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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 find support for the hypothesis that this change is driven by increased labour market flexibility. In response to a 1% increase in real sales 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
JEL classification: D22, E24, E32

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1 Introduction

The behaviour of aggregate labour productivity has changed substantially since the onset of the Great Moderation in the mid-1980s. Labour productivity used to be strongly pro-cyclical, moving together with output over the business cycle. Since the onset of the Great Moderation, however, this relationship has entirely disappeared. It is now nearly acyclical when labour productivity is defined as output per worker or moderately countercylical when labour productivity is defined as output per hour. Explaining this change in contemporaneous cyclicality – the *labour producitivity 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)).[1] At the same time labour productivity also lost its positive leading economic indicator property and now negatively lags the business cycle (Brault and Khan 2020). Motivated by recent research on the role of large firms in the aggregate economy, we ask the following question: Does the cyclical behaviour of labour productivity among large firms resemble the cyclicality observed at the aggregate level?

Several recent contributions have studied the role of large firms from both short and long-run perspectives. 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 (2021) 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. Autor, Dorn, Katz, Patterson and Van Reenen (2020) provide a new interpretation of the fall in the labour

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

share based on the rise of 'superstar firms'.[2] 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.

A separate literature emphasizes the role that sectoral shocks play in aggregate business cycle dynamics. Foerster, Sarte and Watson (2011) and Garin, Pries and Sims (2018) provide evidence in favour of a decline in the importance of aggregate shocks, increasing the relative importance of sectoral shocks. The latter build a model with costly labour reallocation and calibrate shock sizes to those found in the pre- and post-1984 data. The rise in the relative size of sectoral shocks generates a substantial decline in the output-labour productivity correlation. vom Lehn and Winberry (2019) argue that because the majority of investment goods are produced in what they refer to as 'investment hubs', shocks to these sectors generate large employment effects. They show using a multisector real business cycle model that a rise in sector specific shocks relative to aggregate shocks is capable of explaining the decline in the procyclicality of labour productivity.

Our contribution to the literature is threefolds. First, we present novel stylized facts on the short-run behaviour of labour productivity by firm size and compare them to those observed in aggregate labour productivity. Second, using the firm-level data set we find support for the hypothesis from Galí and van Rens (2020) that the observed decline in aggregate labour productivity procyclicality since the onset of the Great Moderation is driven by changes in labour market flexibility. Third, our findings can serve as a useful benchmark to evaluate the properties of theoretical models in which large firms play an essential role.

From the Computstat database which covers all publicly listed firms, we compute firm specific measures of labour productivity. Using these, we construct a weighted-average of labour productivity conditional on firm size. We then 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

[2]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*).

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 et al. (2021). We label as 'small firms' those with 1,000 or less employees. Our results, however, are robust to a range of definitions for large firms. Notably, as we show below, large firms account for the bulk of employment and sales in Compustat.

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, close to 0.77 observed at the aggregate level. In the post-1985 period, the large firm labour productivity correlation declines significantly to 0.28, consistent with the observed decline in the aggregate correlation to 0.17. In contrast, small firm labour productivity cyclicality is not statistically different from zero in the either the pre- or 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. Finally, using our firm-level data we find support for a hypothesis proposed by Galí and van Rens (2020) that the decline in the procyclicality of labour productivity can be attributed to firms' increased use of extensive margin labour adjustments in response to demand changes since the onset of the Great Moderation. We find that the elasticity of employment growth to real sales growth (our measure of firm output) for large firms has increased from 0.535 in the pre-1985 period to 0.604 in the post-1985 period.

[3] Early work by Burnside and Eichenbaum (1993) emphasized the ability of factor-hoarding to explain lead-lag correlations in labour producitivty. 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).

This implies that the average large firm in the pre-1985 period hires roughly an additional 75 workers for a 1% change in real sales, while they hire roughly an additional 90 workers in the post-1985 period. Over the same period small firm employment elasticity to firm output falls.

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 can 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 the aggregate state 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. We take logs and detrend output, employment, 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 which covers all publicly listed firms in the US. 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. Since our measure of the aggregate business cycle is the non-farm business sector, we exclude all firms with NAICS codes below 20 (agriculture, forestry, fishing and hunting) and above 90 (government). We focus exclusively on firms located in the US and 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 indexes. Industry accounts roughly correspond to NAICS 3 digit codes. In

[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 the first-difference filter.

