

Essays on Macroeconomics and Labor Markets

by

Vasco Botelho

Department of Economics
Duke University

Date: _____

Approved:

Craig Burnside, Supervisor

Matthias Kehrig

Kyle Jurado

Andrea Lanteri

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
2018

ABSTRACT

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Abstract

This dissertation consists of three essays. In the first essay, “The Structural Shift in the Cyclicality of the U.S. Labor Income Share: Empirical Evidence”, I document a structural shift in the cyclicality of the labor share from countercyclical to procyclical. I conclude that this structural shift is due to a decline in the usage of labor hoarding at the firm level and to an increase in the volatility of real wages. I also provide evidence suggesting this shift is widespread to the entire economy and is not due to structural changes in the industrial composition for the U.S. economy. In the second essay, “The Cyclicality of the Labor Share: Labor Hoarding, Risk Aversion and Real Wage Rigidities”, I explore whether the decline in the usage of labor hoarding is able to jointly generate the vanishing procyclicality of labor productivity and the shift in the cyclicality of the labor share. I conclude that while these models are able to generate the vanishing procyclicality of labor productivity, they will generate counterfactually a more countercyclical labor share. This counterfactual result also occurs when I consider instead a decline in the workers’ bargaining power in the wage bargaining process and an increase in the relative importance of aggregate demand shocks. In the third essay, “The Public Sector Wage Premium: An Occupational Approach”, I characterize the strategy undertaken by the U.S. government to provide insurance to workers in occupations that are on the left-tail of the private wage distribution. I conclude that the government is effectively offering a high wage premium to non-routine manual workers and a wage penalty to non-routine cognitive workers.

To my parents, who are my ultimate role models, and to my grandmother, who is a second mother to me.

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Introduction

This dissertation consists of three essays. In the first essay, “The Structural Shift in the Cyclical Behavior of the U.S. Labor Income Share: Empirical Evidence”, I contribute to the macroeconomic literature by reassessing the cyclical behavior of the labor share for the United States over time. Traditionally thought as countercyclical by the macroeconomic literature, the labor share started to move procyclically with the business cycle in the last three decades. I trace the shift in the cyclical behavior of the labor share to two key structural changes faced by the U.S. economy: the decrease in the usage of labor hoarding at the firm level and an increase in the flexibility of the labor market. I show that the shift in the cyclical behavior of the labor share occurred in the wage bargaining process between employers and employees, and that it was widespread across the majority of industries in the U.S. economy. On the other hand, cross-sectional evidence shows an interesting relationship between the cyclical behavior of the labor share and the cyclical behavior of labor productivity. The general implication of the analysis is that the decline in the labor market insurance is mostly due to a change in the firm-level behavior on the hiring and firing process.

In the second essay, “The Cyclical Behavior of the Labor Share: Labor Hoarding, Risk

Aversion and Real Wage Rigidities”, I assess the performance of standard dynamic stochastic general equilibrium models to match the shift in the cyclicality of the labor income share. In particular, I look to real business cycles models embedded with an incentive for labor hoarding, workers’ risk aversion against future income risk, and wage bargaining between workers and firms. I show that incentives for labor hoarding and workers’ risk aversion provide formal labor market insurance mechanisms at the firm side and worker side, respectively. The introduction in this framework of wage bargaining generates almost by assumption a countercyclical labor income share. I show that although these models are able to generate a decline in the procyclicality of labor productivity following a decrease in labor hoarding or following a decrease in the workers bargaining power, they counterfactually make the labor share to be even more countercyclical. On the other hand, the introduction of real wage rigidities decreases starkly the volatility of real wages. Since there is no change to the behavior of labor productivity in this scenario, real wage rigidities generate very countercyclical labor shares. This essay provides a note of caution to the usage of real business cycle models embedded with labor hoarding and wage bargaining mechanisms, or embedded with real wage rigidities.

These two essays should be seen as companion essays. They document a new structural change in the U.S. economy and assess the qualitative performance of current state-of-the-art models used in policy such as the real business cycles models with labor adjustment costs, hiring frictions, search and matching frictions, reallocation and training costs, and variations on the New Keynesian Model with real wage rigidities. Without an additional ingredient this models fail to reproduce the shift in the cyclicality of the U.S. labor income share following a decrease in incentives for firms to perform labor hoarding, following de-unionization, and following an increase in the relative importance of aggregate demand (labor supply) shocks in the economy. Further research is needed to incorporate the shift in the cyclicality of the

labor share in the package of facts to be addressed in the study of macroeconomic fluctuations and to link the explanations for this fact with those used to account for the decline in the level of the labor share for the U.S. economy.

In the third essay, “The Public Sector Wage Premium: An Occupational Approach”, I characterize the strategy undertaken by the U.S. government to provide insurance to workers in occupations that are on the left-tail of the private wage distribution. I provide three empirical facts relating the occupational heterogeneity with the determination of the public sector wage differential. The first shows a negative monotonic relationship between the public sector wage differential and the private sector hourly wages across occupations. The second suggests the existence of a public sector wage differential polarization, in which low-skill and low-wage occupations have very high wage premiums, high-skill and high-wage occupations have wage penalties. Lastly, the third fact concludes that the public sector wage differential is indeed affected by the occupational employment composition across sectors. The main conclusion is that the occupational composition is among the most important factors for both the determination of the average public sector wage differential and the determination of the public sector labor market share over time.

The Structural Shift in the Cyclicity of the U.S. Labor Income Share: Empirical Evidence

2.1 Introduction

In this chapter, I contribute to the macroeconomic literature by reassessing the cyclical behavior of the labor share for the United States over time. Traditionally, the labor's share is characterized by two stylized facts: (1) the labor share is roughly constant in the long run, as documented by Kaldor (1957); and (2) the labor share moves countercyclically with the business cycle. The “constancy” of the labor share is viewed with skepticism since Solow (1958) and its recent pronounced decline in the U.S. propelled a debate on whether the labor share is mean-reverting or converging towards a new steady state.

On the other hand, there is a strong consensus in the macroeconomic literature on the countercyclicality of the labor share. This countercyclicality of the labor income share is usually explained by the presence of insurance mechanisms for both the households and firms in the wage bargaining process. On the household side,

risk averse workers attempt to insure themselves against future income and unemployment risk. On the firm side, the presence of labor hoarding¹ incentives makes the firm be willing to insure themselves against downturns.

I document a structural change in the cyclical movements of the U.S. labor's share. Traditionally thought as countercyclical, the labor share started to move procyclically with the business cycle in the last three decades. Looking at the peak-to-trough movements, the labor share decreased by an average of 1.157 percentage points in the last three recessions, while it increased by an average of 0.386 percentage points in the previous recessions.

The shift in the cyclicalities of the labor share can be traced to two key empirical structural changes in the U.S. economy: the vanishing procyclicality of labor productivity and the increase in the volatility of real wages.² I show that the shift in the cyclicalities of the labor income share is due in 76.8% to the vanishing procyclicality of labor productivity, in 41.4% to the secular increase in the relative volatility of real wages with respect to the volatility of real output. On the other hand, the relatively stable procyclicality of the average real hourly wage explains -19.8% of the change in the cyclicalities of the labor income share.

The shift in the cyclicalities of the labor share can also be due to the secular decline in the value added shares for the manufacturing and wholesale and retail trade sectors, and to the corresponding rise of the services and financial activities. Na (2017) observes that differences in sectoral compositions between tradables and

¹ Labor hoarding refers to the practice in which a firm does not lay off workers in downturns in order to guarantee these workers' contribution to the firm's production in good times. This behavior is most commonly generated under the presence of labor adjustment costs or search and matching frictions. This concept was initially applied to real business cycle fluctuations by Burnside et al. (1993) and Burnside and Eichenbaum (1996).

² The decline in the procyclicality of labor productivity and the decline in the correlation between labor productivity and total hours worked is a recent empirical fact documented in Stiroh (2009), Galí and Gambetti (2009), Gordon (2010), Barnichon (2010), McGrattan and Prescott (2012), and Galí and van Rens (2017). The increase in the volatility of real wages is looked at in Champagne and Kurmann (2013).

non-tradables are an important channel to explain the cross-county heterogeneity in the observed cyclicity of the labor share. Workers in manufacturing and trade industries are subject to a higher unemployment risk due not only to globalization and the competition from international outsourcing, but also to the increasing automation of routine-based tasks and job polarization. This can potentially lead to workers in manufacturing and trade industries requiring a higher degree of insurance when bargaining their contracts with firms. If so, this would imply manufacturing and trade industries having a more countercyclical labor share than the one observed in services and finance.

Under this scenario, and assuming the cyclicity of the sectoral labor shares remain constant over time, the structural change from manufacturing to services is able to generate a decline in the countercyclicity of the aggregate labor share. However, the shift towards a procyclical labor share happens not only for the aggregate labor share but also at the sectoral level. Using a sectoral decomposition analysis for the U.S. economy, I quantify the contributions of variations in the level and cyclicity of sectoral value added shares and sectoral labor shares to the cyclicity of the aggregate labor share. In a counterfactual analysis in which I vary the sectoral composition in the U.S. economy over time, I provide evidence that the structural change from manufacturing to services is not able to explain the shift in the cyclicity of the labor share.

The dynamics of the U.S. labor income share are amongst the most important research subjects in macroeconomics during the last decade. The recent trend decline in the U.S. labor share has sparked a renewed interest in the medium-run dynamics of factor shares. In particular, the literature relates the fall in the labor share to structural changes in the economy. Elsbey et al. (2013) argue that the recent decline in the labor share is due to the decline in self-employment and to globalization and offshoring. Karabarbounis and Neiman (2014) show that the decline in the labor

share happens at a global level and that it can be explained by a fall in the relative price of investment goods. Barkai (2017) provides evidence that the decline in the labor share is due to an increase in markups. Autor et al. (2017) and Kehrig and Vincent (2017) look to micro-level data and conclude that the fall in the labor share comes from the reallocation of production towards superstar (or hyper-productive) firms. Grossman et al. (2017) claim that the decline in the labor share is due to a global productivity slowdown. Finally, Martinez (Martinez) focuses on the role of automation to the secular changes in the labor share.

On the other hand, there has been an established consensus in the literature that the labor share is countercyclical. The earlier contributions of Boldrin and Horvath (1995) and Gomme and Greenwood (1995) highlighted the role of labor contracts in generating a countercyclical labor share by providing an insurance mechanism against unemployment risk. On the other hand, Andolfatto (1996) embeds a standard real business cycle model with search and matching frictions and argues that this model generates a countercyclical labor share because these frictions manifest a labor hoarding mechanism. More recently, the literature has shifted away from explaining the cyclicity of the labor share using non-competitive factors towards looking to changes in aggregate technology and in the elasticity of substitution between capital and labor.

In particular, Ríos-Rull and Santaeulàlia-Llopis (2010) use a Cobb-Douglas production function with time-varying factor shares and find that the labor share decreases contemporaneously with a technological innovation, but it increases in the medium-run as a result of the same innovation. Choi and Ríos-Rull (2009) assess the relative importance of noncompetitive factor prices and different specifications for the aggregate production function. They argue that the literature should shift away from introducing frictions in the economy and move towards a technological explanation for the cyclicity of the labor share by considering a constant elasticity

of substitution (CES) technology.

Koh and Santaaulàlia-Llopis (2017) build on this idea and use a production function that is CES in the short-run, but Cobb-Douglas in the long-run. They argue that the cyclical-ity of the labor share can be explained by a countercyclical elasticity of substitution between capital and labor. In a related paper, Hansen and Prescott (2005) notices how capacity constraints at the plant level will translate into an aggregate production function that is not Cobb-Douglas and generate a countercyclical labor share in a one-sector growth model.

I structure this chapter as follows. In section 2, I describe the shift in the cyclical-ity of the labor share and its robustness across different measurements. In section 3, I propose a decomposition relating the cyclical-ity of the labor share to the cyclical-ity of labor productivity and real wages. In section 4, I provide evidence that changes in industry composition are not able to generate the shift in the cyclical-ity of the aggregate labor share. In section 5, I look to international cross-country evidence to see how the cyclical-ity of the labor share evolved over time in other advanced economies. Finally, in section 6, I conclude the chapter.

2.2 The Structural Shift in the Cyclical-ity of the U.S. Labor Share.

The labor share is conceptually equal to the ratio of labor compensation to gross value added.

$$\lambda_t = \frac{W_t H_t}{P_t Y_t} \tag{2.1}$$

where W_t is the average compensation per hour of work, H_t the total number of hours worked, and $P_t Y_t$ the (nominal) gross value added, in which P_t stands for the price level and Y_t for the quantity produced. In practice, correctly measuring the

labor share is not a trivial task³.

The main difficulty lies in the allocation (and imputation) of proprietors' income between capital and labor income. The estimation of the labor compensation for the self-employed encompasses a measurement error component that generates an additional bias in case this income is allocated to the labor share without further adjustment. Additionally, the researcher needs to choose which sectors to include (exclude) from the analysis as there are sectors that have no labor income (housing) or no capital income (government), which can generate further methodological issues. For example, not including the government sector in the analysis raises the question of how to handle the income generated by the net indirect taxes and taxes on production. A related question would be whether to consider the agricultural sector in the analysis, as it is a sector with different features from the rest of the economy. Finally, the researcher needs to decide on whether or not to include depreciation in the measure of output. Although the labor share is a relatively simple concept, it is significantly difficult to measure.

The literature has converged to five alternative methodologies to measure the labor share⁴:

- i. payroll share for employees in the nonfarm business sector;
- ii. headline BLS labor share, following Kravis (1959) labor basis methodology;
- iii. economy-wide labor share measured using the unambiguous income shares;
- iv. payroll share for employees in the corporate business sector;

³ A more detailed overview of the challenges faced by researchers when measuring the labor share can be found in Gollin (2002), Gomme and Rupert (2004), Elsby et al. (2013), and Rognlie (2015).

⁴ A more extensive description for the different methodologies can be found in Appendix A. The construction of the payroll share for the nonfarm business sector is described in Appendix B.

- v. BLS annual multifactor productivity labor share, which is an updated methodology based on Kravis (1959) asset-basis approach.

Notice that regardless of the measurement used the labor share is a variable that captures the ratio of a measure of aggregate compensation to a related measure of aggregate income.

I construct the time series for the five alternative measurements of the labor share using the Productivity and Costs dataset from the Bureau of Labor Statistics (BLS) and the National Income and Product Accounts (NIPA) from the Bureau of Economic Analysis. I also obtain the corresponding time series for real output from NIPA. I identify business cycle fluctuations by applying the Christiano and Fitzgerald (2003) approximate bandpass filter with frequencies between 6 and 32 quarters⁵ The second column in Table 2.1 shows the point estimates for the cyclicity of the labor share for the entire sample for the five different variables considered above. When we look at the entire sample, and regardless of our preferred measurement for the labor share, the labor share is countercyclical. The estimated correlations between the cyclical components for the labor share and real output lie between -0.069 for the payroll share for the nonfarm business sector and -0.274 for the payroll share for the corporate sector. The headline labor share published by the BLS is countercyclical with a correlation of -0.217 with real output.

However, looking to the cyclicity of the labor share for the entire sample masks a considerable heterogeneity in the cyclical movements of the labor share over time. In fact, the labor share has become considerably more procyclical in the last three decades. After obtaining the cyclical components for the labor share and real output,

⁵ My sample goes from 1947:1 to 2016:4. I extract the cyclical component for the variables of interest after applying the filter to the natural logarithm of the original time series. To understand whether my findings were an artificial result coming from the particular filtering procedure used and not a true structural change in the business cycles dynamics for the U.S. economy, I have performed a robustness check in which I use the filtering methodology proposed in Hamilton (2017). The results are qualitatively the same using this alternative approach.

Table 2.1: The Cyclicity of the Labor Share Over Time: Alternative Measures

$\rho(\hat{\lambda}_t, \hat{g}_t)$	1947-2016	1947-1987	1988-2016	Change
Payroll Share NFB	-0.069 [-0.196,0.058]	-0.181 [-0.338, - 0.024]	0.280 [0.094,0.467]	0.461 [0.218,0.704]
Headline Labor Share	-0.217 [-0.341, - 0.093]	-0.361 [-0.504, - 0.217]	0.254 [0.071,0.437]	0.615 [0.383,0.847]
Economy Wide	-0.153 [-0.265, - 0.041]	-0.264 [-0.397, - 0.130]	0.134 [-0.139,0.406]	0.365 [0.121,0.609]
Payroll Share Corporate	-0.274 [-0.392, - 0.155]	-0.411 [-0.542, - 0.281]	0.022 [-0.196,0.239]	0.433 [0.179,0.686]
Asset Basis (MFP)	-0.109 [-0.315,0.098]	-0.232 [-0.492,0.029]	0.266 [0.033,0.498]	0.497 [0.151,0.844]

Sources: Bureau of Economic Analysis, Bureau of Labor Statistics, and author’s calculations. In squared-brackets is shown the 95% confidence interval. The data for the asset basis (MFP) measure is only available annually. The business cycles identified for this variable correspond to fluctuations between 2 and 8 years. Standard errors obtained by using the “Delta Method”.

I partition the sample and compute the cyclicity of the labor share for two distinct periods. The earlier period comprises 1947-87 and the latter period 1988-2016⁶.

I present the cyclicity of the labor share for both sub-samples in the third and fourth column of Table 2.1. While the labor share is countercyclical in the earlier period, it becomes procyclical in the latter period. The correlation between the headline labor share and real output goes from -0.361 in 1947-1987 to 0.254 in 1988-2016. The shift in the cyclicity of the labor share towards procyclicality is robust compared to the usage of the alternative measurement methodologies used in the

⁶ There is not a clear break point between sub-samples. I calculate the time-varying correlation between the cyclical components of the labor share and real output using rolling windows of 10, 15, 20, and 25 years. Then, I test for a structural break with an unknown date for this series and I retrieve the estimated break (window)date. For the rolling correlations with a 10-year window, the estimated break in the cyclicity of the labor share occurs in the time interval 1987:3 to 1996:3. The estimated break using rolling correlations with a 25-year window occurs in the time interval 1982:4-2006:4. Therefore, any partition break between 1983:1 and 1987:4 would reflect the shift in the cyclicity of the labor share.

Table 2.2: Cyclical Movements of the Headline Labor Share (BLS) in Upturns and Downturns.

$\Delta \hat{\lambda}$		1947-2016	1947-1987	1988-2016
Payroll	Upturns	-0.115 s.d.	-0.265 s.d.	0.102 s.d.
Share NFB	Downturns	0.123 s.d.	0.275 s.d.	-0.113 s.d.
Headline	Upturns	-0.374 s.d.	-0.665 s.d.	0.046 s.d.
Labor Share	Downturns	0.372 s.d.	0.678 s.d.	-0.104 s.d.
Economy	Upturns	-0.099 s.d.	-0.396 s.d.	0.330 s.d.
Wide	Downturns	0.173 s.d.	0.428 s.d.	-0.224 s.d.
Payroll Share	Upturns	-0.211 s.d.	-0.361 s.d.	-0.006 s.d.
Corporate	Downturns	0.233 s.d.	0.416 s.d.	-0.015 s.d.

literature. To see this, in the last column of Table 2.1 I show how the cyclical-ity of the labor share changed across sub-samples. To do so, I regress the cyclical component of real output in the cyclical component of the labor share and I interact it with a dummy variable that takes all periods starting from the first quarter of 1988 into account,

$$\hat{y}_t = \alpha_0 + \alpha_1 \cdot \mathbf{1}[\text{year} \geq 1988] + \beta_1 \cdot \hat{\lambda}_t + \beta_2 \cdot \hat{\lambda}_t \cdot \mathbf{1}[\text{year} \geq 1988] + \epsilon_t \quad (2.2)$$

where $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are approximately equal to zero. Using the estimates for $\hat{\beta}_1$ and $\hat{\beta}_2$, I calculate the changes in the correlations over time and its statistical significance by using the ‘‘Delta Method’’. The shift towards a procyclical labor share is largest for the headline labor share and smallest for the economy-wide labor share. However, for all measurements of the labor share considered, $\hat{\beta}_2$ is positive and statistically significant, which reflects a structural change in the cyclical-ity of the labor share.

I characterize also the cyclical behavior of the labor share by looking at its behavior during upturns and downturns. In particular, I define a downturn as the

peak-to-trough (and upturn as trough-to-peak) movements in the cyclical component of real output. In Table 2.2 I present the cumulative variation in the cyclical component for the labor share for each upturn and downturn, across the different measurements of the labor share⁷.

The results for the entire sample reflect that the labor share decreases in upturns and increases in downturns, reinforcing the traditional consensus on the countercyclicality of the labor share. The variations in the labor share in both upturns and downturns almost double in 1947-1987 in comparison to the average variations observed in the entire sample. On the other hand, the cyclical movements in the labor share completely shift after 1988. In the last three decades, an upturn has been associated with an increase in the labor share, while a downturn with a decrease in the labor share. The evidence in Table 2.2 confirms the idea that there is a structural shift in the cyclical movements of the labor share and its robustness across measurement methodologies.

To study the stability of the shift in the cyclicity of the labor share over time, in Figure 2.1, I plot the correlation between the headline labor share and the real value added for the nonfarm business sector over time using 20-year rolling windows. The labor share is countercyclical in the initial part of the sample, but it has become clearly procyclical over the last three decades. The recent procyclicality of the labor share does not disappear even in the aftermath of the Great Recession.⁸

One interesting result is that the shift in the cyclicity of the labor share is driven by changes in the labor market conditions for employees. In Figure 2.1 I

⁷ I use the entire sample to obtain the standard deviation of the labor share. Then, I normalize the changes in the cyclical component of the labor share in each upturn and downturn by dividing its absolute value by previously calculated standard deviation.

⁸ The shift in the cyclicity of the labor share from countercyclical to procyclical is also robust compared to the size of the rolling windows shown. In particular, the shift in the cyclicity of the labor share is starker when we consider 30-year rolling windows instead of the 20-year windows shown in this paper.

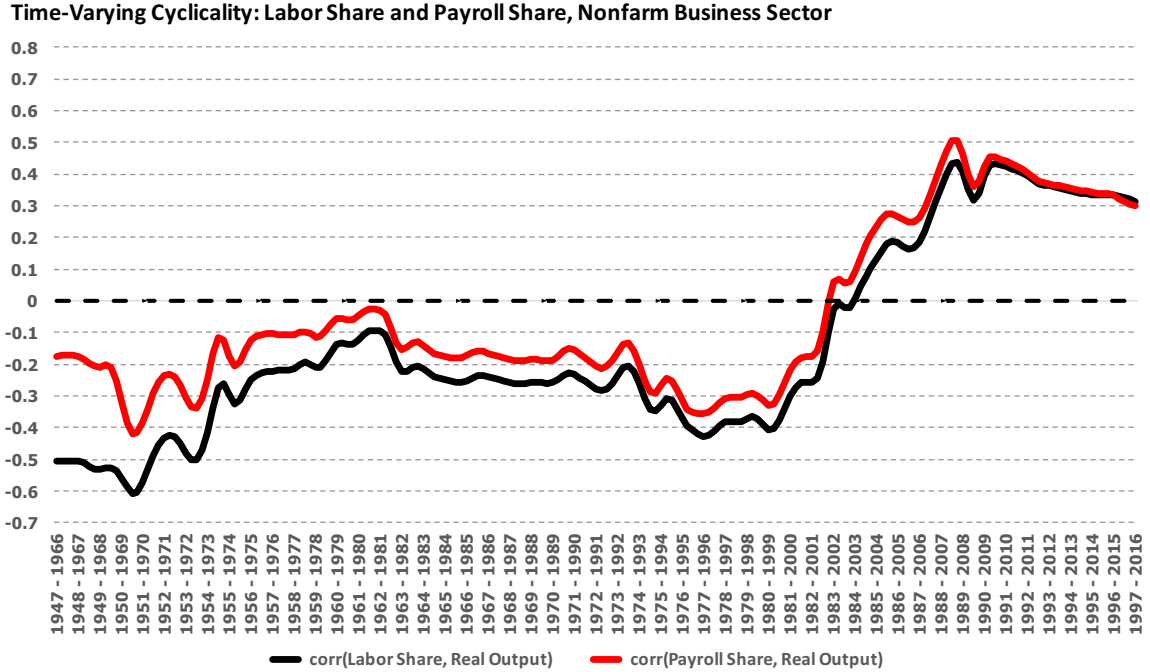


FIGURE 2.1: Time-Varying Cyclicity of the Headline Labor Share (BLS) and the Payroll Share for the Nonfarm Business Sector.

also plot the time-varying cyclicity of the payroll share for the nonfarm business sector. The inclusion of self-employment introduces a countercyclical pressure on the cyclicity of the labor share throughout the entire sample, but it does not affect its shift towards procyclicality in the late period. The two series track each other very closely, and almost exactly in the latter periods of the sample since the relative share of hours worked by self-employed workers decreases from roughly 15% in 1947 to 8% in 2016. This is an important result as Elsby et al. (2013) argues that “one third of the decline in the headline labor share appears to be a by-product of the methods employed by the BLS to impute the labor income of the self-employed.”. The methodology followed by the BLS is also affected by the decline in the relative share of total hours worked by self-employed workers in the economy⁹.

⁹ Throughout the remainder of this paper, I use the nonfarm business sector payroll share as my preferred measure for the labor share. The shift in the cyclicity of the labor share is robust

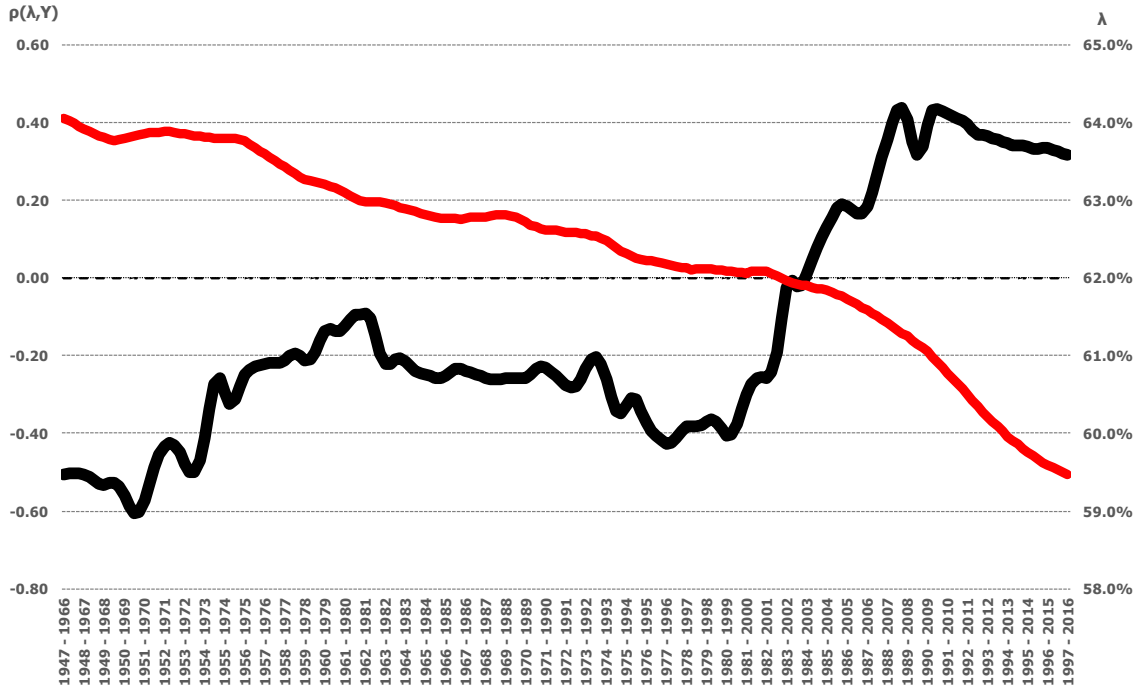


FIGURE 2.2: The Structural Shift in the Stylized Facts for the Labor Share.

