	Aggregate	$\rho(Y^{agg}, Prod_t^{size})$ All firms	$<= 1k$	$> 1k$
1964-1984	0.79	0.61	0.43	0.60
	[0.055]	[0.095]	[0.119]	[0.096]
1985-2018	0.32	0.26	0.04	0.27
	[0.101]	[0.127]	[0.142]	[0.124]
Firm-year obs.		258,975	141,580	117,395

Notes: The table reports the correlations between labour productivity and aggregate output (Y^{agg}). The 'Aggregate' column shows the correlation based on aggregate productivity. Numbers in square brackets are standard errors computed using the Delta method with a Newey-West estimator and 4 lags. It is worth noting that we lose the first observation due to first differencing which means are pre-1985 sample now spans the periods 1964-1984.

Table 7: CYCLICAL LABOUR PRODUCTIVITY: MANUFACTURING AND NON-MANUFACTURING

Panel A		**Manufacturing** $\rho(Y^{agg}, Prod_t^{size})$		
Sample	Aggregate	All firms	$<= 1k$	$> 1k$
1963-1984	0.77	0.61	0.63	0.60
	[0.046]	[0.134]	[0.149]	[0.137]
1985-2018	0.17	0.21	0.16	0.21
	[0.103]	[0.245]	[0.087]	[0.249]
Firm-year obs.		107,507	60,140	47,367

Panel B		**Non-manufacturing** $\rho(Y^{agg}, Prod_t^{size})$		
Sample	Aggregate	All firms	$<= 1k$	$> 1k$
1963-1984	0.77	0.60	0.07	0.58
	[0.046]	[0.068]	[0.199]	[0.076]
1985-2018	0.17	0.25	0.05	0.25
	[0.103]	[0.124]	[0.162]	[0.120]
Firm-year obs.		151,468	81,440	70,028

Notes: The table reports the correlations between labour productivity and aggregate output (Y^{agg}). The 'Aggregate' column shows the correlation based on aggregate productivity. Numbers in square brackets are standard errors computed using the Delta method with a Newey-West estimator and 4 lags. Our definition of manufacturing firms is firms with NAICS codes between 30 and 40.

Table 8: CYCLICAL LABOUR PRODUCTIVITY: ALTERNATIVE CUTOFFS FOR LARGE FIRM DEFINITION

Panel A		**Large firms** $> 10k$		
		$\rho(Y^{agg}, Prod_t^{size})$		
Sample	Aggregate	All firms	$<= 10k$	$> 10k$
1963-1984	0.77	0.68	0.47	0.68
	[0.046]	[0.092]	[0.078]	[0.100]
1985-2018	0.17	0.28	0.28	0.25
	[0.103]	[0.134]	[0.157]	[0.137]
Firm-year obs.		258,975	226,937	32,038

Panel B		**Large firms** $> 20k$		
		$\rho(Y^{agg}, Prod_t^{size})$		
Sample	Aggregate	All firms	$<= 20k$	$> 20k$
1963-1984	0.77	0.68	0.65	0.60
	[0.046]	[0.092]	[0.058]	[0.118]
1985-2018	0.17	0.28	0.37	0.16
	[0.103]	[0.134]	[0.150]	[0.170]
Firm-year obs.		258,975	241,020	17,955

Notes: The table reports the correlations between labour productivity and aggregate output (Y^{agg}). The 'Aggregate' column shows the correlation based on aggregate productivity. Numbers in square brackets are standard errors computed using the Delta method with a Newey-West estimator and 4 lags.