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

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

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

where N 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., $\omega_{i,t} \equiv \frac{n_{i,t}}{\sum_{i=1}^{N} n_{i,t}}$).[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.

[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 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.

Table 1: AVERAGE LARGE FIRM SHARES

Sample	% of total firms	% of employment	% of real sales
1963-1984	62.49	98.34	98.18
1985-2018	42.53	97.66	96.74

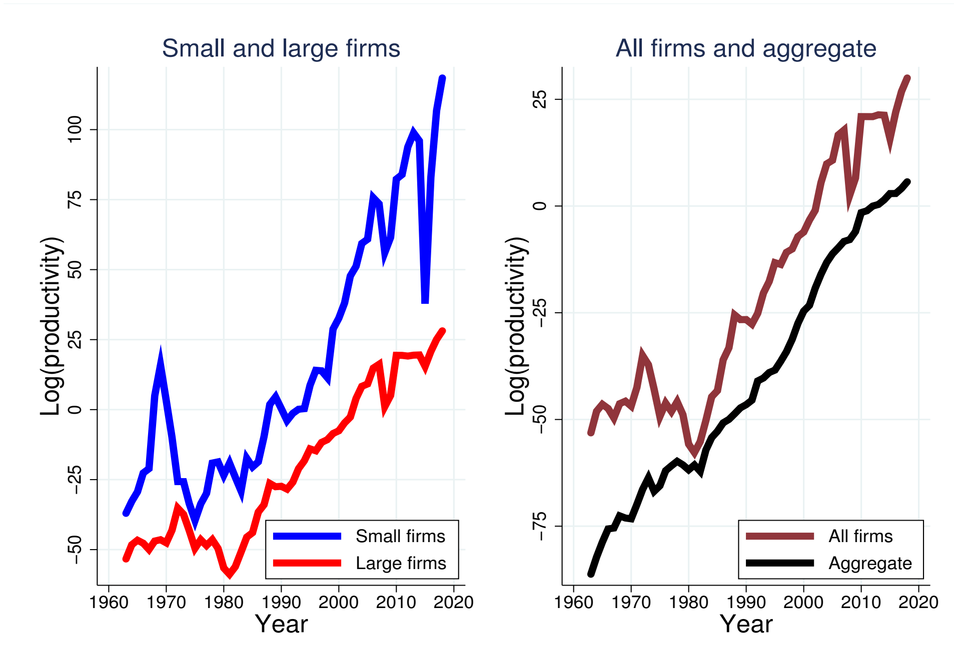
Notes: Large firms are firms with greater than 1,000 employees. By definition the small firm share is one minus the large firm share. These shares are the averages over each sample period. The variable real sales in the table does not subtract input costs as done in the construction of labour productivity in equation (1).

First, and perhaps unsurprisingly, large firms account for nearly all of employment and real sales in Compustat. Table 1 reports the large firm shares of total firms, employment, and real sales. 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 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 has become more skewed in the post-1985 period.

Second, when comparing the levels of labour productivity across small, large, and all firms in Compustat to the aggregate, we find substantial differences. Figure 1 plots the log level of labour productivity 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: One is that small firms are on average more productive than their larger counterparts, as the level of labour productivity of small firms is consistently above the level of large firms; Two, there has been a noticeable divergence in the level of labour productivity between small and large firms, this is particularly evident from the late 1980s onward. In fact, since 1990 labour productivity growth in small firms is more than double that of large firms (3.93% versus 1.92%).

Third, all firms in the Compustat database have, on average, higher labour productivity than the aggregate. This result is not particularly surprising since Compustat represents publicly traded companies and more productive firms are more likely to become public.

Figure 1: LEVELS OF AVERAGE LABOUR PRODUCTIVITY



Notes: Our measures of the average labour productivity level are defined as in Equation 2 above.

However, movements in aggregate labour productivity do share similarities with all firms in Compustat and the average growth rate between the two is quite close, with average labour productivity growth in all firms being 1.51% versus 1.67% in the aggregate.

The above long-run facts show significant differences between small and large firms in terms of labour productivity, particularly in their growth trajectories 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 2 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.