In fact, it is quite likely that the shift in the cyclicity of the labor share is related to its trend decline. In Figure 2.2, I plot the time-varying cyclicity of the headline labor share, as well as its average level for the same time period. The labor share declined by two percentage points from 1947-1966 to 1983-2002, but it decreased by 2.5 percentage points from 1983-2002 to 1997-2016. This acceleration in the fall of the labor share occurs at the same time the labor share shifts from countercyclical to procyclical.

Figure 2.2 provides the main empirical motivation for the remainder of the paper. The dynamics of the labor share are characterized by two main stylized facts: the apparent constancy of the labor share over time, and its countercyclicity. In the last three decades, the labor share started to fall at an accelerated rate and has

compared to the methodology used to measure the labor share and the payroll share provides a clearer interpretation of the labor share and a deeper analysis at the industry level.

become procyclical. This suggests that both the level and cyclical movements of the labor share are affected by another structural change in the U.S. economy which is making the labor share converge to a new steady state. The robustness of the shift in the cyclical movements of the labor share across different measurement methodologies and the unimportance of cyclical movements in the labor input provided by self-employed workers hint that the main explanation for these two facts lie in a structural change to the labor market conditions for employees.

In the following section, I trace the shift in the cyclical movements of the labor share to two key facts: the vanishing procyclical movements of labor productivity, and the imperfect and positive relationship between real wages and labor productivity. This empirical evidence imposes discipline to macroeconomic models that attempt to replicate the cyclical dynamics of the U.S. economy.

2.3 The Cyclical Behavior of Real Wages and Labor Productivity.

The definition for the labor share described in (2.1) can be reinterpreted as the ratio between the real wages earned per hour of work (W_t/P_t) and labor productivity, defined as the number of units of output produced per hour of work (Y_t/H_t). This reinterpretation implies the following decomposition for the cyclical movements of the labor share

$$\rho\left(\hat{\lambda}_t, \hat{y}_t\right) = \frac{\sigma\left(\hat{w}_t\right)}{\sigma\left(\hat{\lambda}_t\right)} \cdot \rho\left(\hat{w}_t, \hat{y}_t\right) - \frac{\sigma\left(\hat{y}_t - \hat{h}_t\right)}{\sigma\left(\hat{\lambda}_t\right)} \cdot \rho\left(\hat{y}_t - \hat{h}_t, \hat{y}_t\right) \quad (2.3)$$

where $\hat{w}_t \equiv \hat{W}_t - \hat{P}_t$ is the cyclical component for the real hourly wage, $\hat{y}_t - \hat{h}_t$ is the cyclical component for labor productivity, \hat{h}_t is the cyclical component for the total number of hours worked by employees, and $\hat{\lambda}_t$ is the cyclical component for the

labor share¹⁰.

Table 2.3 explores how each component in (2.3) has changed over time. There are three key features in the data, which are important when explaining the shift towards a procyclical labor share in the U.S. economy.¹¹

1. The “vanishing procyclicality” of labor productivity: labor productivity was historically procyclical but it has become acyclical in the last three decades. This reflects a perfect comovement between total hours and real output in the latter period and is associated with a decline in labor hoarding at the firm level and an increase in labor market flexibility.
2. The increase in the relative volatility of real wages: after the Great Moderation, the volatility of output almost halved, but the volatility of real wages increased over time. This finding contrasts with the slow and steady decline in the relative volatility of labor productivity over time.

The first two empirical facts generate a procyclical force to the cyclicity of the labor share since the real wages are procyclical throughout the sample and their relative volatility with respect to the volatility of the labor share increases over time. The decline in the cyclicity of real wages is not as strong as the one observed by the cyclicity of labor productivity, which is in contrast to the predictions of a large

¹⁰ $\rho(x, z)$ is defined to be the correlation between variables x and z , and $\sigma(x)$ the standard deviation of variable x .

¹¹ These facts are known to the literature but they are usually analyzed in separate contexts. The vanishing procyclicality of labor productivity is first exposed and studied in Stiroh (2009), Galí and Gambetti (2009), Barnichon (2010), McGrattan and Prescott (2012), and Galí and van Rens (2017). The increase in the relative volatility of real wages is documented in Champagne and Kurmann (2013). It is also known that real wages and labor productivity are not perfectly correlated. However, the literature usually introduces a formulation for wage rigidity to break the relationship between the two variables. As argued in the text, this would violate one of the three empirical facts. It is therefore important to consider an environment in which the three facts are considered jointly, which adds further discipline to standard real business cycle models.

class of real business cycle models that assume real wages to be (almost) proportional to labor productivity¹². This notion motivates the introduction of a third key fact.

3. The imperfect comovement between real wages and labor productivity and its constancy over time: real wages and labor productivity are positively but not perfectly correlated. Moreover, the imperfect relationship between real wages and labor productivity is constant over time.

To quantify the contribution of real wages and labor productivity to the shift in the cyclical component of the labor share, I re-write the decomposition in (2.3) in terms of OLS regression coefficients defined by regressing the variable of interest in the cyclical component of real output¹³.

$$\beta_{\hat{\lambda}, \hat{y}} = \beta_{\hat{w}, \hat{y}} - \beta_{\hat{y} - \hat{h}, \hat{y}} \quad (2.4)$$

The results are described in Table 2.3 and Table 2.4. Table 2.3 provides the intuition in terms of correlations and standard deviations. Table 2.4 quantifies the contributions of real wages and labor productivity to the shift in the cyclical component of the labor share. Looking first to the entire sample, the labor share is mildly countercyclical¹⁴. The cyclical component of real wages is roughly the same as the cyclical component of labor productivity. Therefore, the countercyclical component of the labor share comes from

¹² In the following chapter, I show that a model with wage bargaining and labor hoarding is able to generate a decline in the cyclical component of labor productivity but not the shift to a procyclical labor share. The main justification for this is that real wages are tightly linked to labor productivity. Attempts to introduce wage rigidity to break the proportionality of these two variables considerably decreases the relative volatility of real wages and makes the labor share more countercyclical.

¹³ Notice that equation (2.3) can be re-written in terms of covariances as $\text{cov}(\hat{\lambda}_t, \hat{y}_t) = \text{cov}(\hat{w}_t, \hat{y}_t) - \text{cov}(\hat{y}_t - \hat{h}_t, \hat{y}_t)$. Dividing both sides of this new equation by the volatility of real output, we obtain $\frac{\text{cov}(\hat{\lambda}_t, \hat{y}_t)}{\sigma(\hat{y}_t)^2} = \frac{\text{cov}(\hat{w}_t, \hat{y}_t)}{\sigma(\hat{y}_t)^2} - \frac{\text{cov}(\hat{y}_t - \hat{h}_t, \hat{y}_t)}{\sigma(\hat{y}_t)^2}$. Since $\frac{\text{cov}(X, Z)}{\sigma(Z)^2}$ is by definition the ordinary least squares coefficient for the regression $X = \alpha + \beta_{x,z} \cdot Z + \nu$, the previous equation implies a very simple decomposition in terms of OLS regression coefficients: $\beta_{\hat{\lambda}, \hat{y}} = \beta_{\hat{w}, \hat{y}} - \beta_{\hat{y} - \hat{h}, \hat{y}}$.

¹⁴ I consider here the labor share to be the payroll share for the nonfarm business sector.

the fact that real wages are less volatile than labor productivity. This scenario is usually the one predicted by standard real business cycle models. These models are embedded with a labor hoarding or a wage bargaining mechanism and do a great job explaining these aggregate facts. The imperfect comovement between the real wages and labor productivity and the lower volatility of real wages are obtained by introducing some degree of wage rigidity.

In the earlier partition of the sample, when output is one percentage point above trend, the labor share is 0.076 percentage points below its trend. The intuition behind the countercyclicality of the labor share is the same as for the entire sample. The countercyclicality of the labor share is larger in the earlier period due to the larger differences in the volatilities of real wages and labor productivity. As the volatility of real wages increases over time, this shuts down the standard channel for the countercyclicality of the labor share. However, from 1988-2016, when output is one percentage point above trend, the labor share is 0.182 percentage points above trend. The procyclicality of the labor share comes from two different sources. First, there was a decline in the procyclicality of real wages, but real wages remain procyclical in the last three decades. This contrasts with the behavior of labor productivity, which passed from procyclical to acyclical¹⁵. Second, real wages are now more volatile than labor productivity. The increase in the volatility of real wages provides a procyclical force to the cyclicity of the labor share.

Using the results in Table 2.4, we can decompose the change in $\beta_{\hat{\lambda},\hat{y}}$ by looking at the changes in the coefficients for real wages and labor productivity. $\beta_{\hat{w},\hat{y}}$ is positive for the entire sample and it increases slightly by 0.062 percentage points between the early and late samples, due to the increase in the relative volatility of real wages. On the other hand, $\beta_{\hat{y}-\hat{h},\hat{y}}$ declines by 0.205 percentage points, making

¹⁵ Notice that labor productivity being acyclical implies that total hours are proportional to real output. Therefore, this means that a 1% change in output is translated into a 1% change in total hours over the business cycle.

Table 2.3: The Cyclicity of Real Wages and Labor Productivity

$$\rho(\hat{\lambda}_t, \hat{y}_t) = \frac{\sigma(\hat{w}_t)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{w}_t, \hat{y}_t) - \frac{\sigma(\hat{y}_t - \hat{h}_t)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{y}_t - \hat{h}_t, \hat{y}_t)$$

	1947-2016	1947-1987	1988-2016	Change
$\rho(\hat{\lambda}_t, \hat{y}_t)$	-0.069 [-0.196,0.058]	-0.181 [-0.338,-0.024]	0.280 [0.094,0.467]	0.461 [0.218,0.704]
$\rho(\hat{w}_t, \hat{y}_t)$	0.365 [0.240,0.490]	0.460 [0.314,0.605]	0.270 [0.115,0.425]	-0.189 [-0.402,0.023]
$\rho(\hat{y}_t - \hat{h}_t, \hat{y}_t)$	0.352 [0.221,0.484]	0.451 [0.298,0.604]	0.012 [-0.170,0.194]	-0.439 [-0.676,-0.202]
$\rho(\hat{w}_t, \hat{y}_t - \hat{h}_t)$	0.460 [0.369,0.550]	0.444 [0.316,0.572]	0.529 [-0.411,0.647]	0.085 [-0.089,0.259]
$100 \times \sigma(\hat{y}_t)$	2.047	2.436	1.325	-1.111
$100 \times \sigma(\hat{\lambda}_t)$	0.970	1.044	0.859	-0.185
$100 \times \sigma(\hat{w}_t)$	0.806	0.710	0.927	0.217
$100 \times \sigma(\hat{y}_t - \hat{h}_t)$	1.025	1.144	0.833	-0.311

Sources: BEA, BLS, and author's calculations. In squared-brackets is shown the 95% confidence interval.

Table 2.4: Cyclicity of Labor Share, Real Wages, and Labor Productivity (OLS).

$$\beta_{\hat{\lambda}, \hat{y}} = \beta_{\hat{w}, \hat{y}} - \beta_{\hat{y} - \hat{h}, \hat{y}}, \text{ where } \hat{x}_t = \beta_{\hat{x}, \hat{y}} \cdot \hat{y}_t + \nu_t, \text{ for } \hat{x} \in \{\hat{\lambda}, \hat{w}, \hat{y} - \hat{h}\}$$

	1947-2016	1947-1987	1988-2016	Change	%-Contribution
$\beta_{\hat{\lambda}, \hat{y}}$	-0.033	-0.076*	0.182**	0.258	
$\beta_{\hat{w}, \hat{y}}$	0.142**	0.131**	0.193**	0.062	23.2%
$\beta_{\hat{y} - \hat{h}, \hat{y}}$	0.176**	0.212**	0.007	-0.205	76.8%

** denotes statistical significance at 1% level, * is statistical significance at 5%.

labor productivity shift from procyclical to acyclical. These changes imply that the vanishing procyclicality of labor productivity explains 76.8% of the shift in the cyclicity of the labor share. The remaining 23.2% of the shift in the cyclicity of the labor share come from the decline in the procyclicality of real wages and from the increase in the relative volatility of the real wages with respect to real output. The increase in the relative volatility of wages and the slight decline in the procyclicality of real wages account for 41.4% and -19.8% of the shift in the cyclicity of the labor share, respectively¹⁶. The impact of the increase in the volatility of the real wages on the cyclicity of the labor share is dampened by the decline in the cyclicity of real wages. However, this decline is not as strong as the recent acyclicity of labor productivity.

In the earlier work of Burnside et al. (1993) and Burnside and Eichenbaum (1996) labor hoarding was captured by a very procyclical factor utilization. Figure 2.3 shows that the vanishing procyclicality of labor productivity is reflected in a stark decline in the usage of labor hoarding in the U.S. economy, as measured by the recent acyclicity of factor utilization¹⁷.

This may imply a structural change in the labor market turnover behavior at

¹⁶ I considered the following exercise: Let the cyclicity of real wages and labor productivity be that which was observed in the data but fix the relative volatility of real wages and labor productivity to the value observed in the earlier part of the sample ($\sigma(\hat{w})/\sigma(\hat{y}) = 0.710/2.436$ and $\sigma(\hat{y} - \hat{h})/\sigma(\hat{y}) = 1.144/2.436$). The counterfactual $\beta_{\hat{w},\hat{y}}$ and $\beta_{\hat{y}-\hat{h},\hat{y}}$ that would be observed in this scenario are equal to 0.079 and 0.006, respectively. The corresponding counterfactual $\beta_{\lambda,\hat{y}}$ would be equal to 0.073, representing an increase of 0.158 percentage points with respect to $\beta_{\lambda,\hat{y}}$ in the early period of the sample. This would make the contribution of real wages to the shift in the cyclicity of the labor share be counterfactually equal to -19.8%. Since the actual contribution is 23.2%, this means that the increase in the volatility of real wages explains 41.4% of the shift in the cyclicity of the labor share. Finally, notice that the change in the relative of labor productivity has almost no impact on $\beta_{\hat{y}-\hat{h},\hat{y}}$.

¹⁷ I use the time series for factor utilization from the total factor productivity data from the Federal Reserve Bank of San Francisco, which is described in Fernald (2014). I follow Fernald (2014) and assume factor utilization to be 0 (in logs) for 1987:4. After re-constructing the time series for the logarithm of factor utilization, I pass it under a bandpass filter, identifying the business cycles between 6 quarters and 32 quarters, to obtain the filtered series for factor utilization.

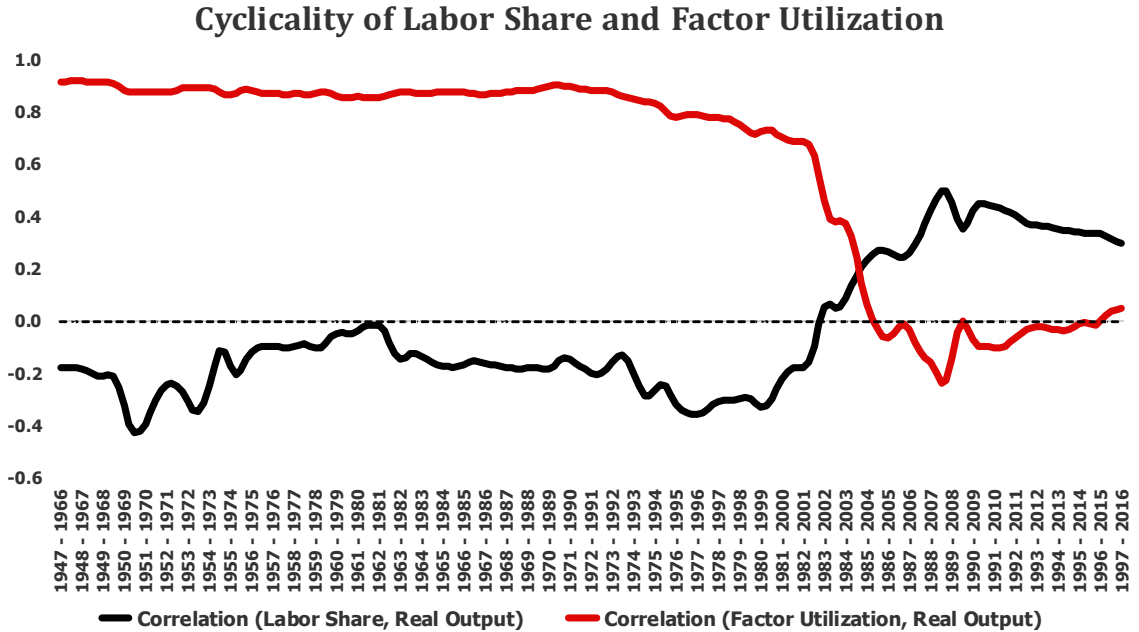


FIGURE 2.3: The Vanishing (Pro)Cyclicality of Factor Utilization in the U.S.

the firm level or a shift in the sectoral composition (or firm distribution) in the U.S. economy. There is considerable evidence that there has been a decline in labor market fluidity for the U.S. economy, Davis and Haltiwanger (2014) and Molloy et al. (2016). One potential explanation for this decline in the labor market reallocation rates is the increase in the average size and age for the firms in the U.S. economy, which would be translated in a shift in the U.S. firm distribution. However, further research needs to be done to conciliate this observed increase in the average size and age for the firms in the U.S. economy with the appearance of hyper-productive capital-intensive firms in the U.S. economy, which is an explanation advanced by Autor et al. (2017) and Kehrig and Vincent (2017) for the recent decline in the level of the labor share.

Finally, one can think that secular changes in sectoral composition may be important to explain the shift in the cyclicality of the labor share. Examples of these changes in sectoral composition can be the shift in production from manufacturing

to services, the increase in the importance of the financial activities sector, or the impact of globalization and outsourcing on the wholesale and retail trade sectors. I show in the following section that changes in industrial composition are not driving the shift in the cyclicalities of the labor share.

2.4 Are Changes in Industrial Composition Driving the Shift in the Cyclicalities of the Labor Share?

I provided evidence that the shift in the cyclicalities of the labor share is driven by three aggregate phenomena: the vanishing procyclicality of labor productivity, the increase in the relative volatility of wages, and the fact that real wages and labor productivity are not proportional to each other. I have shown by means of a counterexample that these features introduce further discipline to macroeconomic modeling and that they constitute a challenge for the traditional literature that ends up relying on labor hoarding and wage bargaining mechanisms. However, the shift in the cyclicalities of the labor share can alternatively be due to secular changes in industrial composition of the U.S. economy, such as the secular decline in manufacturing and trade sectors and the corresponding rise of services and financial activities.

In a related paper, Na (2017) observes that differences in sectoral compositions between tradables and non-tradables are an important channel to explain the cross-county heterogeneity on the observed cyclicalities of the labor share. This will be the case if workers in manufacturing and trade industries are subject to a higher unemployment risk than workers in the services sector. One possibility for this to occur is the increased competition to manufacturing from international outsourcing and, more generally, from globalization. This would lead workers in manufacturing and trade industries to require a higher degree of insurance when bargaining their contracts with firms. If so, manufacturing and trade industries would have a more countercyclical (or less procyclical) labor share than in services and finance.

On the other hand, Elsby et al. (2013) provide evidence that the recent trend decline in the aggregate payroll share comes from declines in the payroll shares within sectors, and not due to changes in the composition of these sectors. If the trend decline and the shift in the cyclicalities of the labor share are related, then the shift in the cyclicalities of the labor share would happen at the sectoral level, and it would not be a byproduct of secular changes in the industrial composition.

In this section, I extend my previous analysis and quantitatively show that the shift in the cyclicalities of the labor share is not due to changes in the industrial composition of the U.S. economy. In fact, the shift in the cyclicalities of the labor share happens not only for manufacturing and for wholesale and retail trade, but also in the professional and business services and financial activities industries. To quantify the impact of sectoral composition on the shift in the cyclicalities of the labor share, I use a decomposition that relates the cyclicalities of the aggregate labor share to the cyclicalities of the sectoral labor shares and sectoral value added shares.

I construct a dataset with the labor share and value added shares for the nonfarm private sector at the two-digit industry level. This data is taken from NIPA at an annual frequency from 1947 to 2015¹⁸. In order to build some intuition that the shift towards a procyclical labor share is not an aggregate result, Figure 2.4 shows the time-varying cyclicalities of the labor share for manufacturing, wholesale and retail trade, financial activities, and professional and business services. The value added share in manufacturing decreased by 20.1 percentage points between 1947 and 2015, while the value added share for wholesale and retail trade declined

¹⁸ The labor share is defined to be the payroll share. There is a structural break in the classification of industries in 1987, when the classification passed from the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS). I divide the nonfarm private sector in 14 industries: Mining, Construction, Manufacturing, Utilities, Transportation and Warehousing, Wholesale and Retail Trade, Financial Activities, Real Estate, Information, Professional and Business Services, Leisure and Hospitality, Educational Services, Health Care and Social Assistance, and Other Services. Appendix C describes in detail the methodology and cross-walk tables used to construct consistent time series for sectoral labor shares and real value added shares.



FIGURE 2.4: The Shift in the Cyclicalty of the Labor Share across U.S. Industries.

by 9.5 percentage points over the same period. On the other hand, the value added share for professional and business services increased by 12.4 percentage points and it increased for financial activities by 5.2 percentage points. The cyclicalty of the labor share has increased considerably in the last three decades for each of these industries. More strikingly, the cyclicalty of the labor share for the manufacturing sector closely resembles the cyclicalty of the aggregate labor share.

In order to quantify the impacts of structural change on industrial composition to the shift in the cyclicalty of the labor share, I decompose the aggregate labor share as a weighted average of each sector's labor share, where the weights are given by the nominal value added shares of each sector. Suppose there are $K \in \mathbb{N}$ industries

in the economy. The aggregate labor share is

$$\lambda_t = \sum_{i=1}^K \left(\frac{P_t^i \cdot Y_t^i}{P_t \cdot Y_t} \right) \cdot \left(\frac{W_t^i \cdot H_t^i}{P_t \cdot Y_t} \right) \equiv \sum_{i=1}^K \gamma_t^i \cdot \lambda_t^i \quad (2.5)$$

where $P_t^i Y_t^i$ is the nominal value added for industry i , $P_t Y_t$ the nominal value added for the nonfarm private sector, $W_t^i H_t^i$ the total compensation for industry i , defined as the product of the nominal wage per hour of worker with the total number of hours worked in industry i . Using these definitions, γ_t^i is the value added share of industry i and λ_t^i is the labor share in industry i . Then, it can be shown that the aggregate cyclicity of the labor share can be approximated by a weighted average of the cyclicity of labor and value added shares at the sectoral level.

$$\rho(\hat{\lambda}_t, \hat{y}_t) = \sum_{i=1}^K \left(\frac{\gamma^i \lambda^i}{\lambda} \right) \cdot \left[\frac{\sigma(\hat{\gamma}_t^i)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{\gamma}_t^i, \hat{y}_t) + \frac{\sigma(\hat{\lambda}_t^i)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{\lambda}_t^i, \hat{y}_t) \right] \quad (2.6)$$

where γ^i , λ^i and λ denote the trend values for the sectoral value added share, sectoral labor share, and aggregate labor share (respectively). $\hat{\gamma}_t^i$ is the cyclical component of the value added share for industry i , $\hat{\lambda}_t^i$ is the cyclical component of the labor share in industry I , \hat{y}_t is the cyclical component for real output in the nonfarm private sector, and $\hat{\lambda}_t$ the cyclical component for the labor share in the nonfarm private sector.

In practice, this decomposition provides an approximation to the cyclicity of the aggregate labor share. In particular, it assumes: (1) that the trend component is not correlated with the cyclical component for any of the time series in the decomposition. If the trend and cycle are correlated, this generates a measurement bias in the sectoral decomposition. (2) it depends on the non-linearity of the filtering procedure. If we use linear detrending to separate the trend from the cyclical component, the trend terms will reflect steady state values. When the filter is more non-linear, as is the case with the bandpass filter, these trends change over time. This generates a bias

if the trend components change considerably over time. (3) if we are working with small-samples. The decomposition converges to equality as the sample size goes to infinity. Since I detrend the data by applying a bandpass filter identifying the business cycle to contain fluctuations between 2 and 8 years, and since I apply the decomposition to a relatively small sample, it would not be surprising if there is an approximation error.

The first two rows in Table 2.5 show the cyclicity of the aggregate labor share when it is directly measured from the aggregate nonfarm private sector data and when it is obtained from the sectoral composition in (2.6). For the entire sample, the sectoral decomposition predicts the aggregate labor share to be mildly countercyclical, with a correlation of -0.072 with real aggregate output. On the other hand, when directly estimated from the data, the cyclicity of the labor share is equal to 0.050. The difference between these two point estimates corresponds to the approximation error.

Most of the approximation error comes from the earlier period of the sample, in which the sectoral composition overestimates the countercyclicity of the labor share. However, this approximation error disappears in the later period of the sample, and the sectoral decomposition is able to accurately predict the shift in the cyclicity of the labor share. The sectoral decomposition predicts a shift in the cyclicity of the labor share from -0.196 in 1947-1987 to 0.443 in 1988-2015. The true aggregate data shows that the cyclicity of the labor share shifts from -0.096 in 1947-1987 to 0.410 in 1988-2015. Therefore, the sectoral decomposition is a good laboratory to study the impact of structural changes in the industrial composition of the U.S. economy on the cyclicity of the labor share.