Table 9: DECOMPOSITION IN THE POST-1985 PERIOD

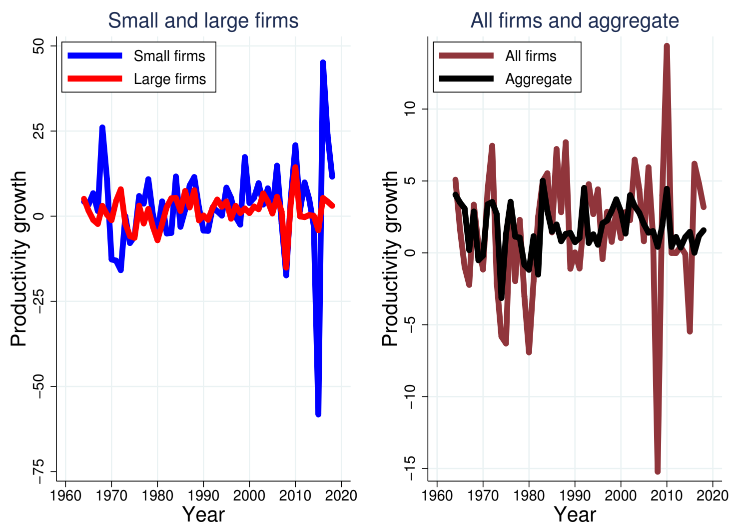
	$\frac{\bar{Y}^i}{\bar{Y}}$	σ_{LP^i}	$\rho(\Delta Y_t, \Delta LP_t^i)$
Compustat	0.28	4.61	0.26
Non-Compustat	0.72	—	—
Aggregate	1	1.18	0.32

Table 10: EMPLOYMENT ELASTICITY TO FIRM AND AGGREGATE CONDITIONS

	(1) Pre-1985	(2) Post-1985	(3) Full sample
Age	−0.342***	−0.157***	−0.342***
	(0.023)	(0.008)	(0.029)
Large	2.551***	4.361***	2.551***
	(0.337)	(0.326)	(0.429)
ΔOutput	0.374***	0.991***	0.374***
	(0.046)	(0.059)	(0.059)
ΔSales	0.336***	0.267***	0.336***
	(0.003)	(0.002)	(0.005)
Large × ΔOutput	−0.208***	−0.792***	−0.208***
	(0.063)	(0.089)	(0.080)
Large × ΔSales	0.199***	0.337***	0.199***
	(0.008)	(0.005)	(0.012)
Post-1985 × Age	—	—	0.184***
			(0.030)
Post-1985 × Large	—	—	1.810***
			(0.529)
Post-1985 × ΔOutput	—	—	0.617***
			(0.081)
Post-1985 × ΔSales	—	—	−0.069***
			(0.005)
Post-1985 × Large × ΔOutput	—	—	−0.584***
			(0.116)
Post-1985 × Large × ΔSales	—	—	0.138***
			(0.012)
Observations	53,968	181,209	235,177
Adjusted R^2	0.2237	0.2148	0.2013
Industry controls	2-digit NAICS	2-digit NAICS	2-digit NAICS