Table 2: 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.

Under the aggregate column we can see the *labour productivity puzzle* - the sharp drop in the procyclicality 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 pattern similar 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).

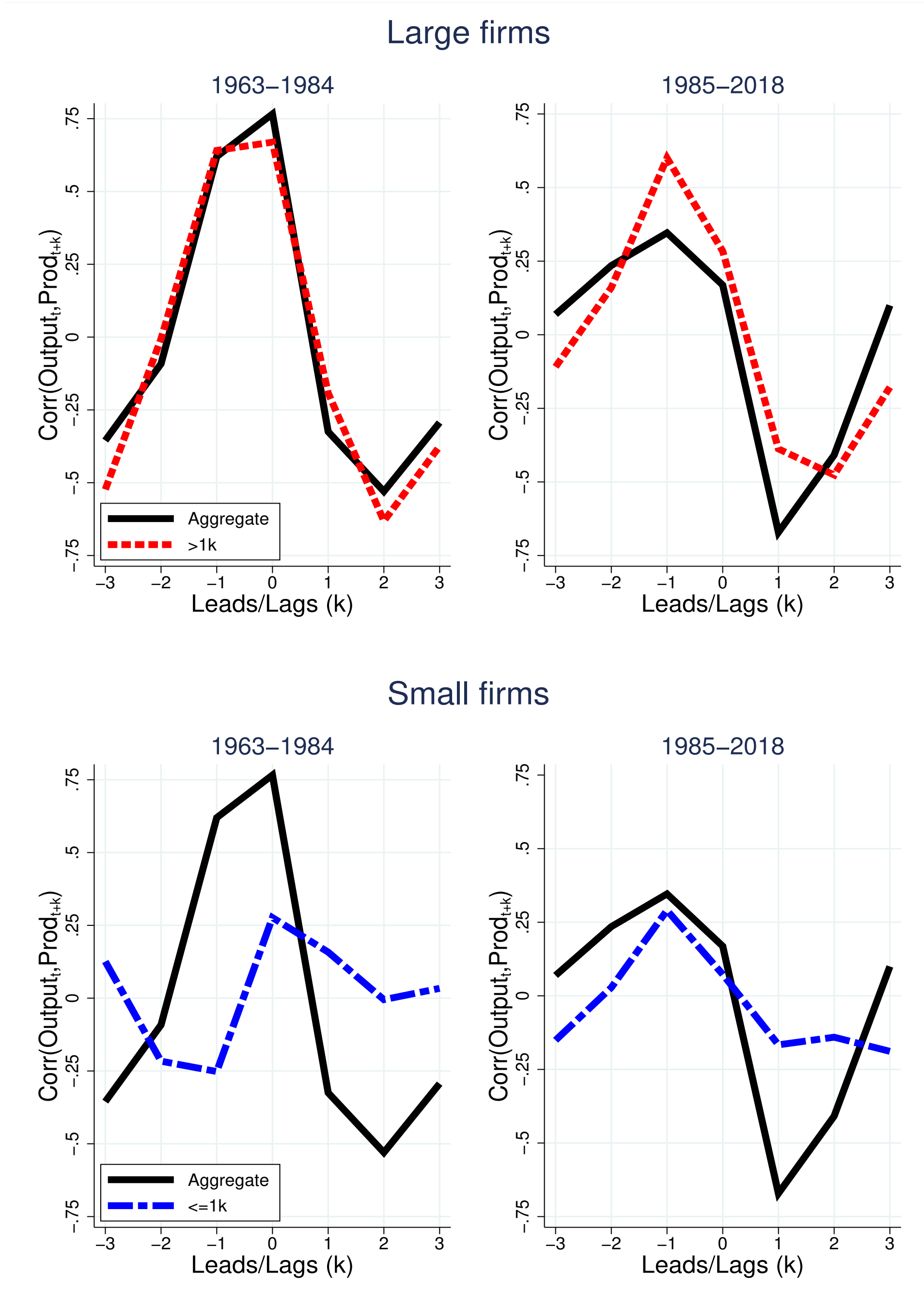
Focusing on the aggregate labour productivity at different leads and lags, we see that since the onset of the Great Moderation it is not only contemporanous cyclicality which has changed dramatically, but also that labour productivity lags output over the cycle. In the pre-1985 period, aggregate labour productivity was strongly correlated with one year ahead output ($Corr(Y_t^{agg}, Prod_{t-1}^{agg}) = 0.62$).[8] 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 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 positive correlated with past output, both facts which are at odds with the aggregate data. In the post-1985 period small firm

[8] The largest correlation is contemporaneous which would indicate that the labour productivity is neither leading nor lagging. However it is 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.