In order to do so, I perform a counterfactual analysis. Instead of considering the actual value added shares observed in the data, I impute constant counterfactual value added shares to each sector. In counterfactual 1, I replace the observed value

Table 2.5: Sectoral Composition and the Cyclicity of the Labor Share.

$$\rho(\hat{\lambda}_t, \hat{y}_t) = \sum_{i=1}^K \left(\frac{\gamma^i \lambda^i}{\lambda} \right) \cdot \left[\frac{\sigma(\hat{\gamma}_t^i)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{\gamma}_t^i, \hat{y}_t) + \frac{\sigma(\hat{\lambda}_t^i)}{\sigma(\hat{\lambda}_t)} \cdot \rho(\hat{\lambda}_t^i, \hat{y}_t) \right]$$

Nonfarm Private Sector	1947-2015	1947-1987	1988-2015
Aggregate Data: $\rho(\hat{\lambda}_t, \hat{y}_t)$	0.050	-0.096	0.410
Sectoral Decomposition	-0.072	-0.196	0.443
Counterfactual 1 ($\gamma_t^i = \gamma_{1947-1987}^i$)	0.002	-0.191	0.516
Counterfactual 2 ($\gamma_t^i = \gamma_{1988-2015}^i$)	-0.172	-0.406	0.443

added shares with their average values between 1947 and 1987, that is $\gamma_{it} = (1/41) \cdot \sum_{t=1947}^{1987} \gamma_{i,t}$, for all time periods t . In counterfactual 2, I replace the observed value added shares with their average values between 1988 and 2015, that is $\gamma_{it} = (1/28) \cdot \sum_{t=1988}^{2015} \gamma_{i,t}$, for all time periods t . I use the time series in the nominal output for the nonfarm private sector to obtain the nominal output for each industry. Then, I compute counterfactual time series for the sectoral labor shares by dividing the actual compensation data by the counterfactual nominal income. I estimate the cyclicity of the counterfactual value added shares and labor shares, and I apply the sectoral decomposition to obtain the counterfactual cyclicity of the aggregate labor share¹⁹.

Table 2.5 shows the results of this analysis. Under both counterfactuals, the cyclicity of the labor share shifts from countercyclical in 1947-1987 to procyclical in 1988-2015. This confirms the intuition from Figure 2.4 that the shift in the cyclicity of the labor share is not an aggregation result, but also occurs at the industry level. The shift in the cyclicity of the labor share is actually larger under counterfactual 2,

¹⁹ Since the counterfactual value added shares are constant throughout the entire sample, the differences over time in the cyclicity of the aggregate labor share is driven solely by changes in the cyclicity of the sectoral labor shares and not by changes in sectoral composition.

where I impose the industrial composition to be equal to its average value in the last three decades. Moreover, the cyclicity of the labor share is always more negative under counterfactual 2 than under counterfactual 1. This countercyclical pressure on the labor share, which comes from changes in the industrial composition of the U.S. economy, is not the correct force to explain the shift in the cyclicity of the U.S. labor share. Therefore, future research needs to track the reasons that caused a joint shift in the cyclicity of the labor share at the industry level. Given the analysis in this section, it seems reasonable to restrict the attention to aggregate structural, technological or policy changes that affect the U.S. labor markets.

2.5 The Shift in the Cyclicity of the Labor Income Share and in the Cyclicity of Labor Productivity: Cross-Country Evidence.

In this section I investigate whether the shift in the cyclicity of the labor income share is specific to the U.S. economy. To do so, I use KLEMS data for 12 Western European countries and for the U.S.²⁰. In Figure 2.5 and 2.6 I show respectively the cyclicity of the labor share and labor productivity for each of these countries in 1970-1987 and in 1988-2015.

The cross-country evidence shows that the shift in the cyclicity of the labor share towards procyclicality did not occur in the vast majority of the Western European countries considered. The lower labor market flexibility in Western Europe is translated into higher hiring and firing costs for firms and induce a more established practice of labor hoarding at the firm level across Western European countries. The

²⁰ This data was obtained from <http://www.euklems.net/>. I took the data for the European countries that had the longest time series available. These 12 Western European countries are Austria (AT), Belgium (BE), Denmark (DK), Finland (FI), France (FR), Germany (DE), Italy (IT), Netherlands (NL), Portugal (PT), Spain (ES), SE (Sweden), and the United Kingdom (UK). The data is annual and comprises the years 1970-2015. The only exception is Finland, for which data is available between 1975 and 2015. For each country, I construct time series for real value added, labor productivity, and labor share. I then apply logarithms and filter the data using a bandpass filter identifying the business cycles between 2 and 8 years.

The Cyclicity of the Labor Share: Cross-Country Evidence

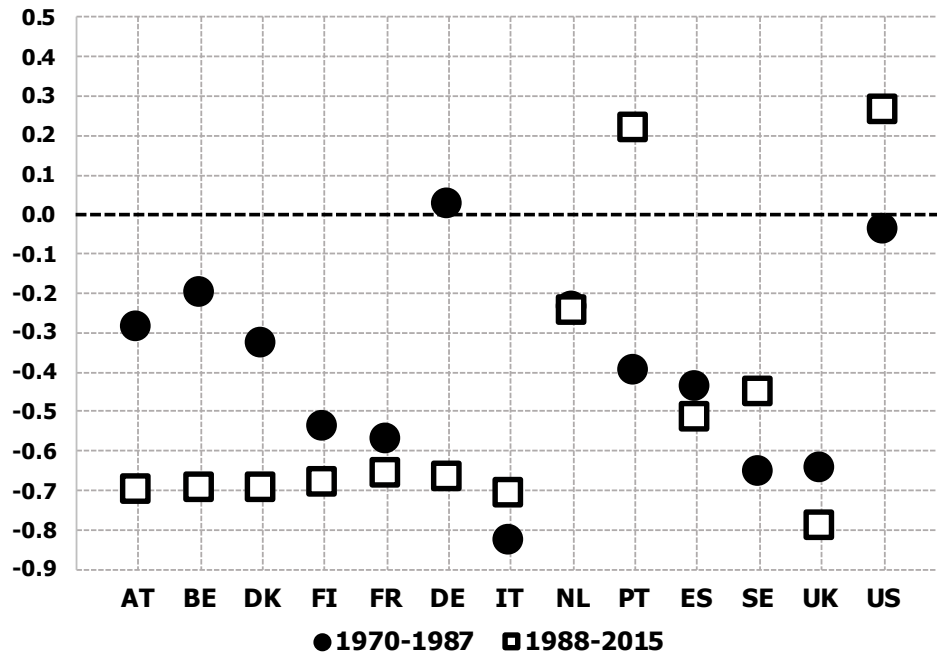


FIGURE 2.5: The Cyclicity of the Labor Share: Cross-Country Evidence.

The Cyclicity of Labor Productivity: Cross-Country Evidence

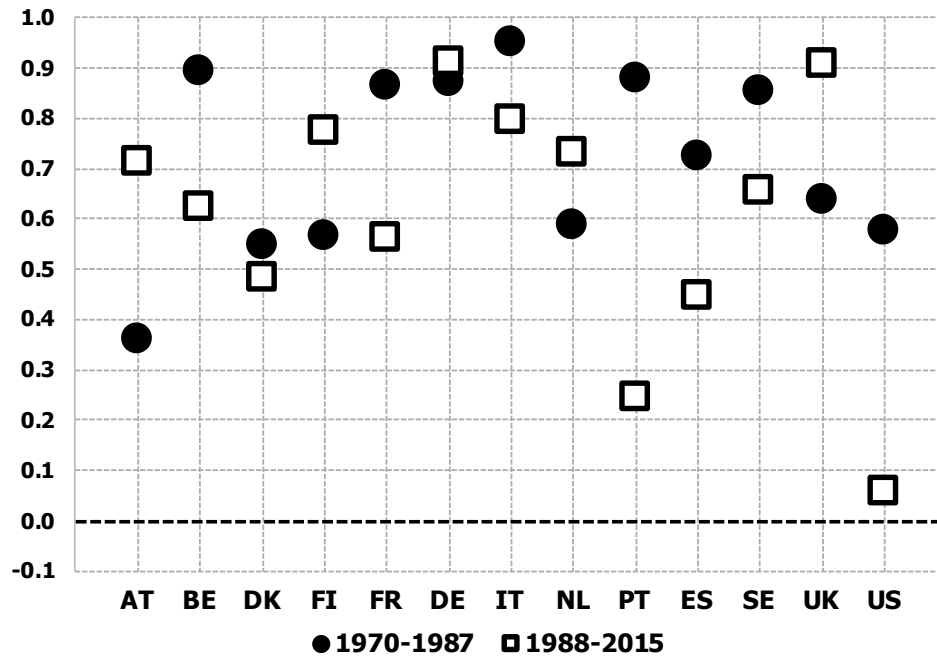


FIGURE 2.6: The Cyclicity of Labor Productivity: Cross-Country Evidence.

usage of labor hoarding is reflected in Figure 2.6 in the observed procyclical labor productivities across Western Europe countries. The procyclicality of labor productivity did not vanish for these 12 countries and remained procyclical both in 1970-1987 and in 1988-2015. On the other hand, the higher interlinkage across these countries over time from a higher labor market integration and the adoption of a single currency in the European Union has strengthened the integration of these separate nationwide labor markets into a unique european labor market. This is reflected in the convergence of the (counter)cyclicality of the labor share in 1988-2015 around -0.7 for the European countries and provides evidence that the workers in the European Union are better insured against downturns than their counterparts in the United States.

Two interesting case studies arise from this analysis. The first is the case of Portugal, which looks very similar to the United States. The Portuguese labor share shifted from being countercyclical in 1970-1987 to being procyclical in 1988-2015. This shift was accompanied by a stark reduction in the procyclicality of labor productivity, which reflects a decline in the usage of labor hoarding at the firm level. However, even if these economies behave in a similar according to the cyclicality of the labor share and labor productivity, a note of caution should be taken since employment protection is higher in Portugal than in the United States. Therefore, the puzzling similarity for the cyclicality of the labor share and labor productivity between Portugal and the U.S. needs to be studied in a greater detail, in the spirit of Blanchard and Portugal (2001).

The second is the case of Germany, in which the cyclicality of the labor share moves from acyclical to countercyclical. At the same time, the cyclicality of labor productivity remains very procyclical in Germany, suggesting a widespread usage of labor hoarding at the firm level. The difference between Germany and the U.S. is better understood when looking to the changes in total hours worked during Great Recession. While in the U.S. the decline in total hours worked is due solely to a

decline in employment and a large increase in the unemployment rate, in Germany the decline in total hours worked does not come from employment but from a decline in the average hours worked per employee. Burda and Hunt (2011) show that total hours in the U.S. economy decreased by 8.4 percentage points between 2008:1 and 2009:4. Out of this decline, there was a decline in 2.2 percentage points in the number of hours per worker and a decrease in 6.1 percentage points in the employment rate. During the same period in Germany, total hours declined by 2.4 percentage points, almost 25% of the decline in total hours for the U.S. economy. Out of this decline for Germany, there was a decline in 2.6 percentage points in hours per worker and an increase in 0.4 percentage points in the employment rate. According to Burda and Hunt (2011), the success of Germany during the Great Recession in minimizing fluctuations in employment is partly due to a decrease in the price of adjusting working time accounts by changing the intensive margin (rather than employment, the extensive margin) at the firm level. The implication is that Germany was able to avoid a large decline in the employment rate by providing firms with more incentives for labor hoarding and simultaneously allowing for a higher flexibility in the labor market.

This evidence suggests that there is a very close relationship between the cyclical-ity of labor productivity and the cyclical-ity of the labor share at a cross-country level. Still, further research is needed to better understand the time and cross-sectional variations in the cyclical-ity of the labor share. From the evidence presented in this chapter, the most important factors are the degree of labor hoarding used at the firm level and changes in the volatility and cyclical-ity of real wages.

2.6 Conclusion

The labor share is assumed to be a structural parameter or to be countercyclical over business cycles in the macroeconomic literature. In this paper, I unveil the shift

towards a procyclical U.S. labor share in the last three decades, both at the national and sectoral levels. I document that this shift in the cyclicity of the U.S. labor share is due mostly to a decline in labor hoarding at the firm level and an increase in the relative volatility of real wages.

These results suggest not only that there is a decline in the amount of formal insurance against unemployment received by workers, but also that firms are producing under new technology. This technological progress allowed firms to optimize the intensive margin for factor inputs over the business cycle, reducing the incentives for labor hoarding policies and making total hours worked proportional to real output. This technological progress may also be the connection between the fall in the labor share and the shift towards a procyclical labor share.

In the next chapter, I look to the performance of a standard Real Business Cycles model embedded with labor hoarding, workers' risk aversion, and a wage bargaining process, in generating the shift in the cyclicity of the labor share as well as a decrease in the procyclicity of labor productivity.

The Cyclicalities of the Labor Share: Labor Hoarding, Risk Aversion and Real Wage Rigidities

3.1 A Stylized Model with Labor Hoarding and Wage Bargaining

In this chapter, I briefly describe a stylized model embedded with a labor hoarding mechanism and wage bargaining, which I borrow from Galí and van Rens (2017). This is a relatively simple model that incorporates a labor hoarding mechanism and wage bargaining between workers and firms, the traditional mechanisms in the literature to generate a countercyclical labor share. In particular, labor hoarding is modeled as convex hiring costs and wage bargaining as a perfectly flexible Nash bargaining procedure. This stylized model is the perfect laboratory to study the shift in the cyclicalities of the labor share, since it is able to predict a decline in the procyclicality of labor productivity through a decline in the reallocation rates in the labor market¹.

¹ The decline in the reallocation rates in the labor market is consistent with the recent evidence on the decline in labor market fluidity [Davis and Haltiwanger (2014) and Molloy et al. (2016)]. The most common explanation for the decline in the labor market reallocation rates comes from the increase in the average size and age for the firms in the U.S. economy. Older and larger firms are less likely to hire and fire employees. In the model, the decline in the labor market reallocation rates is mimicked by a reduced form decline in the exogenous separation rate faced by an employed

3.1.1 Households

There is a continuum of identical number of households on a unit interval. Additionally, there is perfect insurance within the household. That is, the representative household assigns equal consumption to all members in order to perfectly share consumption risk within the household. Therefore, we can look to the choices made by a representative household.

The preferences for the representative household are defined by

$$U = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \cdot \left(\frac{Z_t \cdot C_t^{1-\eta}}{1-\eta} - g^H(N_t, \epsilon_t) \right) \right] \quad (3.1)$$

where C_t is consumption for the household, N_t the mass of employed individuals² within the household, ϵ_t the effort exerted by employed workers on their jobs, and Z_t a preference shock acting as a (residual) demand shock. $\ln Z_t$ is assumed to be a AR(1) process with white noise innovations.

$$\ln Z_t = \rho_z \cdot \ln Z_{t-1} + \sigma_z \cdot \nu_t^z \quad (3.2)$$

where $\nu_t^z \sim \text{WN}(0, 1)$, $\rho_z \in [0, 1)$, and $\sigma_z > 0$. The disutility from work affecting the employed members of the household is represented by $g^H(N_t, \epsilon_t)$. Galí and van Rens

worker. The decline in the exogenous separation rates increases the relative cost of an additional hire and leads to a decline in the number of workers hired in each period. These changes imply a reduction in the transition rates from employment to unemployment and from unemployment to employment.

² The relevant measure of labor input in the context of the model is labor services. This is composed by employment at the extensive margin and effort at the intensive margin. Although the exertion of effort is not enforceable, the firm and the worker set the amount of effort within the bargaining process. Therefore, the wage payments that are the outcome of the wage bargaining will be such that workers are willing to exert the optimal amount of effort in equilibrium. This optimal allocation can be obtained by creating a market for effort and introducing performance pay compensation, as in Galí (1999). Total compensation would then be the sum of two components: the base wage, which is independent of the effort exerted, and the performance pay component. The labor share is countercyclical in this scenario. The (flexible) performance pay component can be shown to be acyclical in this scenario and the base wage component is countercyclical, reflecting the willingness of both workers and firms to insure themselves against downturns.

(2017) set this function to be $g^H(N_t, \epsilon_t) = \gamma \cdot L_t(N_t, \epsilon_t)$, where L_t is the amount of labor services provided by the employed workers and is defined as

$$L_t = \int_0^{N_t} \frac{1 + \xi \cdot \epsilon_{it}^{1+\phi}}{1 + \xi} di = \frac{1 + \xi \cdot \epsilon_{it}^{1+\phi}}{1 + \xi} \cdot N_t \quad (3.3)$$

The household is assumed to own the representative firm and is subject to a sequence of budget constraints

$$C_t \leq \int_0^{N_t} W_{it} di + \Pi_t = W_t \cdot N_t + \Pi_t \quad (3.4)$$

for all periods t . The household problem can then be written as the choice of consumption C_t and a supply of exerted effort for the employed individuals ϵ_t to maximize their utility subject to the sequence of budget constraints, to the functional form for the disutility of labor, and for the law of motion for the preference shock.

3.1.2 Firms

There is a continuum of identical firms on a unit interval. Each firm employs workers in order to maximize profits. Since all firms are equal we analyze the actions of a representative firm.

The technology used by the representative firm is

$$Y_t = A_t \cdot F(N_t, \epsilon_t) \equiv A_t \cdot \left(\epsilon_t^\psi \cdot N_t \right)^{1-\alpha} \quad (3.5)$$

where A_t is a standard TFP shock, assumed to be a AR(1) process with white noise innovations.

$$\ln A_t = \rho_a \cdot \ln A_{t-1} + \sigma_a \cdot \nu_t^a \quad (3.6)$$

with $\nu_t^a \sim \text{WN}(0, 1)$, $\rho_a \in [0, 1)$, and $\sigma_a > 0$. ϵ_t is the average effort exerted by the workers, and N_t is employment. α controls for the degree of decreasing returns to scale in the labor input, and $\psi \in (0, 1)$ introduces fatigue in production for high levels of effort.

We introduce incentives for labor hoarding. In particular, employment is not easily adjustable and firms need to pay a hiring cost when making job offers to workers in the unemployment pool. Aggregate employment follows the law of motion

$$N_t = (1 - \delta) \cdot N_{t-1} + E_t \quad (3.7)$$

where δ is the exogenous separation rate and E_t the number of net hires in period t , chosen by the firm. As mentioned above, hiring is assumed to be costly for the firm. In particular, Galí and van Rens (2017) assume convex adjustment costs of hiring, defined as $g^F(E_t)$. Therefore, $g_E^F(E_t) > 0$ and $g_{EE}^F(E_t) > 0$ for $E_t > 0$ and $g^F(0) = g_E^F(0) = 0$.

The representative firm chooses how many workers to hire in each period, E_t , and the average effort exerted by their workers ϵ_t to maximize its expected value of profits

$$\max_{E_t, \epsilon_t} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \Gamma_{0,t} \cdot \left(Y_t - W_t \cdot N_t - g^F(E_t) \right) \right] \quad (3.8)$$

subject to the law of motion for employment (3.7). W_t is the real wage (in consumption units) of an additional worker, $\Gamma_{0,t}$ is the discount factor required by the owners of the firm (the household) and it is defined by the marginal rate of substitution of consumption,

$$\Gamma_{t,+1} \equiv \beta \cdot \frac{Z_{t+1}}{Z_t} \cdot \left(\frac{C_{t+1}}{C_t} \right)^{-\eta} \quad (3.9)$$

This condition can be achieved by let the household optimize their savings' using risk-free bonds and firm shares. The household requires the returns of both assets to be the same by the law of non-arbitrage, which equals the stochastic discount factor formula above.

The firm maximizes the expected discounted value of their profits subject to their technology, the law of motion for employment, the convex hiring costs, and the required stochastic discount factor by the households. The optimality conditions from the firm's problem result on a demand function for effort and on a demand function for new hires.

3.1.3 *Efficient Effort and Wage Bargaining*

The household and the representative firm jointly decide on wages and effort. The firm wants to maximize the average effort exerted by their workers, while each worker has incentives not to provide effort due to the increase in their disutility of working. Therefore, in the bargaining process the firm needs to compensate the workers for them to be willing to exert that optimal level of effort³, in the sense that the contract is incentive compatible for the workers to provide the amount of effort required by the firm.

The efficient effort set by workers and firms in the bargaining process is given by

$$\epsilon_t^{1+\phi} = \Psi_\epsilon \cdot \frac{Z_t}{C_t^\eta} \cdot \frac{Y_t}{N_t} \quad (3.10)$$

with $\Psi_\epsilon = \frac{\psi}{1+\phi} \cdot \frac{1+\xi}{\xi} \cdot \frac{(1-\alpha)}{\gamma}$.

The firm's demand for new hires and the efficient effort decision generate a job

³ The bargaining process for effort can be microfounded by considering an efficiency wage model in which firms have the possibility of catching shirkers, as in Alexopoulos (2004). The optimal allocation for effort can also be obtained by considering effort to be observable and a market for effort, which is the approach followed by Galí (1999).

creation equation. When hiring a worker, the firm takes into account that increasing employment changes the effort exerted by the remaining workers and incorporates that decision in the marginal benefits of hiring an additional worker. The optimal job creation satisfies

$$g_E^F(E_t) = (1 - \Psi_F) \cdot (1 - \alpha) \cdot \frac{Y_t}{N_t} - W_t + (1 - \delta) \cdot \mathbb{E}_t [\Gamma_{t,t+1} \cdot g_E^F(E_{t+1})] \quad (3.11)$$

where $1 - \Psi_F = (1 + \phi - \psi) / (1 + \phi - (1 - \alpha) \cdot \psi)$.

$g_E^F(E_t)$ represents the firm's surplus in the bargaining process. The representative firm is willing to offer up to $g_E^F(E_t)$ to hire another worker. These offers represent a sunk cost after they are made. Therefore, the firm will only hire a new worker when it is certain this worker will accept, as the firm does not want to pay the sunk offer cost not to be able to hire that additional employee.

The maximum wage the firm is willing to pay is

$$W_t^{\text{UB}} = (1 - \Psi_F) \cdot (1 - \alpha) \cdot \frac{Y_t}{N_t} + (1 - \delta) \cdot \mathbb{E}_t [\Gamma_{t,t+1} \cdot (W_{t+1}^{\text{UB}} - W_{t+1})] \quad (3.12)$$

This is the highest wage offer that makes the firm indifferent between hiring an additional worker or not. This equation comes from the job creation equation $g_E^F(E_t) = W_t^{\text{UB}} - W_t$.

On the household side, a potential new hire generates benefits and costs. The current-period benefit of having an additional member employed is the increase in average consumption for all household members. The current loss is described by the increase in disutility of working faced by the household. Dynamically, the household understands that this new employed household member continues to be employed next period with a probability of $T_N^N(N_{t-1}, E_t)$ and becomes unemployed again with

a probability $1 - T_N^N(N_{t-1}, E_t)$, where⁴

$$T_N^N(N_{t-1}, E_t) = 1 - \delta + \delta \cdot \frac{E_t}{1 - (1 - \delta) \cdot N_{t-1}} \quad (3.13)$$

The marginal value of an additional employed member satisfies

$$\begin{aligned} V_t^N = & W_t - \frac{\gamma}{1 + \xi} \cdot \frac{C_t^\eta}{Z_t} - \Psi_H \cdot (1 - \alpha) \cdot \frac{Y_t}{N_t} \\ & + \beta \cdot \mathbb{E}_t [T_N^N(N_t, E_{t+1}) \cdot V_{t+1}^N + (1 - T_N^N(N_t, E_{t+1})) \cdot V_{t+1}^U] \end{aligned} \quad (3.14)$$

where $\Psi_H = [\psi/(1 + \phi)] \cdot [1 - (1 + \phi) \cdot (\eta/(1 + \phi - \psi))]$.

Another cost for the household is the loss of an unemployed member. Unemployed workers do not generate any income for the household, they only consume. However, in the future, the unemployed worker may become employed and generate value for the household. The marginal loss for the household of having one less unemployed worker is

$$V_t^U = \beta \cdot \mathbb{E}_t [T_N^U(N_t, E_{t+1}) \cdot V_{t+1}^N + (1 - T_N^U(N_t, E_{t+1})) \cdot V_{t+1}^U] \quad (3.15)$$

where

$$T_N^U(N_{t-1}, E_t) = \frac{E_t}{1 - (1 - \delta) \cdot N_{t-1}} \quad (3.16)$$

is the probability an individual becomes employed in period t conditionally on being unemployed in period $t - 1$. The household surplus of an additional hire is the

⁴ The timing of the model is such that separation occurs on the beginning of the period before any other decision is taken, the new pool of unemployment is formed, and then hiring decisions are made. After hires and wages are bargained and decided, effort decisions are taken and production occurs. Therefore, the employed worker becomes unemployed with δ probability and gets rehired with a probability defined by the number of hires in the current period divided by the pool of unemployment, since all household members are the same and job offers are set to a random household member in the unemployment pool.

difference between the marginal benefit of an additional hire to the marginal loss of having one additional household member in the pool of unemployed workers.

$$\begin{aligned}
V_t^N - V_t^U &= W_t - \frac{\gamma}{1 + \xi} \cdot \frac{C_t^\eta}{Z_t} - \Psi_H \cdot (1 - \alpha) \cdot \frac{Y_t}{N_t} \\
&+ (1 - \delta) \cdot \mathbb{E}_t \left[\Gamma_{t,t+1} \cdot \left(1 - \frac{E_{t+1}}{1 - (1 - \delta) \cdot N_t} \right) \cdot (V_{t+1}^N - V_{t+1}^U) \right]
\end{aligned} \tag{3.17}$$

The reservation wage for the worker is the lowest wage offer making the household member indifferent between accepting the offer or remaining unemployed.

$$\begin{aligned}
W_t^{\text{LB}} &= \frac{\gamma}{1 + \xi} \cdot \frac{C_t^\eta}{Z_t} + \Psi_H \cdot (1 - \alpha) \cdot \frac{Y_t}{N_t} \\
&= - (1 - \delta) \cdot \mathbb{E}_t \left[\Gamma_{t,t+1} \cdot \left(1 - \frac{E_{t+1}}{1 - (1 - \delta) \cdot N_t} \right) \cdot (W_{t+1} - W_{t+1}^{\text{LB}}) \right]
\end{aligned} \tag{3.18}$$

in which I have used the definition of the household surplus $V_t^N - V_t^U = W_t - W_t^{\text{LB}}$.

To close the model, we need to set how wages are bargained. Galí and van Rens (2017) consider a perfectly flexible Nash Bargaining as their preferred wage bargaining rule, which sets wages as

$$W_t = \theta \cdot W_t^{\text{UB}} + (1 - \theta) \cdot W_t^{\text{LB}} \tag{3.19}$$

where θ reflects the workers' bargaining power in the wage determination process.

Notice that in this formulation real wages will be almost proportional to the definition of labor productivity in the model⁵. The bargaining set is shifted upwards

⁵ Since the model considers employment as the measure of labor input and not total hours, labor productivity is here defined in terms of employment. This means that we should not expect the model to be able to fit the data described in section 3. Since this model is highly stylized, I am more interested in the qualitative implications of the model, like a decline in the procyclicality of labor productivity, or any shift in the cyclical of the labor share from countercyclical to procyclical, independently of its magnitude.

when labor productivity is high and downwards when labor productivity is low, implying a close linkage between real wages and labor productivity in this model. This feature has important implications for the ability of the model to be able to jointly predict the decline in the procyclicality of labor productivity and the decline in the countercyclicality of the labor share.

3.2 Structural Changes and the Cyclicity of the Labor Share

In this section I assess the performance of the stylized model introduced in the previous section in its ability to predict a decline in the procyclicality of labor productivity. The model is able to do so following a decline in the labor market reallocation rates, an increase in the volatility of demand shocks, and a decrease in the workers' bargaining power in the wage bargaining process. These changes in the structural parameters of the model are an attempt to capture qualitatively known structural changes in the U.S. economy after the mid-1980s, such as the decline in the labor market fluidity, the high importance of demand shocks for business cycle fluctuations, and the fall in the importance of labor unions. The qualitative implications for the cyclicity of labor productivity introduce some confidence in the usage of the model as a laboratory to study the effects of these structural changes on the cyclicity of the labor share.