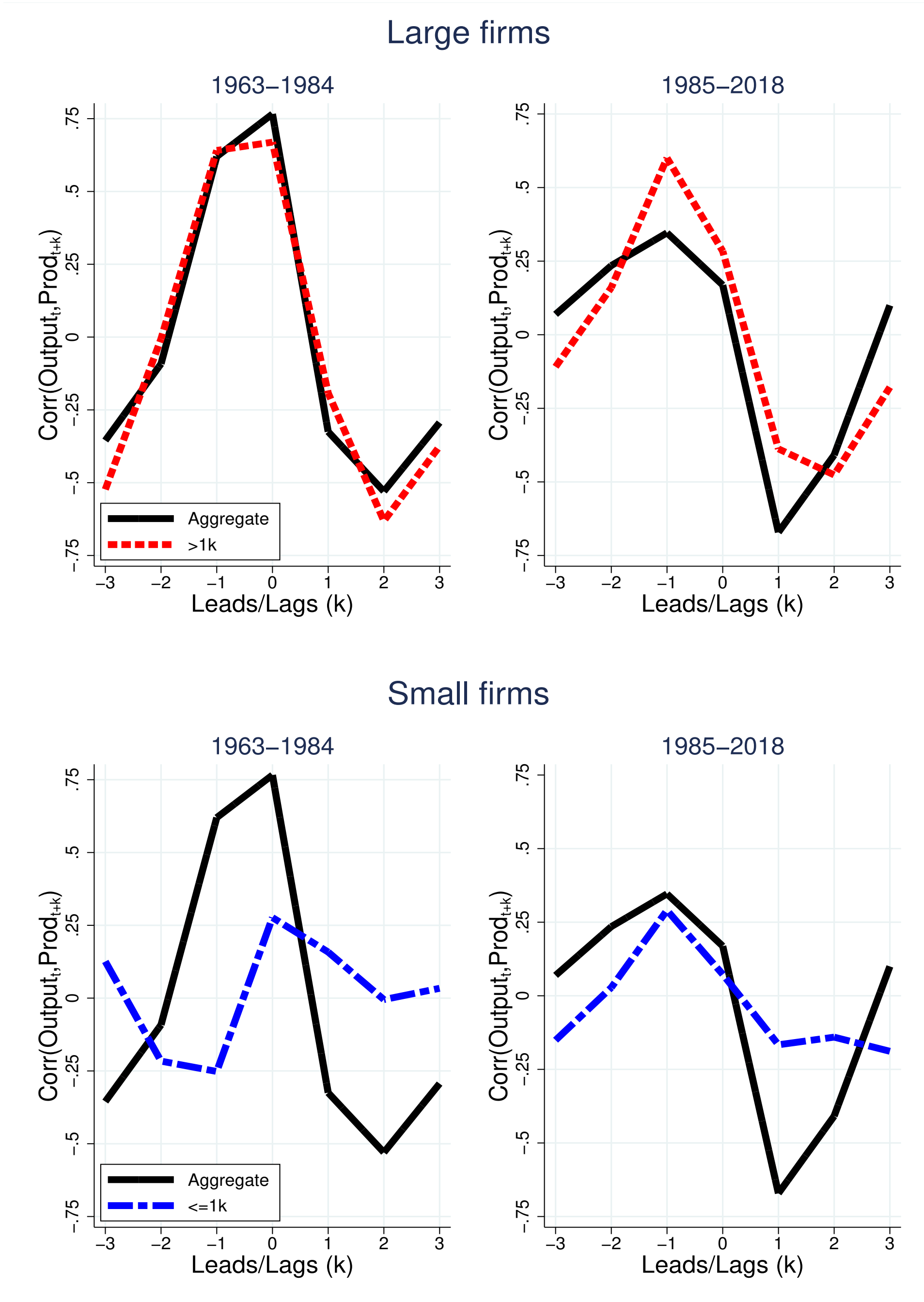
Notes: The dependent variable is firm-level employment growth. Large firms are firms with greater than 1,000 employees. The pre-1985 sample is based on data from 1964-1984 and the post-1985 sample is based on data from 1985 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Figure 1: Average labour productivity growth



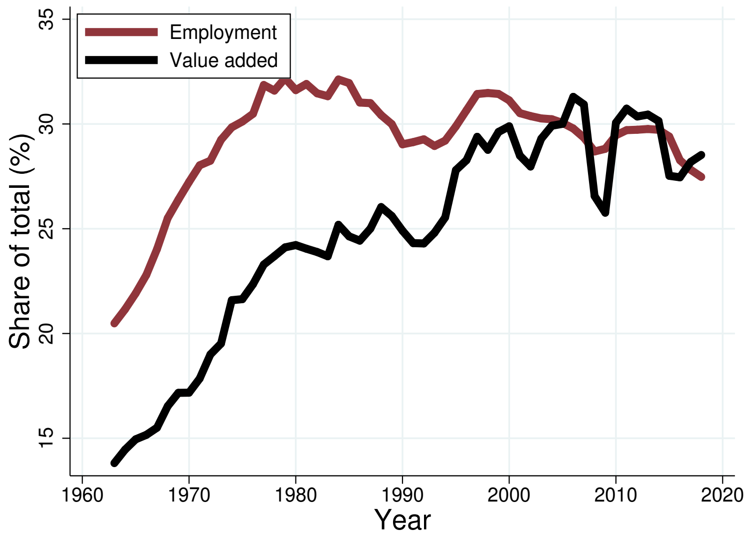
Notes: Our measures of the average labour productivity level are defined as in Equation 2 above. Growth rates are computed by taking the log difference.