Figure 2: CORRELATIONS AT DIFFERENT LEADS AND LAGS



Notes: Leads and lags are annual.

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 Some additional considerations

In the following sections we discuss four 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. Table 3 reports the cyclicality of labour productivity based on this restriction. The number of year-firm observations for large firms decreases from 17,955 in the baseline case to 12,692.

Comparing the results in Table 3 to Table 2 we find little difference, and in fact our large firm properties appear closer to the aggregate. 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. In the following we consider cyclical fluctuations based on a first-difference filter, which corresponds to year-over-year growth rates.

When comparing Table 4 to Table 2 we find differences mainly for small firms. Aggregate labour productivity for small firms is more procyclical in the pre-1985 period and exhibits a larger decline in the post-1985 period, consistent with large firms and the aggregate.

Table 3: 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 4: 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-1984 sample now spans the periods 1964-1984.

But when using a first-difference filter, aggregate and large firm labour productivity remain mildly procyclical in the post-1985 period, while small firm labour productivity is acyclical.

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. We explore labour productivity changes when we distinguish between manufacturing and non-manufacturing firms.[9] These results are reported in Table 5.

In this case we find some differences from our baseline, particularly for manufacturing. Small manufacturing firms also exhibit a substantial decline in the procyclicality of labour productivity, consistent with large manufacturing firms and the aggregate. Small non-manufacturing firms have acyclical labour productivity in both periods, while large non-manufacturing firms exhibit a decline in the procyclicality of labour productivity.

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 et al. (2021). However, the literature has used a range of cutoffs to define large firms. In Table 6, 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 (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

[9] In earlier versions of this paper we also reported these changes for "*investment hubs*" as defined in vom Lehn and Winberry (2019). However, we found significant overlap between manufacturing and investment hubs results and for brevity has chosen to omit those results here. These results are available upon request.

Table 5: 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 6: 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.

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. But the largest decline in procyclicality does appear for the largest firms.

4 Why did the procyclicality of labour productivity decline?

The previous sections 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 declines observed in the aggregate. One prominent explanation proposed for this phenomena by Galí and van Rens (2020) is that this decline is due to improvements in job match quality and consequently there has been a decline in labour market turnover. Further, when firms face convex costs associated with changing their employment levels, a reduction in average job separations permits firms more adjustments along the extensive margin before adjustment costs become prohibitively expensive.[10] This increase in extensive margin adjustments is a potential explanation for the decline in the procyclicality of labour productivity, as (Galí and van Rens 2020, pg. 308) write[11]:

> *The previous evidence [rising relative volatility of aggregate labour inputs] points to a rise in the elasticity of labour input with respect to output. Put differently, firms appear to have relied increasingly on labour input adjustments in order to meet their changes in output.*

[10] Mitra (2020) proposes an alternative explanation that also leads firms to rely on more extensive margin adjustments. However, his explanation rests on the rapid de-unionization which occurred during the 1980s. This led to lower costs of hiring and firing workers and less dependence on labour hoarding behaviour.

[11] To see why this is the case, note that the output labour productivity correlation can be rewritten in the following manner $\rho(y, y-n) = \sigma(y-n)^{-1}(1 - \frac{\sigma(n)}{\sigma(y)}\rho(y,n))$. Since the correlation between aggregate output and employment, $\rho(y,n)$, is quite close to one in the data, a rise in the relative volatility of employment, $\frac{\sigma(n)}{\sigma(y)}$, can generate a decline in the correlation between output and labour productivity.