I calibrate the model similarly to Galí and van Rens (2017), and I compare the resulting simulated moments of the model to the business cycle moments for the U.S. data in 1947-1987⁶. Under this calibration, the exogenous separation rate is calibrated to $\delta = 0.35$ and changes in this parameter vary the labor market realloca-

⁶ The moments generated by the model can be compared to the empirical evidence in Table 3 under the assumption that employment is defined as “full-time equivalent employees”. I use the model to simulate 200,000 data points and I apply the Hodrick-Prescott Filter to the simulated data to obtain the simulated correlations and standard deviations. I apply the HP-Filter to the simulated data for numerical convenience, as the application of a bandpass filter to such a large number of observations is not feasible computationally. The model calibrated parameters can be found on Appendix D.

tion rates. I set the workers' bargaining power to $\theta = 0.5$, and the volatility of both aggregate supply and demand shocks to $\sigma_a = 0.0195$, and $\sigma_z = 0.0242$, respectively. These shocks are assumed to be uncorrelated. Under this scenario, the model predicts the volatility of output to be $\sigma(\hat{y}_t) = 0.0303$, a value that is slightly higher than the average volatility of output in the U.S. data in the earlier period. The calibrated steady state efficiency loss from hiring costs equals 2.73% of aggregate output.

Although this calibration provides a good fit to the cyclicalities of the labor share and to the volatility of output, the model is still very stylized and it does not perform well with respect to other moments. In particular, the model underestimates the relative volatility of the labor share and it overestimates the volatility and the procyclicality of both the real wages and labor productivity. Introducing real wage rigidities helps to fit the cyclicalities and volatility of real wages, but since there are no consequent changes to the cyclicalities and volatility of labor productivity, it makes the model to predict a very countercyclical labor share. These features are shared by a large class of models in the real business cycle literature.

Without real wage rigidities, the model predicts real wages and labor productivity to be almost proportional to each other, which starkly contrasts the empirical evidence. This limitation is the main reason for the model not to be able to jointly generate the decline in the procyclicality of labor productivity and the shift in the cyclicalities of the labor share. When the procyclicality of labor productivity declines, the procyclicality of real wages declines almost by the same amount, which keeps the labor share countercyclical due to labor hoarding and wage bargaining. Therefore, the failure of this model to account qualitatively for the changes in the cyclicalities of the labor share after a decline in the procyclicality of labor productivity implies that the shift in the cyclicalities of the labor share introduces further discipline in modeling real business cycle fluctuations.

3.2.1 *Decrease in Labor Market Reallocation Rates*

Following Galí and van Rens (2017), I perform a comparative statics analysis in which I reduce the exogenous separation rate δ from the calibrated value of $\delta = 0.35$ to the (almost) frictionless version of the model ($\delta = 0.01$). The decline in the exogenous separation rate increases the likelihood of an employed worker to remain employed in the following period and, by doing so, it decreases the amount of hires in the economy. At the limit, when $\delta \rightarrow 0$, the transition rate $T_N^N(N_{t-1}, E_t)$ converges to one, which by (3.13) implies a stark reduction in the amount of hires in the economy ($E_t \rightarrow 0$).

In Figure 3.1, I plot the cyclicity of the labor productivity and labor share for different values of the exogenous separation rate. The procyclicality of labor productivity decreases with a fall in the exogenous separation rate, a prediction consistent with the empirical evidence. On the other hand, the cyclicity of the labor share moves in the opposite direction to the data. The labor share becomes more countercyclical in the model with a decrease in labor market reallocation rates for values corresponding to the pre-1987 ($\delta = 0.35$) and to the post-1987 ($\delta = 0.2$). This is the first sign that the cyclicity of the labor share and labor productivity are moving in the opposite direction in the model. I illustrate quantitatively this result in column 3 to 5 of Table 3.1. The fall in δ implies an increase in the volatility of labor productivity and almost no changes in the volatility of real wages, which creates a countercyclical pressure to the cyclicity of the labor share. Moreover, the correlation between real wages and labor productivity is above 0.960, which imply both variables to be almost proportional to each other. The increase in the volatility of labor productivity then makes the labor share more countercyclical.

For low labor market reallocation rates the labor share becomes slightly less countercyclical while the cyclicity of labor productivity continues to decrease. When

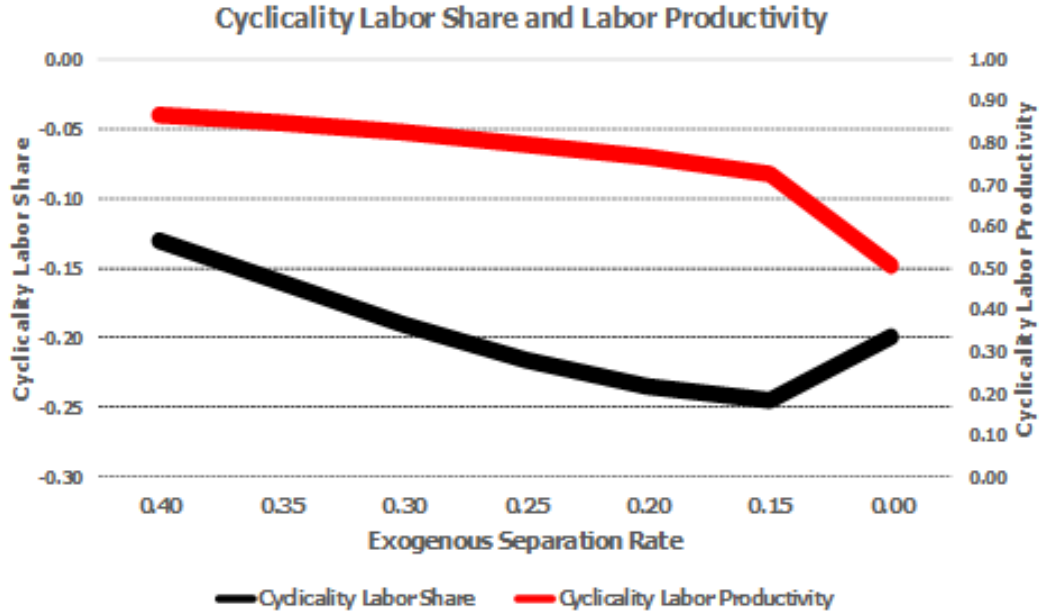


FIGURE 3.1: Changes in the Labor Market Reallocation Rate.

the economy converges to a frictionless labor market, the model generates a countercyclical labor share due to the impact of the aggregate demand shocks in the worker’s reservation wage. The higher volatility of demand shocks, with respect to TFP shocks, and the existence of wage bargaining determine the countercyclicity of the labor share without any incentives for labor hoarding.

3.2.2 Increase in the Volatility of Demand Shocks

It is then natural to question how decreasing the relative volatility of aggregate demand shocks shifts the cyclicality of the labor share and labor productivity. In the first (second) column of Table 3.2, I set the volatility of the TFP shock to be higher than (equal to) the volatility of the aggregate demand shock. I calibrate the model by keeping the same structural parameters as in the calibrated version of the model, and I change the volatility of both demand and supply shocks to keep the volatility of output equal to the calibrated version of the model. When $\sigma_a > \sigma_z$ I set arbitrarily the ratio between both parameters (σ_a/σ_z) to be the inverse of the same

Table 3.1: Model Performance and Empirical Evidence: Variations in δ and θ .

	U.S. Data		Model Performance				
	1947-1987	1988-2016	Calibration	$\delta = 0.2$	$\delta = 0.01$	$\theta = 0.25$	$\theta = 0.75$
$\rho(\hat{\lambda}_t, \hat{y}_t)$	-0.181	0.280	-0.161	-0.239	-0.220	-0.210	-0.090
$\rho(\hat{y}_t - \hat{n}_t, \hat{y}_t)$	0.451	0.012	0.847	0.765	0.560	0.779	0.914
$\rho(\hat{w}_t, \hat{y}_t)$	0.460	0.270	0.713	0.655	0.506	0.545	0.868
$\rho(\hat{w}_t, \hat{y}_t - \hat{n}_t)$	0.444	0.529	0.960	0.963	0.982	0.916	0.990
$100 \times \sigma(\hat{y}_t)$	2.436	0.013	3.034	3.023	3.178	3.079	2.996
$\sigma(\hat{\lambda}_t) / \sigma(\hat{y}_t)$	0.429	0.648	0.247	0.237	0.162	0.400	0.112
$\sigma(\hat{y}_t - \hat{n}_t) / \sigma(\hat{y}_t)$	0.470	0.629	0.775	0.826	0.846	0.781	0.766
$\sigma(\hat{w}_t) / \sigma(\hat{y}_t)$	0.291	0.670	0.864	0.879	0.866	0.962	0.795
δ			0.350	0.200	0.010	0.350	0.350
θ			0.500	0.500	0.500	0.250	0.750
$100 \times \sigma_a$			1.954	1.954	1.954	1.954	1.954
$100 \times \sigma_z$			2.424	2.424	2.424	2.424	2.424
\bar{R}			0.000	0.000	0.000	0.000	0.000
Hiring Costs / Output			0.027	0.010	0.000	0.033	0.019

ratio under the calibrated version of the model. To complement the analysis, Figure 3.2 shows the changes in the cyclicalities of labor productivity and labor share for a unilateral increase in σ_z , without keeping the volatility of output constant.

The higher volatility of aggregate demand shocks introduces a countercyclical force in the cyclicalities of both the labor share and labor productivity. Moreover, it implies a decrease in the relative volatility of real wages and labor productivity. However, as demand shocks became more important, the workers' reservation wage will be more volatile and the wage bargaining process ends up making the realized wage to be more dependent on these shocks and less procyclical. The larger fall in the procyclicality of wages leads to a more countercyclical labor share. Notice that the model is able to generate a procyclical labor share if the volatility of supply shocks is high enough in comparison to the volatility of demand shocks. However, the shift in the volatilities of shocks is not promising as an explanation of the cyclicalities of the labor share, as the higher volatility of supply shocks also increases the procyclicality

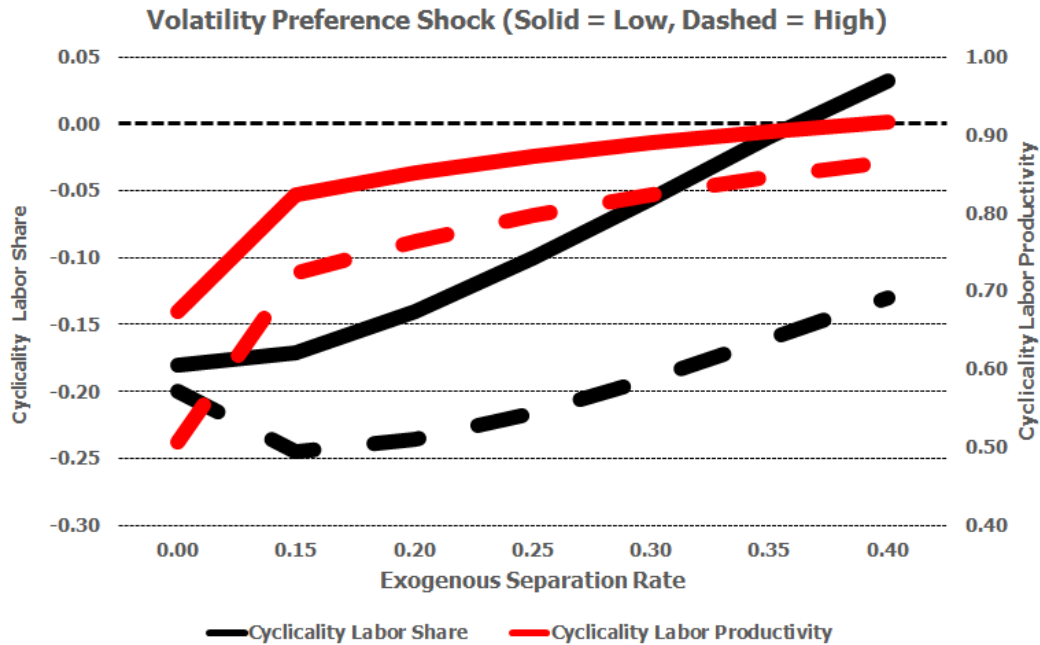


FIGURE 3.2: Changes in the Volatility of Demand Shocks.

of labor productivity, which is at odds with the data.

3.2.3 Deunionization

Another related question is on how deunionization affects the cyclicality of the labor share. Intuitively, the decrease in the importance of labor unions for the labor market decrease the workers' bargaining power in the wage bargaining process and so, it increases the flexibility of wages in the economy. I use the model from Galí and van Rens (2017) to analyze separately both changes. I find that a decrease in the workers bargaining power decreases the cyclicality of labor productivity and makes the labor share more countercyclical. This is so because the bargained wages get closer to the workers' reservation wage, which depends not only from supply shocks but also from the impact of demand shocks to the households' marginal substitution rate between consumption and labor services. Since demand shocks provide a countercyclical force to the labor share and disentangle the real wages from labor productivity in this

Table 3.2: Model Performance and Empirical Evidence: Variations in σ_a , σ_z and \bar{R} .

	Model Performance			
	$\sigma_a > \sigma_z$	$\sigma_z = \sigma_a$	$\bar{R} = 0.5$	$\bar{R} = 0.9$
$\rho(\hat{\lambda}_t, \hat{y}_t)$	0.080	-0.041	-0.419	-0.705
$\rho(\hat{y}_t - \hat{n}_t, \hat{y}_t)$	0.929	0.895	0.865	0.882
$\rho(\hat{w}_t, \hat{y}_t)$	0.867	0.803	0.679	0.438
$\rho(\hat{w}_t, \hat{y}_t - \hat{n}_t)$	0.982	0.973	0.920	0.652
$100 \times \sigma(\hat{y}_t)$	3.034	3.034	3.191	3.720
$\sigma(\hat{\lambda}_t) / \sigma(\hat{y}_t)$	0.178	0.210	0.273	0.318
$\sigma(\hat{y}_t - \hat{n}_t) / \sigma(\hat{y}_t)$	0.820	0.801	0.674	0.414
$\sigma(\hat{w}_t) / \sigma(\hat{y}_t)$	0.895	0.882	0.691	0.322
δ	0.350	0.350	0.350	0.350
θ	0.500	0.500	0.500	0.500
$100 \times \sigma_a$	2.080	2.027	1.954	1.954
$100 \times \sigma_z$	1.676	2.027	2.424	2.424
\bar{R}	0.000	0.000	0.500	0.900
Hiring Costs / Output	0.027	0.027	0.027	0.027

setup, the procyclicality of real wages declines more than the procyclicality of labor productivity making the labor share more countercyclical. To reflect one possible impact of deunionization to the cyclicity of labor productivity and to the cyclicity of the labor share, Figure 3.3 shows how a decline in the workers' bargaining power implies again a decline in the procyclicality of labor productivity but a counterfactual increase in the countercyclicality of the labor share.

At the same time, the increase in wage rigidity decreases the volatility of real wages, introducing a countercyclical pressure to the cyclicity of the labor share⁷.

⁷ Real wage rigidities are introduced as $W_t = R_{t-1} \cdot W_{t-1} + (1 + R_{t-1}) \cdot W_t^*$, where W_t^* is the standard Nash Bargaining considered in the main text. $W_t^* = \theta \cdot W_t^{\text{UB}} + (1 - \theta) \cdot W_t^{\text{LB}}$. I use a reduced-form equation for wage rigidity

$$R_t = \bar{R} \cdot \left(1 - \frac{W_t - W_t^*}{0.5 \cdot (W_t^{\text{UB}} - W_t^{\text{LB}})} \right)^{2\rho}$$

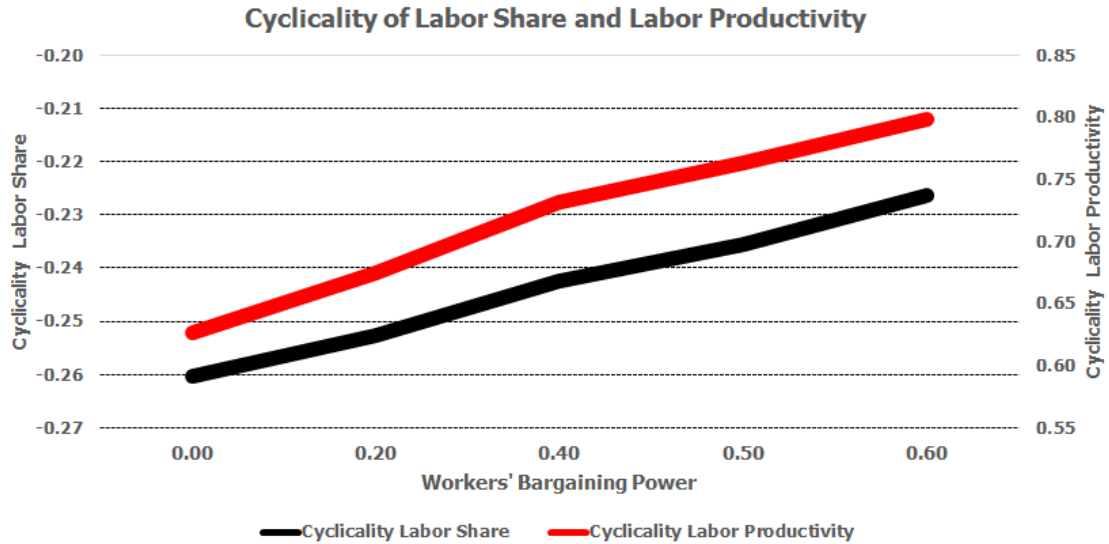


FIGURE 3.3: Changes in the Workers' Bargaining Power.

The last two columns of table 5 show a numerical example for a low and a high level for the workers' bargaining power. When θ decreases from 0.75 to 0.25, the labor share becomes more countercyclical, due to a larger decline in the cyclicity of real wages in comparison to the decline in the procyclicality of labor productivity. The last two columns of Table 3.2 show a numerical example for increases in wage rigidity in the model, through an increase in \bar{R} . Introducing real wage rigidities in the model decreases sharply the procyclicality of real wages, without changing the cyclicity of labor productivity, generating a more countercyclical labor share. A graphical representation of the effects of real wage rigidities on the cyclicity of the labor share and labor productivity is shown in Figure 3.4. The main conclusion is that a decrease in real wage rigidities decreases the procyclicality of labor productivity while making the labor share less countercyclical. This suggests that the cyclicity of the labor share and labor productivity are important variables to pin down the degree of real wage rigidities in the economy. I leave for future research a more

which makes wages to adjust more when they are on close to the boundaries of the bargaining set.

This formulation follows Thomas and Worrall (1988), MacLeod and Malcomson (1993), Hall (2003), and Galí and van Rens (2017) (in a previous working paper version).

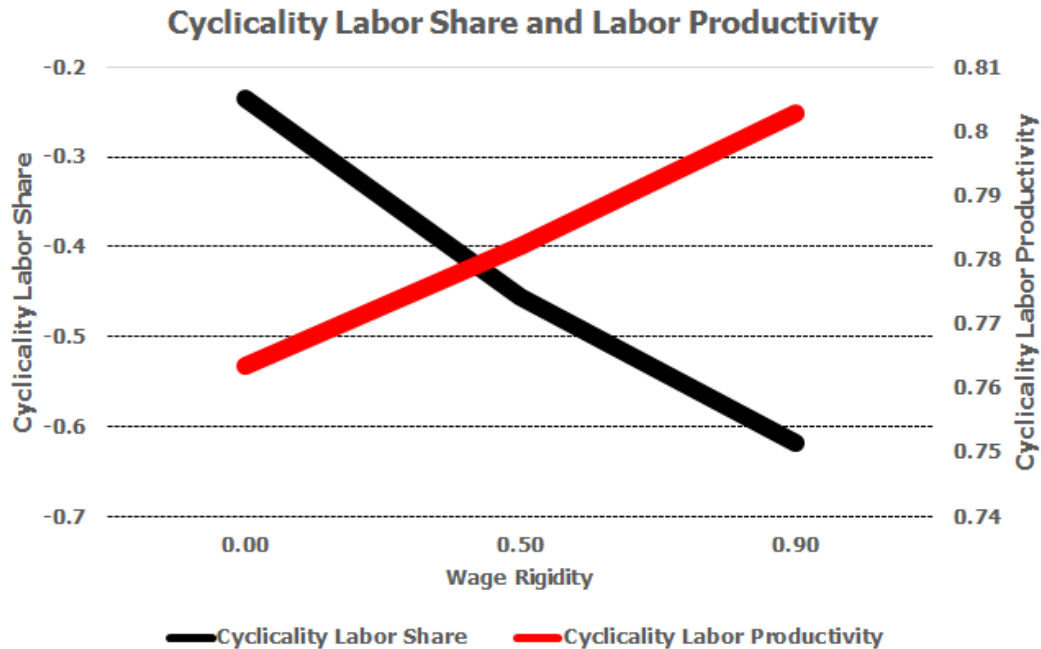


FIGURE 3.4: Changes in the Degree of Wage Rigidity.

quantitative study of the impact of real wage rigidities to the cyclical of the labor share.

3.3 Conclusion

In this chapter, I have studied whether the shift in the cyclical of the labor share can be obtained qualitatively as a byproduct of other important structural changes observed for the U.S. economy after the mid-1980a. The answer is that it cannot. Out of my results, the most promising interpretation for the shift in the cyclical of the labor share is that the labor market became more flexible.

However, the perfect flexibility of wages is not a sufficient condition for the labor share to become procyclical. This evidence suggests that there is a technological change in the economy affecting the cyclical of the labor share. In particular, this technological change is changing the incentives for labor hoarding at the firm level. The incentives for labor hoarding policies are identified from the procyclical of the

intensive margin of factor inputs, defined as factor utilization⁸.

In order to check whether the procyclicality of factor utilization has changed over time, I look to the factor utilization series provided by the San Francisco Fed. This dataset provides a quarterly series on total factor productivity for the U.S. business sector, which is adjusted for variations in factor utilization as measured by labor effort and capital's workweek⁹. Figure 2.3 shows the cyclicity for both the labor share and for the factor utilization series for the nonfarm business sector over time using 20-year rolling windows. The factor utilization series remained procyclical for most of the sample, consistent with the existence of a strong labor hoarding mechanism in the economy. However, in the last three decades, factor utilization became acyclical. This means that both labor effort and capital workweek became independent from the business cycles and that firms are not adjusting the intensive margins of factor production depending on whether there is a recession or an expansion.

There are two potential justifications for this. The first is that there are currently no incentives for labor hoarding, which lets firms to optimize factor utilization independently of the business cycles. The advances in logistics and supply chain management technologies can contribute to the decrease in factor hoarding through this channel. Without incentives for labor hoarding, firms are able increase the flexibility of adjustments in employment and real wages, which can potentially make the labor share less countercyclical, or even procyclical if capital and labor inputs are complementary factors of production.

The second is that there is a change in the production process for these firms, or

⁸ Refer to Burnside et al. (1993), Burnside et al. (1995), and Burnside and Eichenbaum (1996) for the earlier literature on the cyclicity of factor utilization. In particular, Burnside et al. (1995) studies the implications of procyclical capital utilization rates for inference regarding cyclical movements in labor productivity and the degree of returns to scale.

⁹ This dataset is described in Fernald (2014) and the utilization adjustments follow the methodology developed in Basu et al. (2006). Using this data, I construct an index variable for the factor utilization series and I assume the factor utilization series to be the same for the U.S. business and nonfarm business sectors.

a technological change that modifies the production functions for the average firm in the economy. This technological justification would be consistent with the notions brought by Choi and Ríos-Rull (2009) and Koh and Santaaulàlia-Llopis (2017) towards a technological explanation to the cyclicalities of the labor share. However, in this setup the shift in the cyclicalities of the labor share would come from changes in the elasticity of substitution between capital and labor, towards a higher complementarity between the two factors of production. There is an ongoing debate on the measurement for the elasticity of substitution at the micro- and macro- levels. For the macro-elasticity of substitution between factors of production, Eden and Gaggl (2017) looks to the welfare implications of automation and argues that the fall in the price of capital goods happened for the type of capital that is more substitutable with labor. The increase in the usage of this type of capital, and consequent increase in the automation of tasks usually performed by workers, increased the aggregate substitutability between capital and labor inputs over time. In their calibration, capital and labor are always relative substitutes, which generates a countercyclical force to the labor share under a constant elasticity of substitution (CES) production function. This evidence suggests difficulties also for this technological story.

One alternative explanation is that the importance of U.S. industries has changed over time. The structural change in the industrial distribution for the U.S. economy passes by a decline in the value added production of manufacturing and trade sectors, and by the corresponding increase in the services and finance sectors. This would mean that the shift in the cyclicalities of the labor share would come from sector reallocation from manufacturing to services, and not from any aggregate phenomenon as considered above. In the following section, I extend my empirical analysis to account for industry composition effects and I show that this is not the case. The shift in the cyclicalities of the labor share is not an aggregation results, since it happens not only at the aggregate level but also for the majority of industries in the economy.

Therefore, the shift in the cyclicality of the labor share adds discipline to the real business cycle literature. An interesting path for future research would be to microfound the shift in the cyclicality of the labor share by looking to an aggregate structural change in the U.S. economy that provokes the vanishing procyclicality of labor productivity and the increase in the volatility of real wages. A difficulty would be to consider a framework not generated by wage rigidity in which real wages and labor productivity are positively (but imperfectly) correlated.

The Public Sector Wage Differential: An Occupational Approach

4.1 Introduction

In the aftermath of the great recession, fiscal policy appeared in the headlines of most Western countries at the top of the governments' agenda to recover the economy. Austerity policies are now the rule, not the exception. After all the efforts that were required to get out of the recession, it is only natural that the public sector payroll has been consistently under the public opinion's spotlight. There is an increased attention to the time series behavior of the wage differential between the public sector workers and their private sector counterparts by both the policy analysts, the social media and the public opinion in general.¹

¹ For example, recently the Organisation for Economic Co-operation and Development developed a broad study where they assess what compensation plan should be adopted by their member countries and how to better manage the wage bill of public sector employees (*OECD (2012)*). In this report it is stated that public sector compensation reduction policies are widespread to face the recent recession. More than half of the OECD countries participating in the OECD Fiscal Consolidation Survey of 2012 have proposed wage cuts or wage freezes like the 5%-10% cuts in Portugal and Spain and the wage freezes in the United Kingdom and United States. Also, several countries are proposing significant reductions in the number of public sector employees like Czech Republic, Ireland and Poland. Their focus is on the design of different compensation schemes for the public sector wages, which I am not analyzing here. Nevertheless, this is a very interesting

This chapter proposes to carefully review the empirical evidence on the wage dynamics for both the private and public sectors of the economy. My main goal is to argue that occupational heterogeneity across workers is the key to properly evaluate the public sector wage premium. This idea is related with the main literature for the public sector wage differential, which emphasizes the importance of considering some heterogeneity across workers to better understand what drives the public sector wage differentials. In particular, Katz and Krueger (1993, 2012) studied the earnings inequality in the US and found that there is a lower inequality for the public sector employees when compared to the private sector employees after correcting for differences in education and experience across sectors. In addition, using a quantile regression analysis Poterba and Rueben (1994) argued that the public sector wage distribution is more concentrated (or less dispersed) than the private sector wage distribution. This implies that the workers in a quantile on the left tail of the public sector wage distribution are more highly paid relatively to the workers that are in the same quantile of the private sector wage distribution. On the other hand, the workers in a quantile on the right tail of the public sector wage distribution are less highly paid relatively to the workers in the same quantile of the corresponding wage distribution for the private sector. The higher wage concentration for the public sector is one of the most robust results in the literature, being also confirmed for example in Gregory and Borland (1999), Melly (2005) and Bargain and Melly (2008).