Figure 2: CORRELATIONS AT DIFFERENT LEADS AND LAGS



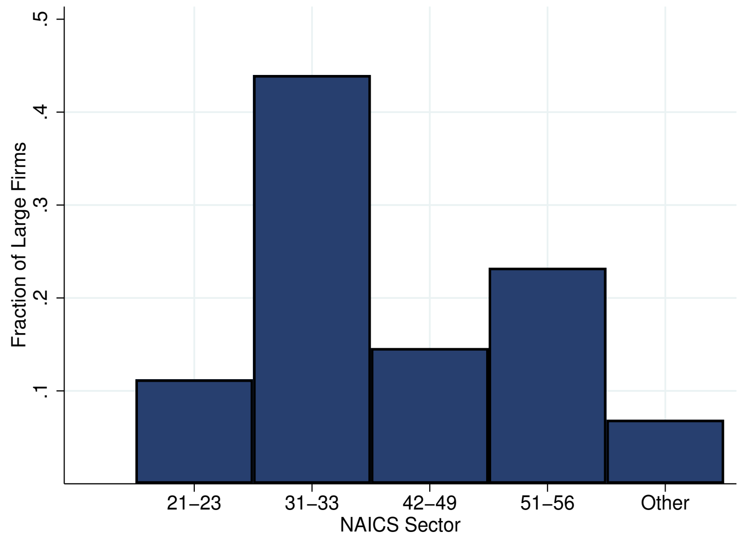
Notes: Leads and lags are annual.

Figure 3: EMPLOYMENT AND VALUE ADDED SHARES OF COMPUSTAT FIRMS



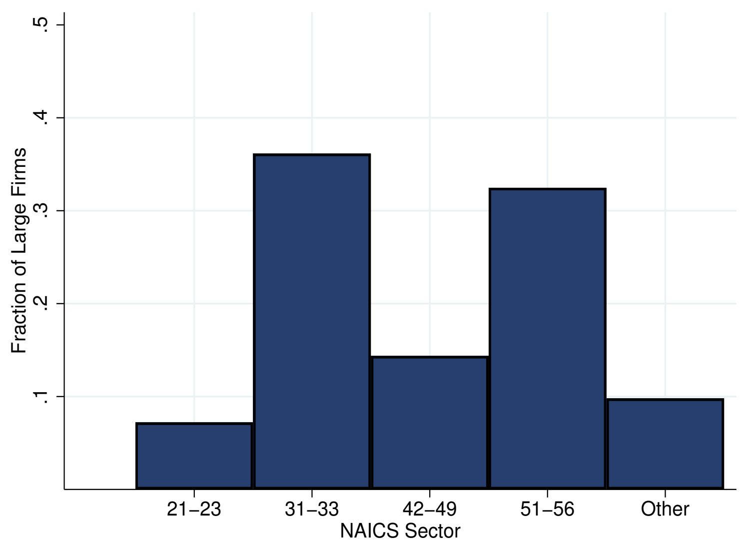
Notes: The employment share is computed as the sum of employees in Compustat divided by all non-farm employees (FRED code: PAYEMS). The value added share is computed by dividing nominal value added in Compustat by nominal GDP (FRED code: GDP) in each year.

Figure 4: PRE-1985 FRACTION OF LARGE FIRMS IN NAICS SECTORS



Notes: There are 2,696 unique large firms in the pre-1985 sample. We collapse firms into one of five categories: [1] Mining (21), utilities (22), and construction (23); [2] Manufacturing (31, 32, 33); [3] wholesale trade (42), retail trade (44, 45), transportation and warehousing (48, 49); [4] Information (51), finance and insurance (52), real estate and rental and leasing (53), professional, scientific, and technical services (54); [5] Administrative and waste management services (56); [6] Other.

Figure 5: POST-1985 FRACTION OF LARGE FIRMS IN NAICS SECTORS



Notes: There are 7,696 unique large firms in the pre-1985 sample. We collapse firms into one of five categories: [1] Mining (21), utilities (22), and construction (23); [2] Manufacturing (31, 32, 33); [3] wholesale trade (42), retail trade (44, 45), transportation and warehousing (48, 49); [4] Information (51), finance and insurance (52), real estate and rental and leasing (53), professional, scientific, and technical services (54); [5] Administrative and waste management services (56); [6] Other.