We test this hypothesis at the firm level. Specifically we investigate if employment has become more elastic to firm-level and aggregate output since the mid-1980s. Second, since our results in Section 2 find that large firms most closely resemble the aggregate, we investigate if this elasticity is different for large firms. We estimate the elasticity of firm-level employment growth in response to aggregate output growth and firm-level real sales growth.[12] We consider real sales as the measure of firm output. The model we estimate is

$$\Delta \text{Emp}_{i,t} = \alpha + \alpha_1 \text{Age}_{i,t} + \delta_0 \text{Large}_{i,t} + \gamma_j + B_1 \Delta \text{Output}_t + B_2 \Delta \text{Sales}_{i,t} + \delta_1 \text{Large}_{i,t} \times \Delta \text{Output}_{i,t} + \delta_2 \text{Large}_{i,t} \times \Delta \text{Sales}_{i,t} + \epsilon_{i,t}, \tag{3}$$

where i identifies a firm, t a year, and j an industry. ΔEmp is the log difference of employment multiplied by 100. We define *Age* using a proxy as the length of time that a firm is in the Compustat database.[13] Large is a binary variable indicating whether a firm has more than 1,000 employees (equals 1 if employment $> 1,000$). γ_j are industry specific intercepts which are defined at the 2-digit NAICS level. ΔOutput is the growth rate of non-farm US output which is common to all firms, and ΔSales is the growth rate of firm-specific real sales (both computed as the log difference multiplied by 100). δ_1 and δ_2 are intended to capture any differential effects of changes in output and real sales on large firm's employment growth. Table 7 reports estimates for Equation 3 for the pre-1985 and post-1985 periods.

Our estimates for age, α_1, implies 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. Estimates of average large firm employment growth relative to small firms, δ_0, vary quite dramatically between the pre-1984 and post-1984 periods. In the pre-1984 period large firms grew close to 2.5% more

[12] While our previous section emphasized HP filtered output and labour productivity as the baseline, here we consider growth rates for three reasons. First, we found little difference between our baseline results (HP filtered) and growth rates (see Section 3.3). 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 the claim in Galí and van Rens (2020).

[13] Fort et al. (2013) argue that firm age is an important factor in employment dynamics. Unfortunately Compustat does not track firm age and as such we resort to a proxy using time in the database. A similar approach was taken by Crouzet and Mehrotra (2020).

Table 7: EMPLOYMENT ELASTICITY TO FIRM AND AGGREGATE DEMAND

	Pre-1985	Post-1985
Age	-0.342	-0.157
	(0.023)	(0.008)
Large	2.551	4.361
	(0.337)	(0.326)
ΔOutput	0.374	0.991
	(0.046)	(0.059)
Large × ΔOutput	-0.208	-0.792
	(0.063)	(0.089)
ΔSales	0.336	0.267
	(0.003)	(0.002)
Large × ΔSales	0.199	0.337
	(0.008)	(0.005)
Observations	53,968	181,209
Firms	5,355	5,355
Adjusted R^2	0.2237	0.2148
Industry controls	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. All parameter estimates are statistically significant at the 1% level against a null hypothesis that the parameter is equal to 0. Standard errors are reported in brackets.

per year on average than smaller firms. In this post-1984 period this effect nearly doubles with large firms employment growth being on average 4.36% higher than smaller firms. We find that small firms are more sensitive to the business cycle than large firms, a finding that resonates quite closely with the findings in Crouzet and Mehrotra (2020). We find that this sensitivity for small firms has increased in the post-1985 period, while the sensitivity for larger firms has remained relatively constant.

Turning to the parameters of particular interest as it relates to the hypothesis of Galí and van Rens (2020), we find that employment elasticity to firm output has fallen for small firms. A 1% change in real sales was associated with a 0.34% change in employment in the pre-1985 period, and only a 0.27% change in the post-1985 period. In sharp contrast large firm employment elasticity, $B_2 + \delta_2$, has risen from 0.535 in the pre-1985 period to 0.604 in the post-1985 period. Translating these elasticities into employment terms, large firms on average hired an additional 75 employees for a 1% change in real sales (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).

Moreover since large firms account for nearly all of employment in our database, this implies that the aggregate response of employment to changes in output has increased in the post-1985 period.[14] This finding provides direct firm-level evidence in support of the hypothesis proposed by Galí and van Rens (2020). The increasing reliance on labour input adjustments is then a promising candidate to explain the decline in the procyclicality of labour productivity since the onset of the Great Moderation period.