I argue that it is important to reinforce the role of occupational composition to better structure the heterogeneity in the public sector wage differential. To do so, I follow the “routinization” hypothesis approach proposed by Autor et al. (2003) and outstandingly surveyed in Acemoglu and Autor (2011). I relate the public sector wage differential to both wage and job “polarization” arguing that the most relevant comparison across the private and public sectors is the composition of employment theoretical research topic for the future.

across occupations. The differentiation of (non-)routine manual/cognitive occupation categories should therefore be key in explaining the wage premium for the public sector that we observe using aggregate data. In particular, Acemoglu and Autor (2011) argue that occupational heterogeneity is becoming more relevant to account for wage differences across workers as time goes by. Therefore, it is the perfect environment to compare the private and the public sectors.

I contribute to the literature by providing three new robust empirical facts relating the occupational heterogeneity with the determination of the public sector wage differential. The first reflects a negative monotonic relationship between the public sector wage differential and the private sector hourly wages across occupations. The second signals the existence of a public sector wage differential polarization, in which low-skill and low-wage occupations have very high wage premiums, high-skill and high-wage occupations have wage penalties, and the occupations in the middle of the distribution have smaller differentials across sectors. Lastly, the third fact argues that the public sector wage differential is affected by the occupational employment composition across sectors and therefore it is affected by the job polarization structural trend that is occurring in the labor market since 1990. To test the robustness of these results I execute a battery of Oaxaca-Blinder counterfactual decompositions for the average worker. The main conclusion is that the occupational composition is important both for the determination of the average public sector wage differential and for the determination of the public sector labor market share over time.

Although related in spirit, these results are different in nature from the wage concentration result. Instead of comparing the distribution of workers in both the private and public sectors by understanding the public sector wage differential for different quantiles of the distribution, I proxy the value of a job by the private sector hourly wage for that job and I see how the public sector wage differential varies for each occupation category in relation to the value attributed to the workers belong-

ing to each occupation by the private sector. To understand whether this result is influenced by the wage concentration argument, I study whether this monotonic relationship is robust for different quantiles within each occupational category. I find that the wage concentration has no major effects in my result. Explicitly, the wage concentration result affects the mass of occupational categories with wage premiums or penalties but not the negative relationship between the public sector wage differential for each occupation category and the private sector hourly wages. In particular we expect for lower quantiles within occupations to observe a large mass of points with wage premiums and for higher quantiles within occupations to observe a higher mass of occupations with wage penalties.

The importance of the public sector wage bill on the government budget is by itself self-explanatory. Throughout the Post-World War II period until the present days the average public sector payroll share on government consumption lies above 50% and the average share on total government expenditures above 25%. Although one can argue that the relative importance of the public sector wage bill on government expenditures has decreased over time, this does not decrease its significance. In fact, the share of the public sector payroll bill on the government total expenditures achieved a minimum value of 20.4% and the share on the government consumption expenditures consistently decreased to reach 47% in the year of 2013. These values are still significant enough for the public sector payroll to be one of the first targets in cutting government's spending whenever there are some budgetary pressures to decrease it, as proven by the wave of austerity policies targeting the public sector employees across the Western countries. The public sector has also a big expression in the labor market. The public sector employment share has consistently been above 15% from 1960 onwards and it increases in all NBER recessions. This happens since the private sector employment is considerably more volatile than the public sector employment and so, in a recession, the public sector employment decreases relatively

less than the private sector.

The existence of such a significant and centralized employer in the labor market lead us to think that the government may have some monopsonic power. If this power is exercised, then the government can drive the wage of a given public sector worker down and make it lower than the wage of a “comparable” private sector worker. Or it can let the government to be more rigorous in their recruitment process and allow the public sector to get better (more skilled) employees for the same wage as the private sector would offer for a less skilled worker for the same vacant job. The latter would mean that a comparison for the occupation composition across sectors is extremely important to properly study the public sector wage differential and that we need to be careful when interpreting the time series for the average worker.

On the labor supply side, we need to take into account two different channels. First, the fact that the average public sector job is viewed as having a higher job security and higher non-compensatory benefits (higher pensions, better healthcare insurance, etc) than the average private sector job. Using establishment level data from the Job Openings and Labor Turnover Survey from the BLS, Davis et al. (2013) found for the years 2001 to 2006 that on average the hires and separation rates for the economy’s public sector are less than a half of the same respective rates for the total non-farm employment. One major consequence of this result is that conditionally on being hired, the public sector workers have a higher job security given the lower probability of being fired. The higher job security and the higher non-compensatory benefits associated to the public sector jobs would drive down the wages required by the public sector employees on accepting the job if they are risk averse, conditionally on getting an offer. This idea was first emphasized in Bellante and Link (1981), who argue that more highly risk-averse individuals weigh job stability higher and are more likely to search into public sector. The higher job security would also imply a lower mobility to the private sector or to unemployment and lower vacancies, which

would make the public sector employment to be less procyclical with the business cycle than the private sector employment.

Second, given the higher job security of public sector jobs and the fact that the government may have monopsonic power in the labor market, the public sector workers have incentives to fight for their own jobs by gathering in unions and negotiating their wage through collective bargaining. Collective bargaining would give the public sector workers a higher market power in the labor market and would create an upward pressure on their wages with respect to the private sector. The Wisconsin Budget Repair Bill and the consequent protests and the the fall of Issue 2 in Ohio are recent examples of the action of labor unions to protect the public sector workers benefits and job security. Through the action of collective bargaining we would expect the time series behavior of the public sector wage differential to be biased by the protection of low-skilled workers, whose wages should be higher than their private sector counterparts, rather by the high-skilled workers, whose wages should be lower.

The remaining of this chapter is organized as follows. In Section 4.2, I carefully explore the time series behavior of the employment and wage dynamics of both the private and public sectors. In Section 4.3, I show using micro-level evidence the relevance of the occupational composition in describing the forces behind the aggregate public sector wage premium that we observe in the data. In Section 4.4, I apply a battery of Oaxaca-Blinder counterfactual decompositions (Oaxaca, 1973, and Blinder, 1973) to understand the relative effect of demographics, occupational composition and propensities in explaining the public sector wage differential and to test the empirical facts introduced in Section 4.3. In Section 4.5, I conclude the chapter and discuss future avenues for research.

4.2 Time Series Aggregate Evidence

This section reviews the time series evidence using quarterly aggregate data from the BLS Current Employment Statistics (CES) and compares it with the annual time series data that can be obtained from the March Supplement of the Current Population Survey (CPS) after aggregation across workers². I decompose and describe the dynamics for the total wages for each sector by understanding what happens to the wages per worker, hourly wages and hours worked across sections. I argue that the relevant wage measure to study the public sector wage differential is the hourly wage. For the quarterly data we also apply the Hodrick-Prescott filter to the average public sector wage differential per worker and other relevant variables to study their persistency, comovement with the business cycles and volatility. Using the cyclical components we compare the business cycle dynamics of both sectors to better understand in which way each sector affects the labor market dynamics we observe in the data.

We can decompose total wages in two different margins: an extensive margin for the number of employees (“bodies”), and an intensive margin for wages per worker. The intensive margin can be further decomposed into two different effects: one that represents the contribution to this intensive margin of hours per worker (“quantities”) and one that represents the contribution of wages per hour (“prices”). Therefore, total wages can be decomposed as

² The CPS series used comes from the online Integrated Public Use Microdata Series (IPUMS-CPS) from the University of Minnesota. The data is taken from <http://cps.ipums.org/cps/>. The main advantage of the IPUMS-CPS data is the fact that the dataset is already cleaned and ready to be used by the researcher. For further details about this dataset please refer to “Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]. Minneapolis: University of Minnesota, 2010.”

$$\text{Total Wages} = \text{Employment} \times \underbrace{\frac{\overbrace{\text{Total Hours}}^{\text{Hours per Worker}}}{\text{Employment}}}_{\text{Wages per Worker}} \times \underbrace{\frac{\overbrace{\text{Total Wages}}^{\text{Wages per Hour}}}{\text{Total Hours}}}_{\text{Wages per Hour}} \quad (4.1)$$

Ideally, we should analyze the three effects described above separately. Unfortunately, the BLS does not have publicly available data for total hours for the private and public sectors separately. Nevertheless, I use data for total wages and employment from the CES dataset to analyze both the extensive margin and the intensive margins. To fill the gap in the data to study this decomposition, I use the data made publicly available by Francis and Ramey (2009, referred as FR in what follows) to get the employment and total hours series³. I match both series by comparing the employment series for both datasets to see whether the data for total hours can be seen as reliable enough or if it differs considerably from what we would expect due to the number of workers.

Using FR data I construct a series to represent the private non farm employees by summing the private non farm employees (excluding non-profits) with the non-profits series. I observe that this series slightly over-represents the private sector employment data from the CES. However, since this difference is relatively small (the FR private employment series exceeds the CES series by less than 0.4% for all time periods), we can neglect it and argue, possibly in a slightly naive fashion, that the data on total hours taken from Francis and Ramey (2009) can be considered as a valid proxy for the actual total hours series that could be obtained from the CES aggregate data. For the public sector, the employment series provided by FR

³ This data can be directly accessed from <http://econweb.ucsd.edu/~vramey/research.html>. The authors mention that this data was provided by Shawn Sprague of the Bureau of Labor Statistics (BLS) as the raw series used in the BLS hours index, even though I was not able to find this index on the BLS statistics website. This is a further justification on whether the series for total hours should be used to access on the aggregate what drives the time series behavior for the public sector hourly wage differential.

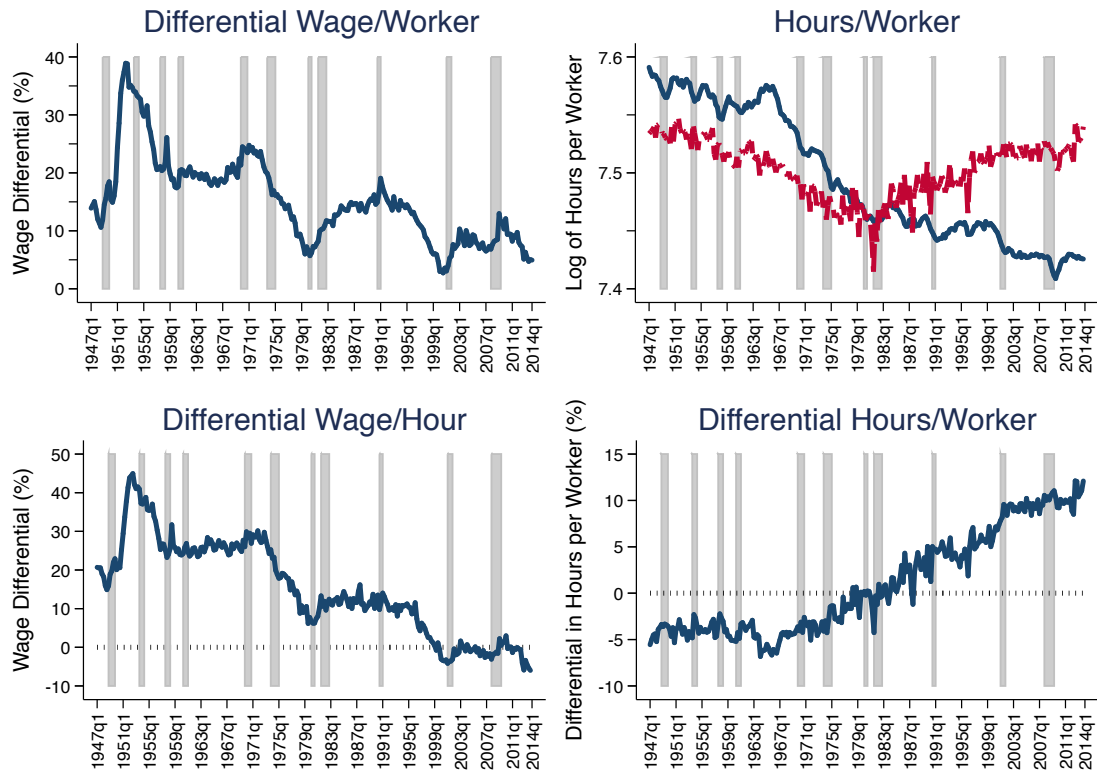


FIGURE 4.1: Public Sector Wage/Hours Differentials (1947-2014).

matches exactly with the one from the BLS. Using this data we are now able to get time series aggregate results for the public sector hourly wage differential, that can provide a better comparison with the Current Population Survey (CPS) time series data.

Figure 4.1 presents the quarterly time series data from 1947 to 2014 for the public sector differentials in wages per worker and in hourly wage, for the public sector hours per worker differential and for the annual hours per worker for both the private and public sectors. The differentials are in percentage terms and the hours in both sectors are in natural logarithms. The data for nominal wages and employment is taken from the CES dataset. The data for the total hours is taken from Francis and Ramey (2009). For the hours per worker panel, the blue line reflects the behavior of

the private sector and the red dashed line reflects the pattern for the public sector. The gray areas show the NBER recessions.

The public sector differential for hours per worker, wage per worker and hourly wage are constructed as the percentage deviation of the corresponding public sector variable with respect to the same private sector variable. For example, I define $(W/N)^G$ to be the public sector average wage per worker and $(W/N)^P$ to be the private sector average wage per worker. Let the public sector wage (per worker) differential to be noted as $\text{Wage}^{n,D}$. Therefore, $\text{Wage}^{n,D}$ can be defined as

$$\text{Wage}^{n,D} \equiv \left(\frac{(W/N)^G}{(W/N)^P} - 1 \right) \times 100\% = \left(\frac{(W/H)^G}{(W/H)^P} \times \frac{(H/N)^G}{(H/N)^P} - 1 \right) \times 100\% \quad (4.2)$$

where for a sector $i \in \{G, P\}$ we have that $(W/H)^i$ is the hourly wage and $(H/N)^i$ is the average number of hours per worker. The above formulation reflects that the public sector wage per worker differential is a weighted average of both the hourly wage and hours per worker differentials.

From the evidence shown in the first panel in Figure 4.1 we observe the existence of a public sector wage premium per worker. This means that the average wage per worker is higher in the public sector than in the private sector. However, the average wage premium per worker has been slowly decreasing in magnitude from 1950 onwards, with extremely long-lasting movements over time. The question can now be further specialized. Are the movements in this public sector average wage per worker premium explained by variations in the quantity of labor, the differential of hours per worker across sectors? Or are these movements due to variations in the actual price, or due to variations in the hourly wage differential between the public and the private sectors?

The public sector differential in hours per worker remained stable around -5%

from 1947 to the middle of the 1960s. This would imply the average private sector employee to work 5% more hours than the average worker in the public sector for this time period. From the 1960s until the present the hours per worker in the private sector systematically decreased by more than the hours per worker in the public sector. The latter even started to increase from 1980 onwards. This results in a positive sloped linear trend for the public sector hours per worker differential. In 2013, the average public sector employee works now between 10.4% and 12.1% more hours per year than the average private sector employee. Given the systematic long-run positive trend in the hours per worker differential, the medium to long run dynamics of the public sector wage premium per worker are mainly described at that frequency by the dynamics of the hourly wage differential across sectors. The main difference is in the level of the differential between sectors. In particular, from 1999 onwards we observe the hourly wage public sector differential to fluctuate around the null, letting us observe both wage premiums and wage penalties as time goes by. This would imply that the public sector wage premium described above for the average employee could be an artificial result that comes from the higher number of hours worked by the public sector employees. However, this upward sloping trend over time in the differential for the hours per worker goes against what we would expect and should be confirmed using the CPS data.

In order to compare and integrate the aggregate evidence described above with the micro-level data, I use the March supplement for the CPS dataset. The information contained in the March CPS dataset allows a richer decomposition for the total annual wage bill. Instead of considering the three distinct effects described in equation (4.1) - employment, hours per worker and hourly wage - we can now decompose even further the hours per worker into two different components: (i) the weeks worked in the year by each worker and (ii) the usual hours worked per week. By doing so, we can check whether the public sector differential in hours obtained

from the CPS dataset is able to match such a high differential as it is indicated in the FR data and the upward sloped time trend. Finally, this specification allows us to ask whether the variations in the average annual hours worked by the average worker across sectors come from the difference in the number of weeks worked or in the amount of time an individual needs to work per week⁴. The decomposition of the annual wage bill is then

$$\begin{aligned} \text{Total Wages} = & \text{Employment} \times \text{Hours per Week} \\ & \times \text{Weeks per Worker} \times \text{Hourly Wage} \end{aligned} \tag{4.3}$$

Since we are dealing with individual-level data we need to be careful when aggregating the variables across individuals. The CPS provides the inverse sampling probability weights of an individual to appear in the dataset. We will use these weights to construct our aggregate variables⁵. I am using the March CPS to get information about the individual annual earnings, implying that I am working with annual data. It is recommended by the IPUMS-CPS to use the 1990 Census methodology for occupations only for data from 1980 onwards. This happens due to some structural changes in the occupational classification over time. Anchoring the Census 1990 methodology lets all observations in the sample to pass through at most only one major occupational classification restructuring, making the homogenization of

⁴ The variable introduced to measure the annual weeks worked by each individual reports the number of weeks, in entire weeks per year, that the respondent worked for profit, pay, or as an unpaid family worker during the preceding calendar year. Respondents were prompted to count weeks in which they worked for even a few hours and to include paid vacation and sick leave as work. This explains why in Figure 4.2 reported for the number of weeks worked per year for the average worker extremely high values, from 48.5 weeks to 50.5 weeks per year.

⁵ The key variables we use in this and the following sections are the annual earnings (incwage), the number of weeks worked per year (WKSWORK1), the usual hours worked per week (uhrswork), the occupation classification according to the 1990 Census methodology (OCC1990) and according to the Standard Occupational Classification System for the year 2000 (SOC 2000), and finally to identify whether the worker is in the private or public sector we use the worker's class (classwkr). Other important variables that will be used later in this work are the age, race, gender, education and employment status of the individuals in the sample.

these occupational categories to be easier and less prone to noise. Therefore, I will only consider data from 1980 to 2013.

On the micro-level I apply several restrictions to the sample to make it usable. First, I restrict the age of the individuals in the sample to be between 16 years and 67 years. The former is the legal working age for the majority of jobs in the United States and the latter is the full retirement age. Second, to be able to properly understand the wage differential between the public and private sectors, I exclude the unemployed, the individuals not in the labor force, the self-employed, the unpaid family workers and the armed forces. Therefore, only the persons that are actually formally working in the labor market are considered. The armed forces are the exception, since it is a specific task of the public sector. For the formal workers considered, I follow the literature and drop the ones that have occupations related to farming, forestry and fishing. For the annual earnings observed in the data we need to deal with the outliers that may be misspecified. In order to do so, I exclude the individuals that earn per hour less than 25% of the federal minimum wage and I multiply the top-codes for annual earnings by 1.5 for the time period comprising all the years between 1980 and 1995. These top-codes are a feature of the CPS dataset to prevent identifying the individuals that were surveyed. Additionally, I deflate all monetary values in 2010 dollars for a higher comparability over time.

Finally, to decompose the annual hours worked by each worker, I follow the methodology used in the literature that uses the CPS dataset and, in particular, Bowlus and Robinson (2012). Explicitly, I define the annual hours worked by each individual in the sample as the usual annual working hours. These are the product of both the weeks worked in the year and the usual hours worked per week. We use the usual working hours to proxy for the hours worked in each week to control for possible holidays, sickness periods and other sorts of noise in the data. We drop from the sample all the workers that usually work less than 20 hours per week or less than

20 weeks per year. This would imply that some (but not all) part-time workers are dropped from the sample.

Figure 4.2 presents the time series evidence for 1980 to 2013 using the March CPS dataset. From the decomposition of total wages provided by equation (4.3), the relevant variables are the number of employees, the annual hours worked per individual and the hourly wage. To further decompose the annual hours worked, we use the methodology above to consider the number of weeks worked per year and the usual hours worked per week. Also, to compare our results to the ones found using more aggregate data, we compute both the hourly wage and the wages per worker for each sector. On each panel in Figure 2, the blue line reflects the behavior of the private sector and the red dashed line reflects the pattern for the public sector.

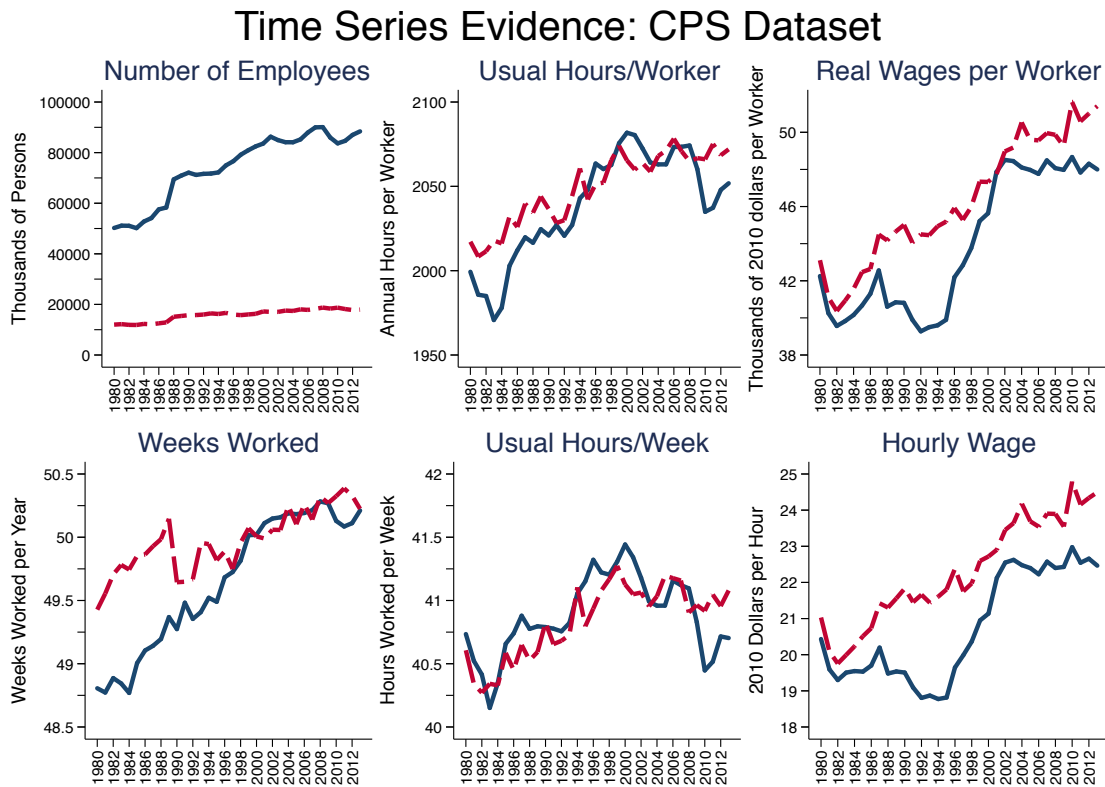


FIGURE 4.2: Time Series Evidence - CPS Dataset (1980-2013).

The first observation is that, even after cleaning the data, the CPS has a good national coverage of the US labor market. In 2013, it represents 88.4 million workers in the private sector and 17.9 million workers in the public sector. This implies the public sector employment share to be between 16% and 20%, being roughly 19.30% in 1980 and 16.87% in 2013. These values are in accordance with the ones shown on Figure 4.1, implying that the CPS is not representing excessively one sector with respect to the other. With respect to the wages of the average worker in each sector, the public sector average worker wage is consistently increasing in a linear fashion while in the private sector there are larger swings. This would imply that the private sector average worker wage time series defines the dynamics of the public sector wage differential. Since this wage differential is always positive for the hourly wage and almost always positive for the wages per worker, we can think of a public sector wage premium. The exception holds for 2001 in which the public sector wage (per worker) differential is negative ($\text{Wage}_{2001}^{\text{p,D}} = -0.28\%$), but the public sector hourly wage differential is still positive. It is also important to differentiate between the contribution of the hourly wage and the contribution of usual hours worked per individual. Notice that the hourly wage has the most important role in explaining the dynamics observed in the wages per worker and that there is a considerable public sector hourly wage premium for all time periods.

The public sector wage per worker differential dynamics are matched pretty well both using the CES aggregate data and the CPS data. On the other hand, this match is far from perfect for the levels of these differentials. According to Abraham et al. (1999), there are some possible explanations for this fact. First, the CES underrepresents the workers from young establishments. Second, there are differences in the earnings concepts employed across data series and in the worker populations covered in each dataset. In particular, for the CPS dataset I am filtering the data

by removing some of the part-time workers that usually work less than 20 hours per week or less than 20 weeks per year. Due to the type of contracts used in each sector this would have a higher impact on the private sector, pushing upwards the usual hours per worker in this sector. Lastly, the CPS data may understate the growth in hourly wages for both sectors since workers tend to over report the number of hours they work per year. Independently of the reason, I will continue this analysis using the CPS data.

Finally, to confirm if the upward sloping time trend exists for the public sector average annual hours per worker differential, I use the usual annual hours per worker from the March CPS. The usage of the usual annual hours prevents us from having so much noise in the data due to extraordinary events but it can also lead to a bias in the hours reported by the workers in both sectors. While for the aggregate evidence presented above in Figure 4.1 we have the average public sector worker to work increasingly more than the average private sector worker as time goes by, from -5% in 1982 to around 15% in 2014, we observe for the CPS dataset a very mild and relatively constant differential over time in the hours worked between the average worker in the public and private sectors, never exceeding in absolute value 2.5%. The usual hours per worker are consistently higher in the public sector between 1980 and 1994 and between 2009 and 2013. For the former period the main driver is the number of weeks worked per worker, which is consistently higher in the public sector. For the latter period the difference is in the usual hours per week, again slightly higher in the public sector. Therefore, given the mild absolute values of both the public sector differential in the hours per worker across sectors and in its main determinants, we can assess that the differences in hours across sectors are not relevant to determine the dynamics of the public sector wage differential. I will follow the results provided by the micro-level data and argue that the hourly wage is the most important component to assess the public sector wage per worker differential.