5 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

[14] 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.

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.

Changes in large firm dynamics can, therefore, be a potential candidate to explain the labour productivity puzzle. We provide support for one proposed explanation for this puzzle from Galí and van Rens (2020), which hinges on employment elasticity to firm output increasing in the post-1985 period. 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 sales, 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.

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A Data Construction

A.1 Compustat Firm Level Data

Our firm level data is comprised of the universe of Compustat firms. We use firm level data from 1963 to 2018. We screen the Compustat data using $consol = "C"$, $indfmt = "INDL"$, $datafmt = "STD"$, $popsrc = "D"$, and $curcd = "USD"$. We only focus on firms located within the United States ($loc = "USA"$). We exclude all firms with NAICS codes less than 20 and greater than or equal to 90. Additionally we drop firms with negative sales and missing values for sales, employment, or the price index.

We deflate firms nominal sales using BEA industries price indices. These indices roughly correspond to 3 digit NAICS codes. In cases where 3 digit codes are not matched, we use two digit matching.

BEA INDUSTRY NAICS CLASSIFICATION

	Assigned NAICS Code
All industries	
Private Industries	
Agriculture, forestry, fishing and hunting	11
Farms	111,112
Forestry, fishing and related activities	113,114,115
Mining	21
Oil and gas extraction	211
Mining, except oil and gas	212
Support activities for mining	213
Utilities	221
Construction	236,237,238
Manufacturing	31,32,33
Durable goods	
Wood products	321
Nonmetallic mineral products	327
Primary metals	331
Fabricated metal products	332
Machinery	333
Computer and electronic products	334
Electrical equipment, appliances, and components	335
Motor vehicles, bodies and trailers, and parts	336
Other transportation equipment	336
Furniture and related products	337
Miscellaneous manufacturing	339
Nondurable goods	
Food and beverage and tobacco products	311,312
Textile mills and textile product mills	313,314
Apparel and leather and allied products	315,316
Paper products	322
Printing and related support activities	323
Petroleum and coal products	324
Chemical products	325
Plastics and rubber products	326
Wholesale trade	423,424,425
Retail trade	44,45
Motor vehicle and parts dealers	441
Food and beverage stores	445
General merchandise stores	452
Other retail	453

BEA Industry NAICS Classification

	Assigned NAICS Code
Transportation and warehousing	48, 49
Air transportation	481
Rail transportation	482
Water transportation	483
Truck transportation	484
Transit and ground passenger transportation	485
Pipeline transportation	486
Other transportation and support activities	487,488,492
Warehousing and storage	493
Information	51
Publishing industries, except internet (includes software)	511
Motion picture and sound recording industries	512
Broadcasting and telecommunications	515
Data processing, internet publishing, and other information services	518,519
Finance, insurance, real estate, rental and leasing	
Finance and insurance	52
Federal Reserve banks, credit intermediation, and related activities	522
Securities, commodity contracts, and investments	523
Insurance carriers and related activities	524
Funds, trusts, and other financial vehicles	525
Real estate and rental and leasing	53
Real estate	531
Housing	
Other real estate	
Rental and leasing services and lessors of intangible assets	532
Professional and business services	
Professional, scientific, and technical services	54
Legal services	541
Computer systems design and related services	541
Miscellaneous professional, scientific, and technical services	541
Management of companies and enterprises	551
Administrative and waste management services	56
Administrative and support services	561
Waste management and remediation services	562
Educational services, health care, and social assistance	
Education services	611
Health care and social assistance	62
Ambulatory health care services	621
Hospitals and nursing and residential care facilities	623

BEA INDUSTRY NAICS CLASSIFICATION

	Assigned NAICS Code
Hospitals	622
Nursing and residential care facilities	623
Social assistance	624
Arts, entertainment, recreation, accommodation, and food services	
Arts, entertainment, and recreation	71
Performing arts, spectator, sports, museums, and related activities	711,712
Amusements, gambling, and recreation industries	713
Accommodation and food services	72
Accommodation	721
Food services and drinking places	722
Other services, except government	81
Government	92

Notes: Our classification is based on the industry code guide provided by the BEA available at https://www.bea.gov/sites/default/files/2018-04/2017-industry-code-guide.pdf.