Up to this moment, I have described the main time series facts that describe the labor market dynamics for both the private and public sectors. I have decomposed the total wages in each sector into four different channels: (i) number of employees, (ii) weeks worked per year, (iii) number of hours worked per week, and (iv) hourly wage. Since the average public sector wages per worker are almost always above the private sector wages we can think of a public sector wage premium. The most important channel to explain the dynamics of the public sector wage premium per worker is by far the hourly wage. Therefore, in the next section when I present the micro-level evidence I will use the hourly wage as the relevant variable to measure the wage premium. For the remaining part of this section I will use the CES data from the BLS and aggregate data for GDP taken from the Bureau of Economic Analysis (BEA) to describe the persistency, comovement with GDP and volatility of some key variables after application of the filter popularized by Hodrick and Prescott (1997) with a smoothing parameter appropriate for quarterly data⁶. I take the natural logarithm of each variable, excepting those that are already in percentage terms that I keep unchanged, and I apply the HP filter to each variable re-expressing it in percentage deviations from long-run trend. I obtain the cyclical components for these variables. For persistency I use the cyclical components' first order autocorrelations, for comovement the contemporaneous correlation with GDP and for volatility the standard deviation.

Table 4.1 presents the results using the methodology considered above. The key variables presented below are the nominal GDP (Y), the public sector wage (per worker) differential ($\text{Wage}^{\text{n,D}}$) and, for both the private and public sectors, total employment (N^i), total hours (H^i), average nominal wage per worker ($(W/N)^i$) and average hours per worker ($(H/N)^i$), where $i \in \{P, G\}$ is the sector considered. Not

⁶ The Hodrick-Prescott filter used for quarterly data was applied using a smoothing parameter equal to 1600. For further reference on what smoothing parameter value to apply for each time frequency see Ravn and Uhlig (2002).

Table 4.1: Business Cycles: Public vs. Private Sector (1947-2014)

	PERSISTENCY		COMOVEMENT		VOLATILITY	
Y	0.8485		1.0000		1.7583	
Wage ^{n,D}	0.8032		-0.0205		1.9795	
	Private (P)	Public (G)	Private (P)	Public (G)	Private (P)	Public (G)
N ⁱ	0.9159	0.8704	0.8218	0.3266	1.6892	0.8776
H ⁱ	0.9044	0.5293	0.8485	0.3384	1.9807	1.2297
(W/N) ⁱ	0.7701	0.8677	0.6221	0.3130	1.0196	1.7376
(H/N) ⁱ	0.8339	0.1482	0.5746	0.1544	0.5021	0.8349

Table 4.2: Public Sector Wage Differential (per worker): Comovement by Time.

COMOVEMENT OF WAGE ^{N,D} OVER TIME.				
1947-1969	1970-2014	1980-2014	1990-2014	2000-2014
0.2510	-0.5718	-0.5960	-0.7123	-0.7750

surprisingly, most of the key variables like output, the public sector wage differential, employment and the wage per worker in both sectors and both total hours and hours per worker in the private sector are very persistent variables. However, it may be surprising that total hours and hours per worker are much less persistent in the public sector than in the private sector. The fact that the public sector is more highly covered by labor unions and by their collective bargaining contracts would make us believe that both employment and hours per worker in the public sector would be at least as persistent as in the private sector. Finally, hours per worker in the public sector are not as persistent as in the private sector. This may be a feature of Francis & Ramey (2009) data and not from the public sector on its own.

For the comovement with the business cycle we have that all the public sector variables - employment, total hours, wages per worker and hours per worker - are less procyclical than in the private sector. This result is particularly well connected with the literature, appearing as well in Quadrini and Trigari (2007). Additionally, the public sector employment share is countercyclical (correlation = -0.6506). Sur-

prisingly the public sector wage differential is acyclical. Since the wage per worker in the public sector is less procyclical than in the private sector we would expect the public sector wage differential to be countercyclical and the fact that we get such a low comovement with the cyclical component of GDP should let us believe that there may be an artificial component in the data that is generating that result. In Table 4.2, I decompose the public sector wage differential by time periods to understand better what happens. We observe that in the first part of the sample, from 1947 to 1969, the public sector wage differential is actually procyclical. As we consider more recent time periods, the public sector wage differential gets more and more countercyclical. This implies that the earlier period in the sample is influencing the cyclicity results for the public sector wage differential, influenced by the large wage premiums observed in the 1950s. It also implies that for the period starting in 1980 to the present we should consider the public sector wage differential to be countercyclical. Finally, we observe that both the total hours and total employment in the private sector are more volatile than in the public sector and that the average wages per worker and hours per worker are more volatile in the public sector than in the private sector.

In this section I have illustrated the time series evidence that describe the dynamics of the public sector wage differential. I develop the analysis by using both the aggregate evidence and by making use of the micro-level CPS dataset. I argue that the hourly wage is the variable that best describes the differential in wages across sectors and I point out some issues that may occur with the aggregate data for the hours per worker. In the next section I will describe the relevance of heterogeneity to properly describe the data. The changing occupational composition in the economy and the adjustment of both sectors to improvements in technology and consequent appearances and disappearances of occupations can be one of the main factors that explains the aggregate public sector wage premium. In particular,

I relate my descriptive results with the widely consistent “wage concentration” result and I describe three novel empirical facts in this literature.

4.3 Importance of Occupational Composition.

Analyzing just the public sector wage differential for the average worker in the economy wildly oversimplifies the dimension of the problem at stake. The fact is that workers are heterogeneous. Not everyone can be a professional football player, an engineer, a carpenter, a teacher, etc.; According to each individual’s skills and interests, each person chooses a set of possible occupations they can perform and their desired career paths. The labor market behavior incorporates these workers’ decisions with the employers’ hirings and firings decisions and determines which actual jobs these workers end up doing. This implies that the worker chooses at an earlier stage her career prospects and occupational category they want to work for and only after this decision she chooses the sector she intends to work for. The occupational categories I define are broad enough to account for the workers’ career prospects that could possibly bias the analysis. For example, the occupational category defined as “Protective Services” includes the “Police and Sheriff’s Patrol Officers” but also the “Bailiffs” and the “First-Line Supervisors/Managers of Police and Detectives”. This implies that the definition we are using for an occupational category can capture both the occupation the workers have at a given point in time and also their career progression expectations over time. On the employer side, we observe that the employers first understand for which position and tasks they need to post vacancies and then who are the best people to fill those vacancies from all the individuals that have applied to the position.

In this section I will introduce some facts that shed the importance of occupational composition when comparing the wages and salaries of the workers in the public sector with respect to their private sector occupational counterparts. I will consider

the labor market equilibrium outcome for the public and private sector wages and employment and I will show that the public sector wage differential is very connected with the occupational composition of each sector. I connect these results with the “routinization” approach proposed by Autor et al. (2003) and developed in Goos and Manning (2007), Goos et al. (2009) and Acemoglu and Autor (2011), by aggregating the major occupation categories by tasks and specific skills into (non-)routine manual and cognitive occupations. However, before doing so, I will show that the results considered in the previous section hide a considerable heterogeneity in the public sector wage differential. In particular, for the individuals that are for each sector on the left tail of their sector’s wage distribution, the public sector wage premium is much higher than what we expected from the analysis above. On the other hand, for the individuals that are in the right tail of their sector’s wage distribution, we cannot argue that there is a public sector wage premium since the differential is not always positive. This is an illustration of the so-called “wage concentration” result, which argues that the public sector wage distribution is more concentrated than the private sector wage distribution⁷.

In order to show the implications of the wage concentration result I define the hourly wage for an individual i on a sector $k \in \{G, P\}$ at a year t as $(w/H)_{i,t}^k$. For an individual that is on a percentile $x\%$ of her sector’s wage distribution the hourly wage is defined as $(w/H)_{x\%,t}^k$. Then, we can construct the public sector (hourly) wage differential for a given percentile $x\%$ as

$$\text{Wage}_{x\%,t}^{\text{h,D}} = \left(\frac{(w/H)_{x\%,t}^G}{(w/H)_{x\%,t}^P} - 1 \right) \times 100\% \quad (4.4)$$

⁷ The “wage concentration” result appeared first in the work of Poterba and Rueben (1994). For a more recent application check Melly (2005). For any interested reader in the literature of the public sector wage differential I would recommend the very comprehensive survey by Gregory and Borland (1999).

Figure 4.3 uses the CPS data from 1980 to 2013 to look at the time series behavior of the public sector wage differential for the average worker and for the workers that lie on the percentiles 25%, 50%, 75% and 90% of each sector's wage distribution. This illustration is in accordance with the "wage concentration" result and clearly show why it is so important to consider the heterogeneity across workers to better understand the differences in the wages paid on both sectors. In particular, it shows that the public sector wage differential is negatively related with the position the individuals are in their corresponding sector's wage distribution at each point in time. The workers that earn the lowest labor wages are better paid in the public sector than in the private sector and the workers that earn the highest labor wages are better paid in the private sector. The dynamics for the public sector wage differential are quite similar across the distribution percentiles considered and also for the mean value. The wage differential increased during the 1980s and beginning of the 1990s, it decreased until the 2000s and then it kept roughly constant until 2013. The relative similar time series paths for the public sector wage differential across all percentiles and the average worker lead us to believe that we can focus on the cross section side. I will confirm the robustness of my analysis by considering the cross-occupational facts over several different time periods.

There is also a considerable heterogeneity in the public sector wage differential. By considering just the relationship between the wages for both the public and private sectors for the average worker, we would believe the public sector hourly wage differential to be a wage premium and to lie between around 3% in 1983 to 16% in 1995. On the other hand, by considering the public sector wage differential for the workers in these different percentiles of their corresponding wage distributions we see the public sector wage differential to span from -5% to roughly 35%, magnifying the range considered for the mean. The main message is that the workers that are on the left tail of their corresponding wage distributions are better off monetarily in the

public sector rather than in the private sector. On the other hand, the workers that are on the right tail of their corresponding wage distributions can be better off both in the private sector or in the public sector, because the wage difference is relatively small.

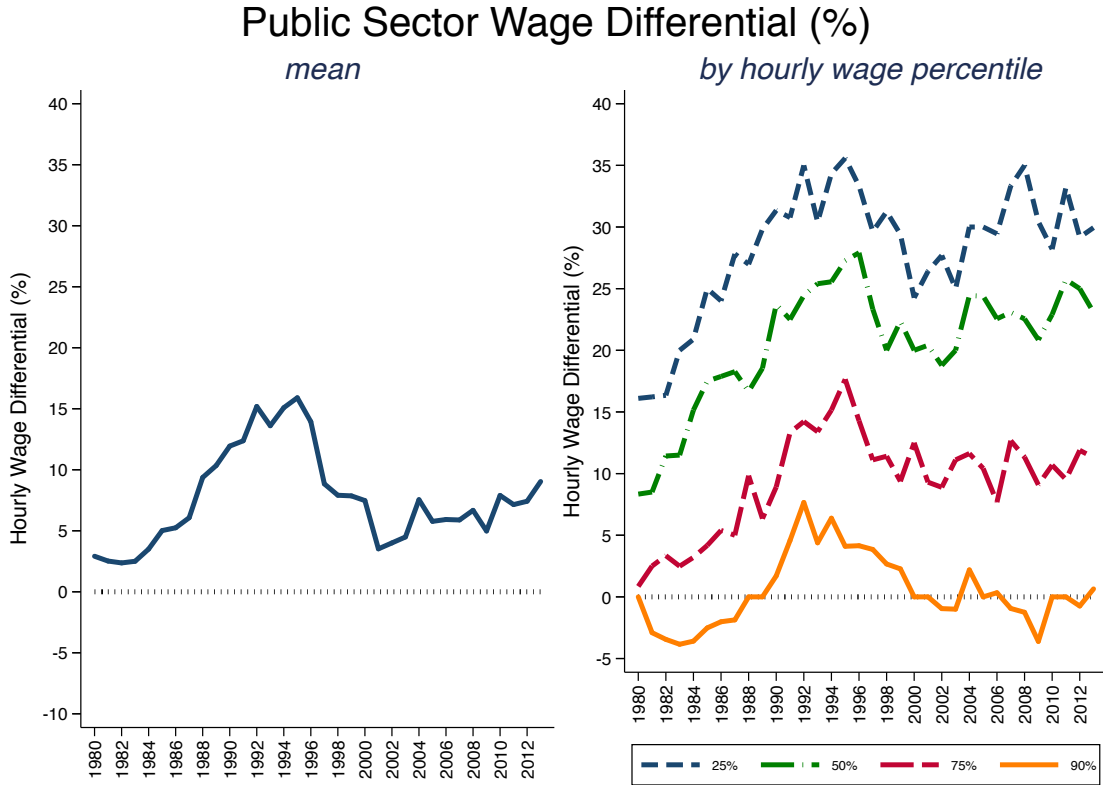


FIGURE 4.3: Public Sector Hourly Wage Differential: March CPS (1980-2013)

These results lead us to believe that the public sector pays in fact a higher compensation to their workers than does the private sector, since only at the 90% percentile we see a negative public sector wage differential for some time periods. Given the higher job security and non-compensatory benefits (such as better retirement benefits or better health insurance) provided to the workers in the public sector, it is puzzling to observe the public sector to give such a higher monetary compensation to their employees in comparison to the employees in the private sector that are on

the same quantile in their own distribution. The literature justifies this fact by arguing that the empirical evidence shows that public sector workers are more highly educated, work in occupations that are more highly paid and are older and more experienced in the labor market than the private sector workers⁸.

Therefore, there are two possible channels to explain this fact: or (i) the public sector has a higher share of workers to work in higher compensation occupations with respect to the share of private sector workers in these occupations; or (ii) the higher compensation occupations are better paid in the public sector than in the private. This would imply occupational composition both in terms of employment shares and relative wages to be crucial in testing the existence of a public sector wage premium and structuring the main drivers of a public sector wage differential and the relation between the public sector and the private sector. Therefore, I check if there is a relationship between the public sector wage differential and the occupational composition of the economy. To do so, I aggregate the individuals in the CPS dataset by major occupational categories, applying the same filters described in the previous section. I also aggregate the occupational data in CPS according to the major occupational categories defined according to the SOC 2000 classification.

In Figure 4.4, I define the major occupational categories according to the SOC 2000 classification and plot the public sector wage differential with respect to the value the private sector attributes to the average in each occupational category, measured by the hourly wage paid by the private sector to that average worker. The marker size reflects the public sector labor market share for the occupations considered and the hourly wages for both the private and public sectors are defined for all time periods in 2010 US dollars. Figure 4.4 shows the existence of a negative

⁸ Check for example Bender and Heywood (2010) note and the Bewerunge and Rosen (2012) mimeo. This branch in the literature tries to assess the monetary value of the non-compensatory benefits to estimate total compensation differentials across sectors. Their work is complementary to mine in the sense that it provides evidence to describe an additional channel that can alter the decision of an individual to work in the private or in the public sector.

Public Sector Wage Differential by Major Occupational Categories

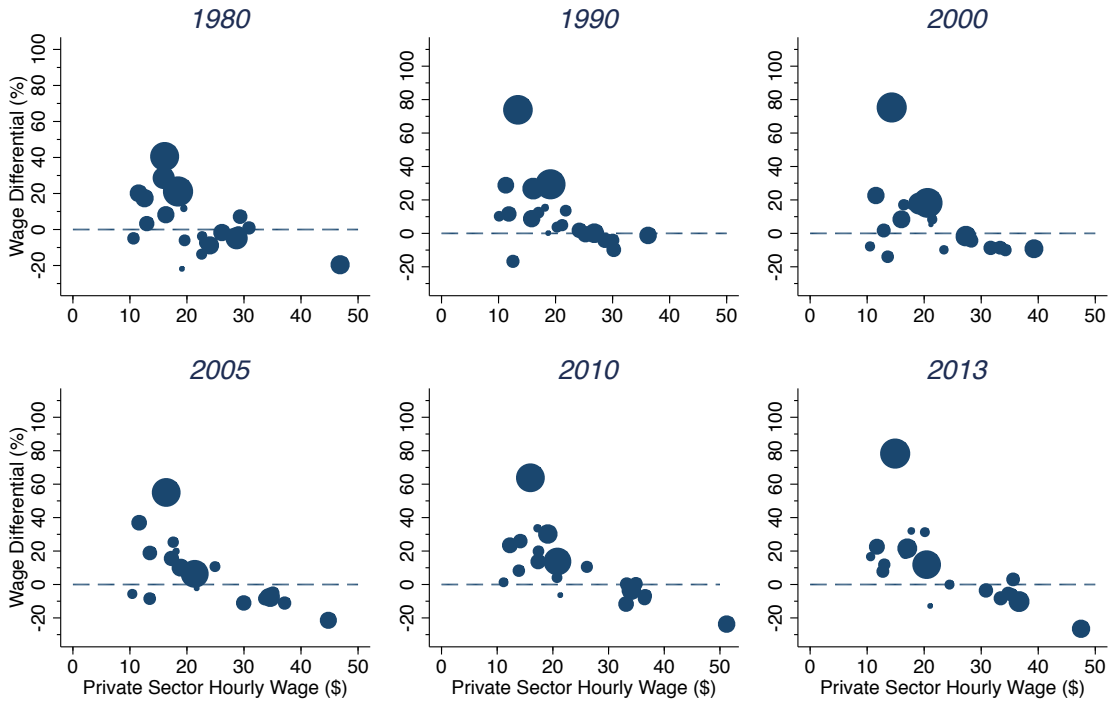


FIGURE 4.4: Occupational Composition and the Public Sector Wage Differential.

relationship between the private sector wage of a given occupation category and the public sector wage differential for that category⁹. For occupation categories that are less valued in the private sector we observe a public sector wage premium and for the occupation categories that are more valued by the private sector we observe a higher public sector wage penalty.

The main message that can be taken is that for the average worker in each occupation category we observe that the higher the private sector values that occupation,

⁹ I link the value of an occupation category for both sectors using the private sector hourly wage as the main anchor. Since the public sector provides mostly public goods, the absence of a competitive market and the existence of the free rider problem make the measurement of the public sector worker marginal productivity to be unclear. For example, Groves and Ledyard (1977) model the private sector using competitive markets and the public sector using the information communicated from the consumers to the government about their preferences as the main driver in the government decision. The valuation problem for the public sector worker wage needs to be addressed properly when modeling the labor market to match the empirical evidence for both sectors.

the lower the public sector values it. This implies that there is a relatively high wage income substitutability between these two sectors across occupation categories. This result is robust for all the time periods but it seems to be more accentuated from 1990 onwards, with a larger dispersion in the private sector valuation for the high compensation occupations. The robustness of this result across different time periods and data sources¹⁰ allow me to establish as a fact this finding.

Fact 1 (Negative Monotonicity). *The public sector wage differential for the average workers in a given occupation category is decreasing across occupations in the hourly wage of the average private sector worker. This finding is robust across time and for different percentiles in the wage distribution.*

Taking as an example the year of 2013 and analyzing Figure 4.4 more carefully let us understand that public sector wage differential for the average worker in a given major occupational category has a higher range than the one considered above for the wage distribution percentiles in each sector. Using this structure, the public sector wage differential lies between a penalty of around 30% to a premium of around 80%. The maximum wage premium observed (78%) belongs to the average worker for the Protective Service occupations and the highest penalty (26%) to the average worker for the Legal occupations. Fact 1 lead us to expect an occupation category less valued by the private sector to have a higher public sector wage premium and a category that is more highly valued by the private sector to have a lower wage premium (or alternatively, a higher public sector wage penalty). Thinking of the

¹⁰ I have applied the same approach to the Occupational Employment Statistics (OES) from the BLS for the years 2012 and 2013 and Fact 1 is also robust in this dataset for these years. I chose not to present the graphical results here since they would be a repetition of the findings presented for the March CPS and this dataset is less detailed than the CPS. The OES dataset is gathered through a semiannual mail survey in which roughly two hundred thousand establishments are surveyed per panel. Each establishment is surveyed at most once every 3 years, summing up to a total of one million and two hundred thousand different establishments. The data is then yearly updated to include all the information from all the establishments. The level of disaggregation in the OES dataset is quite high, differentiating up to 800 occupations, 450 industries and geographical areas up to metropolitan areas.

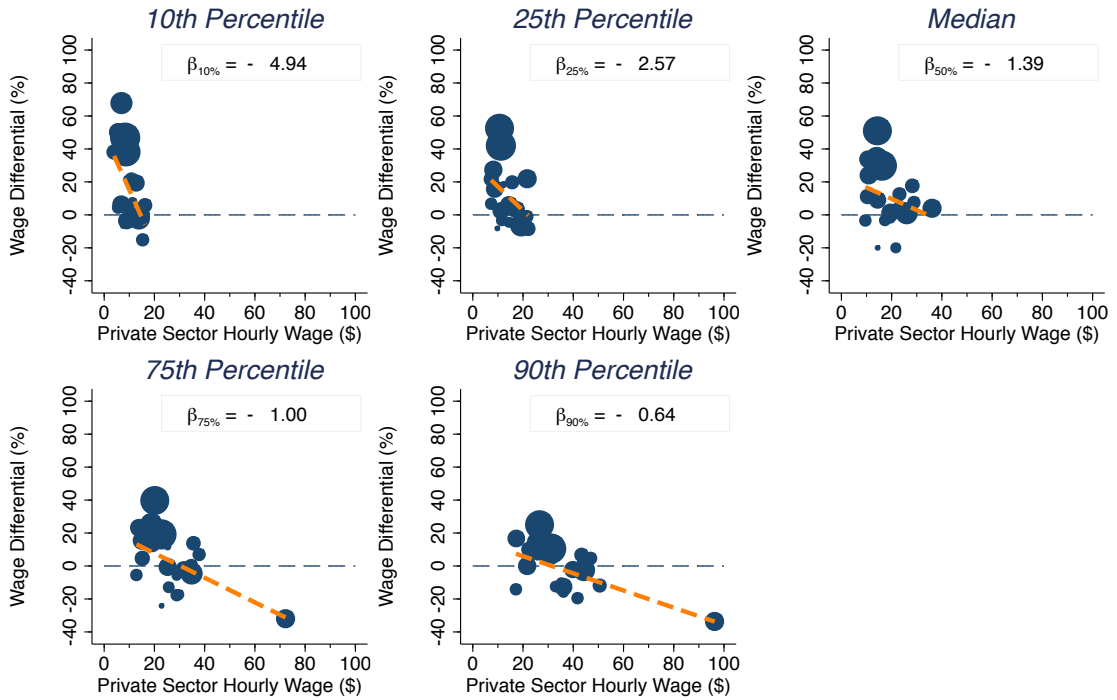
public sector wage differential as a decreasing function on the private sector hourly wage reveals a meaningful substitution effect across sectors.

It is important to differentiate Fact 1 from the “wage concentration” result. Although similar in spirit, these two empirical facts differ in their nature. The higher wage concentration in the public sector lead us to expect a higher (lower) public sector wage differential for the workers that are on lower (higher) quantiles of their respective wage distribution when compared to a worker on the same quantile in the other sector’s wage distribution. It is therefore a result about the wage distributions on both sectors, in which the public sector wage differential is negatively related to the relative position the worker is on her sector’s wage distribution, if sorted from the lowest to the highest wage. On the other hand, Fact 1 shows that the public sector wage differential is negatively related to the value attributed by the private sector to an hour of labor of the average worker in a given occupation category. It is therefore an argument that relates the study of the public sector wage differential with the economy’s occupational composition and relative importance of the public sector for each occupational category.

To extend Fact 1 to different positions in the wage distribution I sort the workers in each occupational category by their wage and I construct the public sector wage differential for these workers. Define the hourly wage for an individual i working on occupation category j on a sector $k \in \{G, P\}$ at a year t as $(w/H)_{i,j,t}^k$. The hourly wage for an individual that is on a percentile $x\%$ is defined as $(w/H)_{x\%,j,t}^k$. Then, we can construct the public sector (hourly) wage differential for the worker that is on the percentile $x\%$ for the wage distribution of occupation j and sector k in a year t as

$$\text{Wage}_{x\%,j,t}^{\text{h,D}} = \left(\frac{(w/H)_{x\%,j,t}^G}{(w/H)_{x\%,j,t}^P} - 1 \right) \times 100\% \quad (4.5)$$

Public Sector Wage Differential (1980) by Major Occupational Categories



Public Sector Wage Differential (2013) by Major Occupational Categories

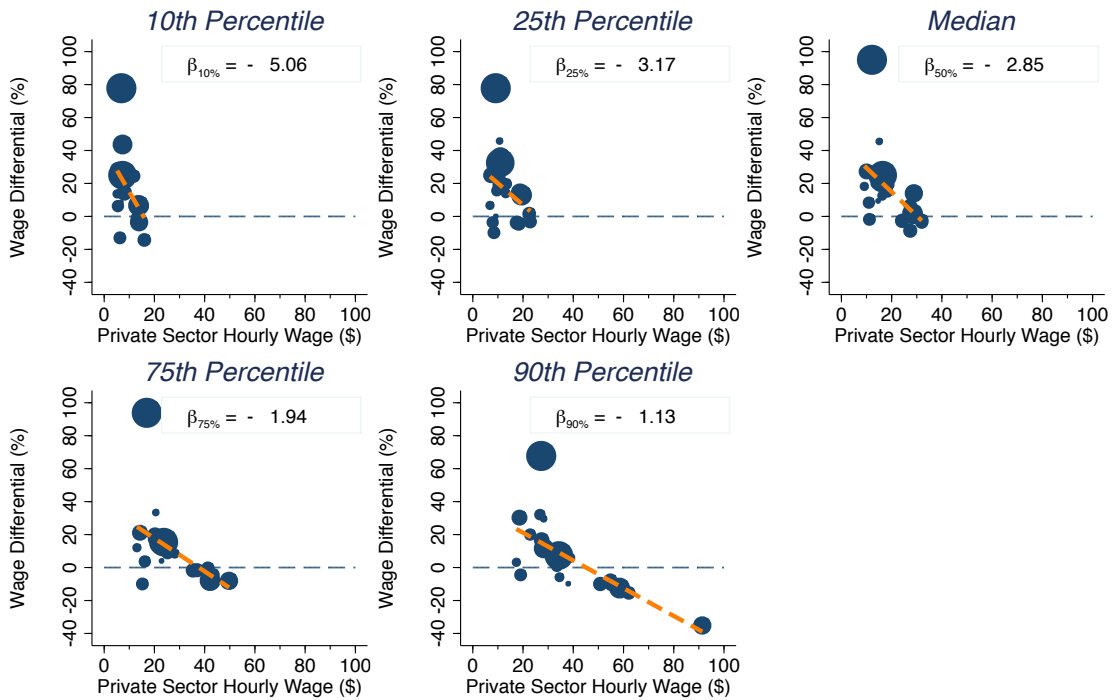


FIGURE 4.5: Public Sector Wage Differential by Major Occupational Categories

In Figure 4.5, I present some empirical evidence that relates the public sector wage differential with the private sector hourly wage for workers sorted into major occupational for the years 1980 and 2013. In particular, I consider the wages for the workers that are on the percentiles 10%, 25%, 50%, 75% and 90% of their corresponding wage distributions. The marker size reflects the public sector labor market share for the occupation categories considered. The orange dashed line represents the fitted values of a weighted regression that have as dependent variable the wage differentials and as independent variables a constant term and the private sector hourly wage. The weights are defined by the public sector employment share for each occupation category and so, they measure the relative public sector expression in the labor market for these occupation categories. The value for β that appears in each panel is the coefficient of the private sector hourly wage on the public sector wage differential in this weighted regression. The value of β is highly statistically significant for all percentiles and for both year considered, being the t-statistic associated to these coefficients always more negative than -2.62, with an associated p-value below 1.8%. Intuitively, β measures how much do we expect the wage differential to change in percentage points if we consider an occupation category that has a private sector valuation of an additional US dollar, keeping everything else constant.

The first idea that pops up from the analysis of Figure 4.5 is that the public sector wage differential is decreasing across occupations in the hourly wage valuation attributed by the private sector to the workers in these occupations for all the percentiles considered and for both the year 1980 and 2013. This strengthens the results synthesized in Fact 1, since it allows an extension of the result considered for the average worker in each occupation category and each sector to workers in completely distinct positions in their corresponding wage distributions. This result can also be observed by checking that $\beta_{x\%}$ is negative. That is, by checking that the coefficient on the impact of the private sector hourly wage on the public sector wage differential for

the workers that are in the percentile $x\%$ in their occupational wage distributions is negative. This implies that we expect the public sector wage differential to be higher (lower) for occupation categories that have a low (high) private sector valuation, keeping everything else constant. Interestingly enough, the absolute value of $\beta_{x\%}$ decreases as we consider higher percentiles in the occupational wage distribution for both sectors. This implies a relatively large variation in the public sector wage differential with respect to the private sector hourly wage valuation for the workers that are on lower percentiles in their corresponding sector-occupation wage distribution, and a relatively smaller variation in the public sector wage differential with respect to the private sector hourly wage valuation as we consider workers that are in higher percentiles (that are more highly paid) in their corresponding sector-occupation wage distribution.

On the cross-occupational side two occupation categories should be mentioned separately from the remaining ones given their intrinsic labor market characteristics across sectors: the Protective Services occupations and the Sales and Related occupations. The former is mainly concentrated in the public sector, with a public sector market share of 73.7% and the largest public sector wage premium in 2013 for all percentiles considered. The latter has a very small labor market expression in the public sector, being the public sector share around 1.5%, and it has a high public sector wage penalty (of almost 13% for the average worker in 2013) considering the low hourly wage that the private sector is paying to the average worker in this occupation category (around 21 dollars). The fact that these occupation categories are so concentrated in one of the sector magnifies the public sector wage premium or penalty to be higher than what we would otherwise expect. This happens because one of the sectors specializes in services that use these occupation categories and the other does not need many workers in those occupations. This generates the issue of analyzing comparable workers across sectors.

For the remaining occupation categories in 2013, we observe large public sector wage premiums for Education, Training, and Library; for Community and Social Services; for the Production; and for the Construction and Extraction occupations. It is not surprising that the Education, Training, and Library category and the Community and Social Services category have larger public sector wage premiums. The former set of occupations are a textbook case for labor union coverage and collective bargaining agreements that increase both the salaries and the benefits of the majority of the workers in these occupations. The later set of occupations provide services that increase the well-being of citizens in the community they are inserted and these services are usually provided by public entities or non-profit entities that may or may not be subsidized by the government. However, there is (still) no apparent reason in the inherent characteristics of each set of occupations that would explain the Production and the Construction and Extraction occupations to have high public sector wage premiums. However, notice that these occupations have in common the fact that they share the same sets of skills and tasks. In the literature developed by Autor et al. (2003), they are defined as non-routine manual occupations. On the other hand, we observe lower public sector wage differentials (and even public sector wage penalties) for the Legal; Healthcare Practitioners and Technical; Life, Physical, and Social Sciences; Management; Business and Financial Operations; and Computer and Mathematical occupations to name a few. Again, these occupations have in common the fact that they require similar skills and tasks, being considered non-routine cognitive occupations.

In fact, there is a large similarity on the public sector wage differentials across some specific occupations that can be defined according to their necessary set of skills and tasks. This leads me to follow the literature on the routinization approach to explain the impact of occupational composition in the determination of the public sector wage differential. This approach has been very successful in providing answers

to questions like the determinants of the recent technological change (in Autor et al., 2003) and the disappearance of the routine jobs as the main cause of the recent jobless recoveries (Jaimovich and Siu, 2014). Therefore, I aggregate these major occupation categories according the “routinization hypothesis” proposed by Autor et al. (2003) and developed by Goos and Manning (2007), Goos et al. (2009) and surveyed in Acemoglu and Autor (2011). In particular, I follow the aggregation procedure used in Jaimovich and Siu (2014). The Non-Routine Cognitive Occupations (NRC) category comprises all the workers that are in the Management; Business and Financial Operations; Computer and Mathematical; Architecture and Engineering; Life, Physical and Social Sciences; Community and Social Service; Legal; Education, Training, and Library; Arts, Design, Entertainment, Sports and Media; and Healthcare Practitioners and Technical occupations. The Routine Cognitive Occupations (RC) category contains all the workers in Sales and Related and Office and Administrative Support occupations. The Routine Manual Occupations (RM) category includes all the workers in Production; Transportation and Material Moving; Construction and Extraction and Installation, Maintenance, and Repair occupations. Finally, the Non-Routine Manual Occupations (NRM) category comprehends the workers in Healthcare Support; Protective Service; Food Preparation and Serving Related; Building and Grounds Cleaning and Maintenance; and Personal Care and Service occupations.

The public sector hourly wage premium for the average worker in each sector was constructed by comparing the hourly wage of the public sector average worker with the hourly wage of the average worker in the private sector. We can decompose this relative wage across sectors to account for the occupational heterogeneity after separating the workers by their occupation category. In particular, let $(w/H)^k$ be the hourly wage for the average worker in sector $k \in \{G, P\}$ and N^k to be the total employment in each sector. For an occupation $j \in \Gamma \equiv \{NRM, RM, RC, NRC\}$

define the hourly wage for the average worker in occupation j and sector k to be $(w/H)_j^k$ and N_j^k to be the total employment for occupation j in sector k . Using these definitions, we have that the relative hourly wage for the average public sector worker in relation to the average private sector worker can be deconstructed as

$$\frac{(w/H)^G}{(w/H)^P} = \sum_{j \in \Gamma} \left[\frac{(w/H)_j^G}{(w/H)_j^P} \cdot \frac{(w/H)_j^P}{(w/H)^P} \cdot \frac{N_j^G}{N^G} \right] \quad (4.6)$$

where the first term reflects the hourly wage differential for the average worker in the public sector with respect to the average worker in the private sector. The second term reflects the relative ratio between the private sector hourly wage for the average worker in occupation category j with respect to the average private sector worker. Finally, the last term reflects the occupational composition for the public sector by presenting a weighting term that yields the relative importance of occupation j in the public sector employment. This term tells us that the employment share of each occupation j is also important for the dynamics of the public sector hourly wage differential. The second term in equation (4.6) hides also the important of the occupational composition for the private sector employment in determining the public sector average hourly wage premium. Intuitively, $(w/H)^P$ can be defined as a weighted average of the private sector hourly wage per occupation, weighted by the employment share this occupation has on the private sector employment

$$(w/H)^P = \sum_{j \in \Gamma} \left[(w/H)_j^P \cdot \frac{N_j^P}{N^P} \right] \quad (6\star)$$

implying that we end up with four different mechanisms that can affect the public sector hourly wage differential for the average worker when we consider the occupational heterogeneity as the main decomposition factor: (1) the public sector hourly

wage differential for the average worker in each occupation category; (2) the private sector hourly wage valuation of each occupation category; (3) the private sector occupational composition of employment; and (4) the public sector occupational composition of employment.

Figures 4.6 and f:ch3f7 present the empirical evidence that allows the identification of the contribution for each factor described in (4.6) and (6★) to the dynamics of the public sector hourly wage differential between the average workers in each sector. In particular, Figure 4.6 reports the relationship between the public sector wage differential and the private sector hourly wage for the occupation categories defined by the (Non-)Routine Manual/Cognitive Occupations for all the years in the sample (1980 to 2013). Figure 4.7 top panels describe the public sector hourly wage for the average workers in each sector and the public sector hourly wage differential for the average workers each occupation category for each sector. The bottom panels show the occupation employment composition for each sector. The orange solid line and the orange triangles represent the average worker in Non-Routine Manual Occupations (NRM). The red long-dashed line and squares represent the average worker in Routine Manual Occupations (RM). The green dashed-dotted line and rhombi represent the average worker in Routine Cognitive Occupations (RC). Finally, the blue dashed line and circles represent the average worker in Non-Routine Cognitive Occupations (NRC).

Figure 4.6 relates the public sector hourly wage differential for the average worker in each occupation category to the private sector hourly wage valuation of each occupation category. The public sector wage differential for the years 1980 to 2013 and more aggregate occupation categories is decreasing in the private sector hourly wage valuation of these occupations' average worker as it was before for the major occupational categories defined according to the SOC 2000. This implies Fact 1 to be robust to this more aggregate occupation classification.

Public Sector Wage Differential: 1980-2013

(Non-)Routine Manual/Cognitive Occupations

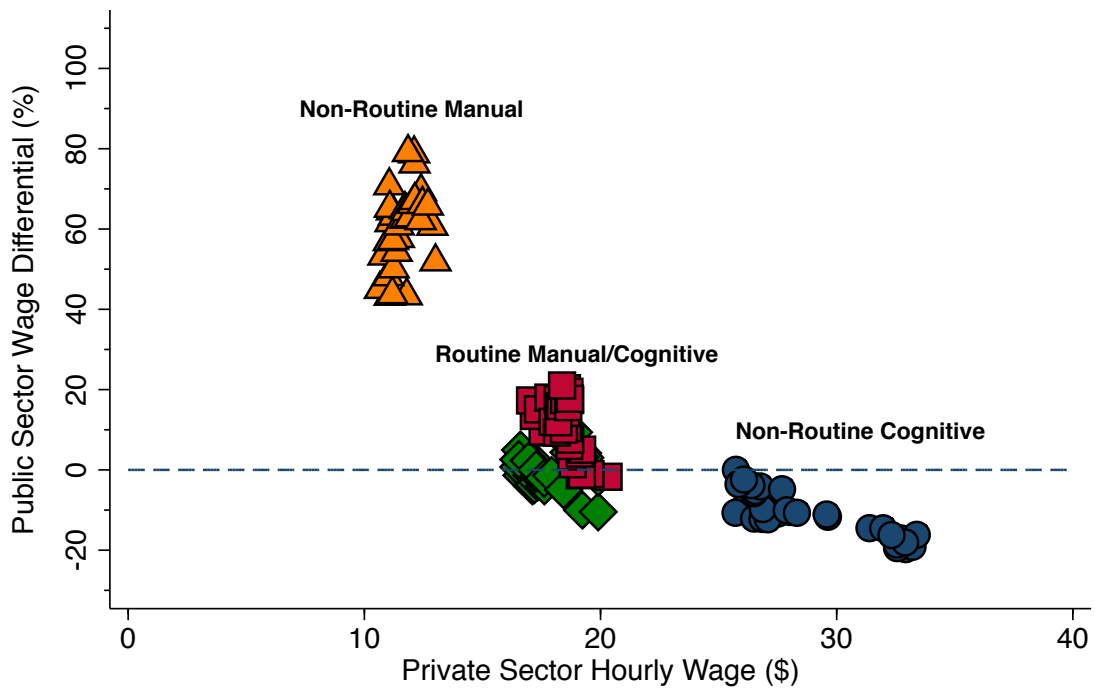


FIGURE 4.6: (Non-)Routine Manual/Cognitive Occupations: Wage Differential Decomposition.

There is also a certain labor market polarization for the public sector wage differential. The Non-Routine Manual Occupations are characterized by having a very high public sector wage differential and a low private sector hourly wage. The Non-Routine Cognitive occupations are on the other hand characterized by a negative public sector wage differential and a very high private sector hourly wage. For this set of occupations, I would like to stress the positive bias in the public sector wage differential created by the Community and Social Service occupations. Accounting for the inherent characteristics in these occupations we would find that the Non-Routine Cognitive occupations would have a much lower (higher) public sector wage differential (penalty). The average workers in Routine Manual/Cognitive occupations have a similar relationship between the public sector wage differential and the

private sector hourly wage. There is a polarization in the labor market for the public sector wage differential because non-routine occupations are both in the high public sector wage differential / low private sector hourly wage (for the manual occupations) or in the low public sector wage differential / high private sector hourly wage (for the cognitive occupations) positions. On the other hand, the routine occupations for both manual and cognitive skills and tasks have a middle public sector wage differential and a middle private sector hourly wage valuation. These results are summarized in Fact 2 that states the existence of a public sector wage differential polarization in the economy.

Fact 2 (Public Sector Wage Differential Polarization). *There is a public sector wage premium for low-skill, low-wage occupations (NRM) and a public sector wage penalty for high-skill, high-wage occupations (NRC). For the middle wage occupations (RC, RM) the difference between the public and private sector hourly wages is positive but moderate.*

A closer inspection to the public sector wage differential polarization result with respect to the hourly wage valuation attributed by the private sector to the routine occupations uncovers the fact that manual occupations have for the average worker higher public sector wage differentials than cognitive occupations. In particular, sorting the occupation categories from highest public sector wage premium to the largest public sector wage penalties we would have first the Non-Routine Manual occupations, then the Routine Manual, the Routine Cognitive and finally the Non-Routine Cognitive occupations. This implies that the polarization result stated in Fact 2 has two different small-scale results attached. On the one hand, Non-Routine Occupations are polarized in the sense that they have the lowest and highest private sector hourly wage valuation in the labor market. This implies that Routine occupations are the middle wage jobs in the economy. On the other hand, the Manual occupations

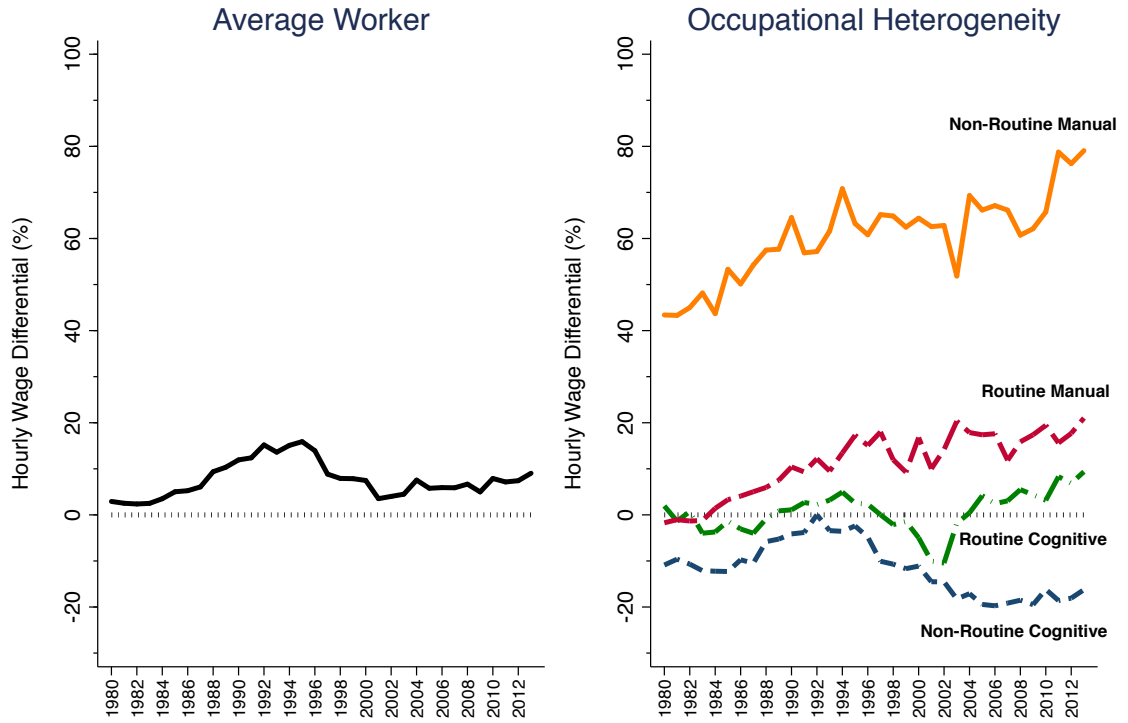
have larger public sector wage premiums than the Cognitive occupations.

Figure 4.7 analyzes the importance of the employment occupational composition for both the private and public sectors and the dynamic evolution of these employment shares and of the public sector wage differential over time. The heterogeneity present for the public sector wage differential for the average worker for the different occupations is high enough for it to be one very important channel in explaining the dynamics of the aggregate public sector wage premium. On the other hand, the occupations that are have a higher (lower) public sector wage differential are the ones that have the lower (higher) hourly wage in the private sector. This implies that the employment composition for each sector is also a key factor in determining the aggregate public sector wage differential.

The Public Sector Wage Differential Polarization fact summarizes the relationship between the public sector hourly wage differential for the average worker in each occupation category and the private sector hourly wage valuation of each occupation category. However, it keeps silent about the fact that the employment occupational composition for both the private and public sector can affect the public sector aggregate wage premium as shown in (4.6) and (6★) and its relationship with the public sector wage differential in each occupation. Figure 4.7 shows the evidence to explicitly analyze these channels.

Given the importance of the occupational employment composition for each sector in the determination of the aggregate public sector wage differential, it is straightforward to relate this literature with the growing trend (both in the empirical evidence and in the literature) of “Job Polarization”. The shrinking concentration of employment in Routine occupations and the increasing trend in the concentration of employment in Non-Routine occupations extends not only to the private sector but also to the public sector. However, the magnitudes of these variations across sectors can have very distinct effects to the public sector wage differential. Job Polarization

Public Sector Wage Differential: 1980-2013



Occupational Composition: 1980-2013

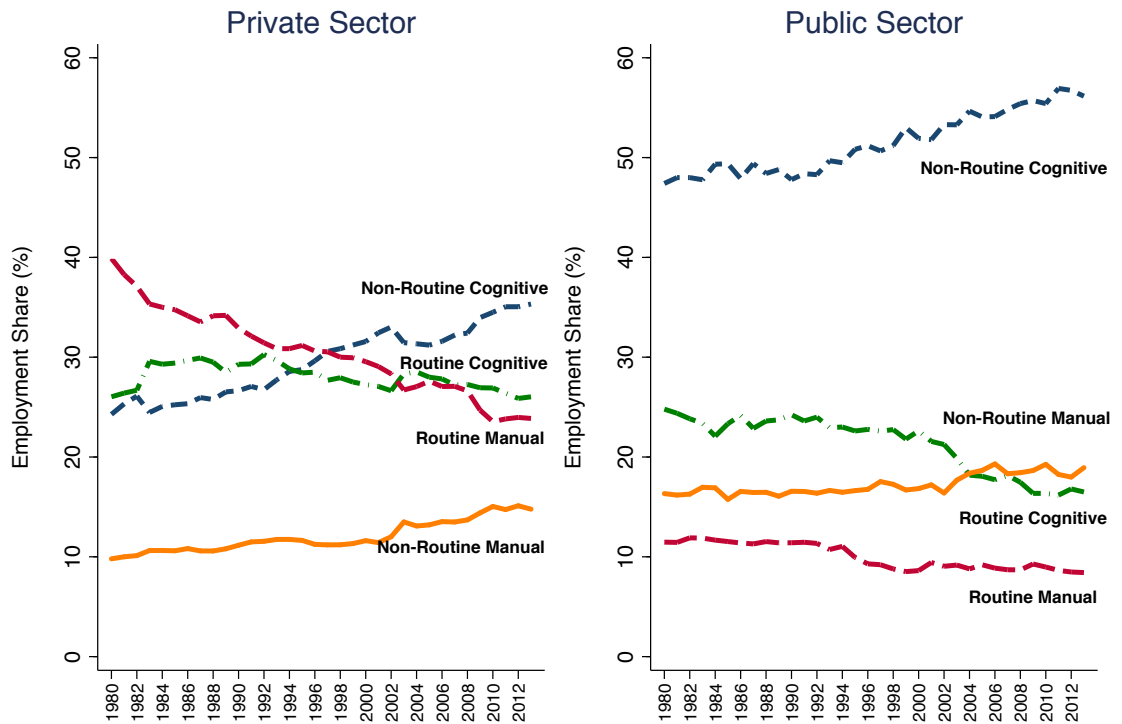


FIGURE 4.7: Wage Differential and Labor Composition by Occupational Category.

implies that the Routine employment is decreasing over time in the entire economy. Figure 4.7 shows that it is actually the case for the occupational employment composition for each sector in this analysis.

We observe a decrease in the employment share for Routine occupations in both sectors. There is a larger decrease in the Routine Manual occupations in the private sector, passing from roughly 40% of the employment in this sector in 1980 to around 24% in 2013. In the public sector this reduction is not as expressive, since there is only a decrease from an employment share in this sector of 11.5% in 1980 to an employment share of 8.4% in 2013. On the other hand, there is a larger variation in the employment share for Routine Cognitive occupations in the public sector, decreasing from an employment share of 25% in 1980 to 16.5% in 2013. In the private sector, there is virtually no change in the employment share of routine cognitive occupations between 1992 and 2013, being around 26% for both time periods. In fact, there was an upward swing in the Routine Cognitive occupations from 1980 to 1992, with a maximum of an employment share of 30%, and a downward swing from 1992 to 2013. Therefore, we can argue that the shrinking of Routine occupation employment affected each sector in a different way. The share of workers in Routine Manual occupations has decreased considerably in the private, while in the public sector the largest reduction was in the Routine Cognitive workers.

This immediately implies that the Non-Routine employment must be increasing over time. The Routine occupations were responsible for around 66% of the total employment in the private sector and 35.5% in the public sector in 1980. In 2013, they had in the private sector an employment share of 50% and in the public sector a share of 25%. For the Non-Routine occupations, we need to consider separately the two poles: the NRM and NRC occupations. The Non-Routine Manual employment share is increasing slightly over time for both the private and public sectors. The employment share of the NRM occupations has increased for the private sector from

Table 4.3: Public Sector Hourly Wage Differential Decomposition: 1980 vs 2013.

(1) PUBLIC SECTOR WAGE DIFFERENTIAL: AVERAGE WORKER (%)

Year	NRM	RM	RC	NRC
1980	43.4%	-1.7%	1.9%	-10.9%
2013	79.0%	21.0%	9.4%	-16.2%

(2) PRIVATE SECTOR HOURLY WAGE: AVERAGE WORKER (\$ 2010)

Year	NRM	RM	RC	NRC
1980	11.8	20.3	17.2	27.5
2013	11.8	18.4	18.9	32.3

(3) OCCUPATIONAL EMPLOYMENT COMPOSITION: PRIVATE SECTOR (%)

Year	NRM	RM	RC	NRC
1980	9.8%	39.9%	26.0%	24.3%
2013	14.8%	23.9%	26.0%	35.3%

(4) OCCUPATIONAL EMPLOYMENT COMPOSITION: PUBLIC SECTOR (%)

Year	NRM	RM	RC	NRC
1980	16.3%	11.5%	24.8%	47.4%
2013	18.9%	8.4%	16.5%	56.2%

9.8% in 1980 to 14.8% in 2013, and for the public sector from 16.3% in 1980 to 19.0% in 2013. The largest movements in this occupation category are in the public sector wage differential, that is increasing considerably over time from 43.4% in 1980 to 79.0% in 2013. On the other hand, for the Non-Routine Cognitive occupations we can observe a considerable increase in the employment share for both the private and public sectors. In the private sector, 24.3% of all employment in this sector in 1980 belonged to NRC occupations, while 47.4% of the total employment in the public sector was also directed to NRC occupations. In 2013 the relevance of NRC occupations increased for both sectors. In the private sector the employment share is 35.3% and in the public sector it is 56.2%.

Table 4.3 compares the aggregate public sector hourly wage differential decom-

position factors described above in (4.6) and (6★) for the years 1980 and 2013. It also supports the evidence in Figure 4.6 and Figure 4.7 by providing the actual values across time periods. The evidence provided in Figure f:ch3f7 and synthesized in Table 4.3 allow the importance of occupational composition to the determination of the aggregate public sector wage premium to be seen as an empirical fact.

Fact 3 (Occupational Composition and Job Polarization). *The occupational composition across sectors has an important effect on the aggregate public sector hourly wage premium. The private sector is more concentrated towards middle wage jobs, with the Routine jobs employment share being 65.9% in 1980 and 49.9% in 2013. On the other hand, the public sector is more concentrated towards Non-Routine jobs, with the NRC jobs employment share being 47.4% in 1980 and 56.2% in 2013, and with the NRM jobs employment share being 16.3% in 1980 and 18.9% in 2013.*

The different occupational compositions across sectors are important to differentiate what is the contribution of the public sector wage differential for the average workers in each occupation category, and what is the contribution of the simple fact that one sector may be more concentrated to high wage, high skills occupations than the other. In particular, for the NRC occupations, we observe a public sector wage penalty, implying that for the same employment share in each sector, the NRC occupation workers are driving the aggregate public sector wage differential downwards. However, since the public sector has a higher employment share of workers in these occupations and since the NRC occupations are characterized by having a high wage, this will create an upward pressure in the aggregate public sector wage differential since the additional NRC workers in the public sectors would have been compared with workers in other lower wage occupation categories in the private sector. The opposite result occurs for the NRM occupations. If the employment shares in both sectors were the same, there would be an upward pressure in the aggregate public sec-

tor wage differential due to the fact that for the average worker in these occupations, the public sector worker earns 79.0% more than his private sector counterpart. However, since NRM occupations are low wage occupations, the higher concentration in the public sector of workers in these occupations would create a downward pressure in the public sector wage differential, since these workers would need to be compared with middle wage occupation workers in the private sector. The occupational composition of employment in each sector has therefore a major role in determining the aggregate public sector wage differential and should be considered alongside with the public sector wage differential for the average worker in each occupation category. Therefore, one cannot disregard the effects of Job Polarization in determining the aggregate public sector wage differential.

The descriptive analysis executed in this section accomplished one important objective. The public sector wage differential for the average workers in each sector can not be viewed as an informative statistic for policy analysis. When analyzing the differential in wages across sectors, the policy makers should look in particular to the occupational composition of both sectors. Three facts have been advanced here. Fact 1 argues that the public sector wage differential for the average worker in a given occupation category is decreasing across occupations in the hourly wage of the average private sector worker for those occupations. Fact 2 there is a polarization of the public sector wage differentials. In particular, there is a high wage premium for low-skill, low-wage occupations and a wage penalty for high-skill, high-wage occupations. For the middle wage occupations the difference between the hourly wages for the average worker in each sector is moderate. This polarization in the public sector wage differential opens the path to assess the relevance of occupational composition and job polarization to the determination of the average public sector wage differential. Finally, Fact 3 alleges that this occupational composition is an important channel that is creating a bias in the aggregate public sector wage differential. This

implies that one of the possible reasons for the existence of an aggregate public sector wage premium is the fact that the public sector employment is more concentrated in Non-Routine occupations. For the low-wage NRM occupations, the difference in the wages of both sectors are the main channel creating an upward pressure in the public sector wage differential. For the high-wage NRC occupations, there is a public sector wage penalty for the average workers in these occupations but since it is a high-wage occupation category, the higher employment share for the public sector creates an upward pressure to the aggregate public sector wage premium.

Interestingly enough, not much relevance has been given to the importance of considering the aggregate effects of occupational composition to the determination of the public sector wage premium. Up to my knowledge, this work is the first presenting the results described in Facts 1-3. For Fact 3, I am the first to reinforce the relationship between the public sector wage differential and the Job Polarization and to use the occupational classification for (Non-)Routine Manual/Cognitive occupations popularized in this to study the public sector wage differential. In the next section, I will make use of the full micro-level detail contained in the CPS dataset to understand what are the relative effects of demographics, occupational composition and propensities in the determination of the average public sector wage differential.

4.4 Oaxaca-Blinder Counterfactual Decomposition

The connection between the public sector wage differential for a worker in a given occupation and the private sector hourly wage valuation of that occupation that defined Facts 1-2 can only be established under some aggregation procedure. In the previous section I have employed an aggregation procedure that uses the information about the occupation category the individuals belong to. The usage of these occupation categories as an exogenous instrument to study the public sector wage differential is not something new in the literature. As surveyed in Gregory and Borland (1999),

public sector employment tends to be concentrated in professional and clerical jobs, and to require workers with relatively high levels of educational attainment. It is therefore surprising that not much relevance has been given to the aggregate implications that the occupational composition and job polarization can have on the aggregate public sector wage premium observed in the data.

In this section, I complement the findings described in the three facts above by performing some exploratory Oaxaca-Blinder Counterfactual Decompositions (OB). I assess the effect of occupational composition in the determination of the average public sector wage differential and in the likelihood of belonging to the public sector, after accounting for counterfactual variations in the demographics and propensities. Since the OB decomposition is performed using individual level data, it is impossible to establish a relationship between the public sector wage differential for a given category with the private sector hourly wage valuation of that category. Instead, I identify the effects in the determination of the average public sector wage differential that are due to changes in the occupational and demographic composition, and the effects that are due to unexplained variations in the labor market equilibrium determination of the average public sector wage differential or in the workers' propensities to make the decision to belong to the private or public sector. The identification of these mutually exclusive effects allows me to discuss the job polarization effect and the consequent importance of occupational composition to the determination of the public sector wage differential and to the likelihood of a worker to belong to the private or public sectors.

The Oaxaca-Blinder counterfactual decomposition for the mean and has been widely applied to both the public sector wage differential literature and the general labor economics literature that relies on counterfactual decompositions across different groups¹¹. The methodology in this section follows closely the specification

¹¹ I refer the interested reader to section 4 from Gregory and Borland (1999). For additional

recently proposed in Cortes et al. (2014), although for a completely different application. In particular, let $y_{i,j}$ to be defined as the natural logarithm of the hourly wages for individual i that belongs to group $j \in \{A, B\}$. The existence of just two groups is a necessary condition. In particular, suppose for the moment we consider group A to be given by the private sector workers and group B to be given by the public sector workers. Additional specifications can be considered. To study the effects of job polarization, one can also consider group A to be the pre-polarization time period and group B to be the polarization period. According to Cortes et al. (2014), I will define as the cutoff between the pre-polarization and the polarization period the year of 1990. This implies that in my specifications the pre-polarization period is defined as the 1980-1989 period and the polarization period is defined as the 1990-2013 period. To model the behavior of $y_{i,j}$ in the labor market consider the following linear model

$$y_{i,j} = X'_{i,j} \cdot \beta + \epsilon_{i,j} \quad (4.7)$$

notice that for the case where $y_{i,j}$ is a dummy variable, this is just a linear probability model. In this specification, $X_{i,j}$ is a vector of regressors that includes a set of demographic variables available in the CPS dataset such as a categorical variable to characterize the individuals' age for six different age bins (16-24, 25-34, 35-44, 45-54, 55-64 and +65 years old), a categorical variable that identifies the education level of the individual (high school graduate or lower, college graduate or some college, and higher education than a college graduate), a dummy variable for gender, a dummy variable for race (white vs. other races), and a categorical variable that describes the occupation category that the worker belongs to (NRM, RM, RC

examples of counterfactual decompositions to study the changes in the distribution of wages see Machado and Mata (2005) and Blundell et al. (2007). For a recent and very thorough survey on decomposition methods in economics, see Fortin et al. (2011).

or NRC occupations). For the baseline group I use the 45-54 years old, high school graduates or lower, white females as the omitted group in my specification. When the occupation category is not specified, I consider the routine cognitive occupations as the baseline. The OB decomposition then works with the estimated coefficients $\hat{\beta}$ in the linear model (4.7) to decompose variations in the average value for the dependent variable across groups A and B according to

$$\bar{y}_B - \bar{y}_A = \left(\bar{X}'_B - \bar{X}'_A \right) \cdot \hat{\beta}_B + \bar{X}'_A \cdot \left(\hat{\beta}_B - \hat{\beta}_A \right) \quad (\text{OB})$$

where \bar{y}_j represents the sample average of variable y for the workers in group j . The difference in the average values can be thought as the average public sector wage differential or the average likelihood gap for belonging to the public sector, depending whether I use the hourly wages or a public sector dummy variable as the variable of interest. It can be decomposed in two different components. The first term, given by $\left(\bar{X}'_B - \bar{X}'_A \right) \cdot \hat{\beta}_B$, is the component that can be attributed to changes in the demographic and occupational composition across the different groups. The second term, given by $\bar{X}'_A \cdot \left(\hat{\beta}_B - \hat{\beta}_A \right)$, represents the changes in the estimated coefficients $\hat{\beta}$ across the different groups. This term reflects the intrinsic labor market characteristics each sector has and cannot be explained by the different demographic and occupational compositions across groups.

I conduct first a battery of OB decompositions on the natural logarithm of the hourly wage for each worker in the sample, dividing the workers accordingly to whether they work in the public or in the private sector. The results are presented in Table 4.4. In this specification, group B represents the public sector workers and group A the private sector workers. Column (1) presents the decomposition for the entire sample, defined by the inclusion of all occupation categories for 1980-2013. Column (2) shows the results for the pre-polarization period (1980-1989) and Column (3)

for the polarization period (1990-2013), again considering all occupation categories. In columns (4)-(7) I disregard the categorical variable for the occupation categories and I run the OB decomposition for each occupation category. Finally, Columns (8)-(11) display for each occupation category the results for the pre-polarization period, and Columns (12)-(15) for the polarization period¹².

I present in each panel the average values for the natural logarithm of the hourly wage for both the public and private sectors, and the difference between both sectors as defined in (OB). I exhibit the contribution of the explained composition factors to this wage gap between the public and private sectors, as well as the contribution of the unexplained variations in the coefficients. I highlight the effects of composition changes in gender, education and occupation. I do not report the effects of the age categorical variable because it indicates for all the empirical specifications followed that the public sectors are older than the private sector workers. This creates an upward pressure in the public sector wage differential. Additionally, for the specifications that consider solely one occupation category, the occupation categorical variable is dropped and the category considered is reported instead. Panel A exhibits the general results for the total sample and all time periods, for the total sample defining the differences between the pre-polarization and polarization time periods, and finally for each occupation category separately.

In Column (1) it is shown the existence of a significant public sector wage premium. The public sector workers earn on average a hourly wage premium of 14.9% in relation to the average private sector workers. This premium is due entirely to the “explained” factors. In particular, there is a large demographic contribution from

¹² I run the Oaxaca-Blinder decomposing making use of the Stata command “oaxaca”, created by Ben Jann. For further reference, please refer to <http://www.stata-journal.com/sjpdf.html?articlenum=st0151>. Table 4.4 presents the decomposition in detail for some selected variables in the explained composition effects and leaves the unexplained effect undetailed. Since the dependent variable is in natural logarithm terms, the coefficients should be interpreted after multiplication by 100%. In all OB decompositions presented in this work I define the levels of significance as follows - * : $p < 0.05$, ** : $p < 0.01$. In parenthesis I present also the standard errors.

Table 4.4: OB-Decomposition for ln (Hourly Wage): Public vs. Private Sectors.

Panel A: Total Sample, Pre-Polarization vs. Polarization, and by Occupation Category.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time Period	1980-2013	1980-1989	1990-2013	1980-2013			
Public	2.964**	2.902**	2.983**	3.119**	2.770**	2.894**	2.775**
Private	2.815**	2.791**	2.822**	3.188**	2.696**	2.758**	2.313**
Difference:	0.149**	0.112**	0.161**	-0.068**	0.074**	0.136**	0.462**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Composition	0.149**	0.114**	0.159**	0.074**	0.035**	0.080**	0.157**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Male	-0.029**	-0.029**	-0.029**	-0.033**	-0.027**	0.007**	0.052**
	(0.0003)	(0.0008)	(0.0004)	(0.0005)	(0.0006)	(0.0008)	(0.0008)
Education	0.075**	0.059**	0.080**	0.070**	0.005**	0.018**	0.042**
	(0.0005)	(0.0008)	(0.0005)	(0.0007)	(0.0005)	(0.0006)	(0.0008)
Occupation	0.047**	0.027**	0.052**				
	(0.0005)	(0.0009)	(0.0006)	NRC	RC	RM	NRM
Unexplained	0.0001	-0.0022	0.0015	-0.143**	0.039**	0.056**	0.305**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)

Panel B: Pre-Polarization vs. Polarization by Occupation Category.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Time Period	1980-1989				1990-2013			
Public	3.077**	2.716**	2.862**	2.683**	3.131**	2.790**	2.906**	2.802**
Private	3.111**	2.677**	2.807**	2.271**	3.201**	2.702**	2.740**	2.323**
Difference:	-0.034**	0.039**	0.055**	0.412**	-0.074**	0.089**	0.166**	0.479**
	(0.034)	(0.004)	(0.006)	(0.006)	(0.002)	(0.003)	(0.004)	(0.004)
Composition	0.068**	0.026**	0.094**	0.163**	0.073**	0.044**	0.082**	0.159**
	(0.0021)	(0.0022)	(0.0028)	(0.0032)	(0.0011)	(0.0014)	(0.0017)	(0.0017)
Male	-0.041**	-0.025**	0.026**	0.072**	-0.033**	-0.028**	0.002*	0.048**
	(0.0011)	(0.0014)	(0.0017)	(0.0020)	(0.0005)	(0.0007)	(0.0009)	(0.0009)
Education	0.064**	0.002*	0.010**	0.025**	0.070**	0.008**	0.023**	0.048**
	(0.0012)	(0.0007)	(0.0009)	(0.0013)	(0.0007)	(0.0006)	(0.0008)	(0.0010)
Occupation	NRC	RC	RM	NRM	NRC	RC	RM	NRM
Unexplained	-0.102**	0.014**	-0.039**	0.248**	-0.147**	0.045**	0.084**	0.321**
	(0.0033)	(0.0038)	(0.0054)	(0.0056)	(0.0020)	(0.0026)	(0.0038)	(0.0034)

education (7.5%) and from age (5.8%). The fact is that the public sector workers are on average more educated and older than the private sector workers, driving their wages upwards. This is a very common finding in the literature and can be reviewed in Gregory and Borland (1999). Interestingly enough, the contribution of the occupation composition is extremely significant as well to the public sector wage premium, explaining around 30% of the total wage gap, with an absolute contribution of 4.7% out of the total 14.9% wage premium. The unexplained facts seem to be irrelevant in explaining the public sector wage premium. We can also consider what were the structural changes that were brought by job polarization to the determination of the public sector wage differential across sectors.

Columns (2) and (3) allow us to analyze this specific case. Both in the pre-polarization and polarization periods there is a public sector hourly wage premium. This premium has increased with polarization, passing from 11.2% in the pre polarization period to 16.1% in the polarization period. Again, the wage gap across sectors seems to be fully explained by the demographic and occupational composition. Interestingly enough, the polarization period coincides with a large increase in the explanatory power of both education and occupation to the determination of the public sector wage differential. In the pre-polarization, the differences in educational composition explained 5.9% and occupational composition explained an absolute 2.7% out of the public sector wage premium of 11.2%. After polarization, the public sector wage premium increased to 16.1%. This coincided with an increase in the contribution of this difference from the education and occupational compositions. In summary, the main message for the more general analysis argues that there is a significant public sector hourly wage premium. Interestingly enough, the public sector workers are more educated, older and belong to higher paid occupations than the private sector workers. In addition, there is a consistent decrease of male workers in the public sector in relation to the private sector. The demographic and

occupational composition effects are therefore of extreme importance in explaining the public sector wage premium, as it has been emphasized throughout this text.

The importance of occupational composition in the determination of the public sector wage premium even after controlling for the gender, age and education of the individuals in each sector suggest a very different labor market equilibrium outcome across distinct occupation categories. This should not be surprising after the evidence exhibited in Section III. To develop this idea I consider in columns (4)-(7) an OB decomposition for the public sector hourly wage premium for each of the occupation categories separately and for the time period comprising all years in the sample. In addition, columns (8)-(11) perform the same decomposition for the pre-polarization period, and columns (12)-(15) for the polarization period. By doing so, we can see how polarization has affected the contributions of both the demographic composition factors and the unexplained factors that derives from different labor market equilibrium behaviors across sectors for each occupation. There is a public sector wage penalty for the NRC occupations that is more accentuated in the polarization period than in the pre-polarization, relatively mild wage premiums for the Routine occupations and a large public sector wage premium for the NRM occupations. The effect of polarization in the premium for the routine occupations is astonishing, with routine cognitive occupations passing from a public sector wage premium of 3.9% to a wage premium of 8.9%, and with routine manual occupations increasing their public sector wage premium of 5.5% to 16.6%. The polarization in the public sector wage differential seems to be a consequence of job polarization, with structural variations in the public sector wage differential across occupation categories.

The composition effect seems to create an upward pressure in the public sector wage differential for all the occupation categories individually and for both the total, pre-polarization and polarization time periods. This again is the evidence that over time the public sector workers are older and more educated than the private sector

workers. It is also interesting to observe that the gender composition of both sectors drive the public sector wage differential downwards for Cognitive occupations and upwards for Manual occupations, with higher values in absolute value for Non Routine occupations than for Routine occupations. Controlling for the job polarization does not change the upward pressure influence of the composition effects in the public sector wage differential. This implies that the heterogeneity across the public sector wage premiums for different occupation categories comes not from the composition effects but from the unexplained changes in the coefficients. Interestingly enough for the high-skill, high-wage NRC occupations there is a significant downward pressure from differences in coefficients across sectors, a mild upward pressure for routine occupations, and a large upward pressure for NRC occupations. This implies that the private sector values more NRC occupations and the public sector values more NRM occupations. For the Routine occupations the composition of each sector is more relevant in determining the public sector wage differential, explaining roughly 50% of the observed public sector wage premium, being the other 50% explained by the different variations across sectors.

The results for the contribution of the unexplained differences in the valuation of each sector for the public sector wage differential can be viewed as a statistical test related to the Fact 1 described above. The Negative Monotonicity Fact argued that the public sector wage differential for the average workers in a given occupation category is decreasing in the hourly wage valuation of the average private sector worker. This is exactly the same message translated by the unexplained effects. The private sector values more the NRC occupations (between 10.2% and 14.7% more), has a relatively similar, although in general smaller valuation for the Routine occupations (between -3.9% and 8.4% for the RM occupations and between 1.4% and 4.5% for the RC occupations), and a much lower valuation for the NRM occupations (the public sector attributes a value above 24.8% for these occupations

than the private sector). The effects of job polarization are therefore clear. Not only composition matters for describing the public sector wage differentials for each occupation categories, but especially the intrinsic valuations by each sector to each occupation matter. For the Polarization period, the results of Fact 1 are clear, NRM occupations are the least valued by the private sector and have the largest unexplained differentials. NRC occupations are the mostly valued by the private sector and have a large negative unexplained differential. The Routine occupations are in the middle of the private sector wage distribution and have the smallest unexplained differentials in absolute value. This evidence goes also in line with the Public Sector Wage Differential Polarization described in Fact 2. There is indeed a public sector wage premium for low-skill, low-wage occupations (NRM) and a public sector wage penalty for high-skill, high-wage occupations (NRC). This can be seen in these unexplained differentials after controlling for the demographic composition of the sample. For the middle wage occupations (RC, RM) the public sector wage differential is mild.

The combination of results for the OB decompositions for all the occupation categories presented in Columns (1)-(3) and for each occupation category separately shown in Columns (4)-(15) allows us to argue again that occupational composition affects the determination of the public sector wage differential and that the job polarization has significant effects on the public sector wage differential for each occupation category. From the results in columns (4)-(15) we have concluded that there is a large unexplained variation in the coefficients across different sectors that affect the determination of the public sector wage differential. However, these unexplained variation is higher for the polarization period than for the pre-polarization period. This is provides some exploratory evidence for the argument that job polarization affects the public sector wage differential for each occupation category. Additionally, the inclusion of occupational composition in the empirical specifications for the av-

erage public sector wage differential immediately turn the unexplained components to be not statistically significant. The contribution of the occupation composition to the public sector wage differential is large, being around 30% of the total differential presented. Again the effects of job polarization appear in this specification. In Column (2) the occupational composition explain around 24% of the total public sector wage differential and in Column (3) around 32%. The increase in the relevance of occupational composition for the determination of the public sector wage differential in the polarization period is again evidence that Job Polarization may be affecting the wage differential across sectors¹³.

The results in Table 4.4 have therefore confirmed the relevance of occupational composition and heterogeneity in determining the aggregate wage premium. A related and extremely important question is whether the demographic and occupational compositions have changed the likelihood of a worker to belong to the public sector. From 1980 to 2013 there was a significant decline in the public sector labor share from 19.3% to 16.8%. In order to determine whether the demographic composition, occupational composition, or changes in the unexplained propensities over time have driven the public sector labor share downwards as time goes by, I apply a bunch of OB decompositions with a dummy variable that defines the sector of each worker as the dependent variable.

I define the benchmark group A to be given by the year 1980, while group B is respectively given by the years 1990, 2000, 2005, 2010 and 2013. The vector

¹³ Not shown in this text for the sake of brevity, I have run an OB decomposition similar to (1)-(3) without including the occupational composition in the set of regressors. Two things change in the analysis: (1) the unexplained component turns out to be statistically significant with a p-value of 1%, and (2) the explained contribution from the educational composition is now much higher than the results presented in Table 4.4. The effects of age and gender remain very similar to the ones showed in this analysis. We can take two messages from this. First, occupational composition is the factor that identifies the unexplained components in the analysis in (1)-(3). Second, the occupation categories we have constructed are very linked and even related with the educational composition. Please refer to Acemoglu and Autor (2011) for additional details on the construction of these categories and its relationship with the individuals' education.

of regressors $X_{i,j}$ includes a set of variables that can account for the demographic composition over time such as the age of each worker (with a quadratic formalization), a dummy variable for gender and race (white vs. other races), a categorical variable to identify the level of education for each worker (high school graduate or lower, college graduate or some college, and higher education than the bachelor degree), and finally a categorical variable that describes the workers' occupation. For the baseline omitted group in my specification I consider the white women that are high school graduates or lower working in Management occupations. To highlight the fact that some occupation categories are extremely concentrated in one of the sectors and to make use of the additional occupation heterogeneity that is shown in the previous section, I define the categorical variable for the occupations to match the major occupation categories from the SOC 2000. The richer occupational heterogeneity in comparison to the (Non-)Routine Manual/Cognitive classification is more prone to identify the effects that come from structural changes in the occupational composition over time and the time variations in propensities have in determining the changes over time in the likelihood of a worker to be in the public sector. The empirical results are described in Table 4.5¹⁴. I differentiate between the explained composition effects and unexplained time variations in propensities and I show the full details for both the education and occupation categorical variables.

The dynamics for the public employment share are entirely due to the unexplained factors. The demographic and occupational composition changes over time predict an accentuated increase in the likelihood of the worker to belong to the public sector in comparison to the share observed in 1980, which is not actually a feature of the data. Specifically, the total composition effect implies that if the propensities to

¹⁴ I do not present here the full details that come from the particular specification for the OB decomposition I use. The details for the remaining variables can be provided if requested. In all the columns I define the level of significance as - * : $p < 0.05$, ** : $p < 0.01$. In parenthesis I present the standard errors.

go to the public sector had stayed the same as in 1980, the public sector share would have increased over time, reaching an increase of more than 5 percentage points for 2010 and 2013. This is mainly due to the contribution of the occupational composition, that explains almost half of the total increase predicted by the sum of all composition effects. The total propensity effect implies that the public sector employment share would have decreased if the composition was the same as in 1980. Obviously this second effect is much stronger than the first one, since the public sector employment share has decreased over time. In particular, two propensity effects must be considered. The main driver of the decrease in the public sector employment share seems to come from time variations of the constant term. This term can be interpreted as the change in the conditional change in the public sector employment share for the omitted group (white women, high school graduates or lower, working in a Management occupation). This effect has decreased the public sector employment share by more than 7 percentage points for the years 1990, 2000, 2005 and 2013. The fact that the propensity effect for the occupation categories is positive and statistically significant means that the heterogeneity in the occupation categories can be also seen in these unexplained factors. The fact that the Management occupations are part of the NRC occupations implies that there may be variations for other type of occupations such as the Routine occupations, which have decreased their employment share in the public sector by less than the decrease observed for the private sector and the NRM occupations that have increased their employment share in the public sector by slightly less than in the private sector.

It is not therefore surprising to observe a statistically significant propensity effect for the occupation coefficients over time. Interestingly enough, the effect for the propensities of some key demographic factors such as the age of the workers drives the total propensity effects, after accounting for the contribution in the propensity changes for the omitted group and for the differences in the propensity for the differ-

Table 4.5: OB-decomposition for Worker's Likelihood to Work in the Public Sector.

Year 1980 - Public Sector Labor Market Share: 19.30%					
	1990	2000	2005	2010	2013
Difference:	-1.37% ** (0.003)	- 2.23% ** (0.003)	-1.75% ** (0.003)	-1.04% ** (0.003)	-2.48% ** (0.003)
Composition	1.20% ** (0.001)	2.76% ** (0.002)	4.46% ** (0.002)	5.69% ** (0.002)	5.11% ** (0.002)
Education	0.35% ** (0.0003)	0.68% ** (0.0006)	0.90% ** (0.0006)	1.16% ** (0.0007)	1.16% ** (0.0008)
Occupation	0.33% ** (0.0012)	0.89% ** (0.0013)	2.10% ** (0.0012)	2.75% ** (0.001)	2.25% ** (0.001)
Propensities	-2.57% ** (0.002)	-4.98% ** (0.003)	-6.21% ** (0.002)	-6.73% ** (0.003)	-7.59% ** (0.003)
Education	0.50% (0.0030)	0.36% (0.0030)	0.56% * (0.0028)	0.69% ** (0.0026)	0.60% * (0.0026)
Occupation	1.58% ** (0.0035)	1.57% ** (0.0034)	0.76% ** (0.0032)	0.50% (0.0032)	0.66% * (0.0031)
Constant	-8.59% ** (0.025)	-7.89% ** (0.025)	-7.70% ** (0.024)	-2.22% (0.024)	-8.27% ** (0.024)

ent occupations. These propensities for demographic factors are particularly relevant for 2010, in which we do not observe a significant effect in the propensities for the occupation categories and for the omitted group.

In summary, in this section I have performed a set of Oaxaca-Blinder counterfactual decompositions for the average worker to assess the importance of the occupational composition to the determination of the public sector wage differential. As discussed in the previous section, there are four important factors to understand this question. The first is the private sector hourly wage valuation across occupations that allows us to understand the connection across the two different sectors in the labor market. The second is the public sector hourly wage differential for each occu-

pation, that compares the public sector hourly wage with the private sector hourly wage. From the first set of OB decompositions illustrated in Table 4.4 I manage to establish a negative monotonicity result between the public sector wage differential and the private sector hourly wages across occupations and to signal the existence of a public sector wage differential polarization. The third and fourth important factors to be considered are the occupational employment composition for each sector. Two effects must be considered here: the impact of the occupational composition for the determination of the public sector wage differential and for the likelihood of an individual to work in the public sector. I have shown that the occupational composition creates an upward pressure in the public sector wage differential and that job polarization may be affecting the wage differential across sectors. Additionally, the occupational composition is creating an upward pressure on the public sector employment share, compensating the decrease in this share due to unexplained effects that affect all the workers in the sample.

4.5 Conclusion

Throughout this chapter I have argued that the aggregate public sector wage differential for the average worker in each sector hides a large distributional heterogeneity and so, it is not a very informative statistic for policy analysis. I contribute to the literature by carefully reviewing the empirical evidence on the main drivers and on the existence of the public sector wage differential using individual-level annual data from the March Supplement of the Current Population Survey (March CPS) and providing three new empirical facts that reinforce the role of the occupational composition in the determination of the public sector wage differential. The periodical surge of nationwide headlines on the behavior of the wages in the private and public sectors put the public sector payroll under the public opinion's spotlight whenever there are some budgetary pressures for the government to reduce expenditures. Looking to

the public sector wage differential at the “macro” level, one would find an expressive public sector wage premium over time.

In the current macroeconomics research, in modeling the effects of fiscal policy there is no recognition of the existence of a public sector in the labor market and the budgetary implications of the wages that are paid to these public sector workers. There are few exceptions to this simple remark but three distinct examples can be found in Ardagna (2001), Cavallo (2005), and Quadrini and Trigari (2007).

Ardagna (2001) assesses the effects of fiscal policy composition on the public debt and on the level of economic activity. In particular, she decomposes the government budget constraint in several distinct pieces: final goods bought from the private sector, transfers to the private sector, distortionary taxes on labor and capital, debt issuance and most importantly, the existence of a public sector in a competitive labor market. She shows that in her framework an increase in public employment can have a negative effect on the economy even when this increase is financed by lump-sum taxes. In her analysis the public sector wages are however perfectly matched with the private sector. This happens due to the existence of a representative worker and a perfectly competitive labor market.

Cavallo (2005) distinguishes between the goods and employment expenditures in the government budget constraint to assess the effects of fiscal shocks on the economy. Cavallo (2005) extends the analysis pioneered in Burnside et al. (2004) by including the public sector hours in the set of exogenous fiscal policy variables, including at the same time distortionary taxation on labor and capital income. His results confirm the intuition advanced in Burnside et al. (2004) that the private sector consumption does not decrease much after a large investment in national defense. The application of the public sector employment in this work has a magnification effect. In particular, Cavallo (2005) argues that the neoclassical growth model does not have a very good performance on accounting for the effects of fiscal policy shocks because it considers

the government expenditures to be only on goods.

Finally, Quadrini and Trigari (2007) study the business cycle fluctuations introducing a public sector for employment. They model their economy as a two-sector search and matching model with exogenous policy rules that can be later calibrated to the US economy. In particular, the existence of a public sector in their work implies an increase in the volatility of total employment and output, which are important empirical facts that the standard neoclassical growth model and the standard search and matching model fail to account for. However, in their analysis, Quadrini and Trigari (2007) calibrate their fiscal policy rules to account for a low cyclical volatility of public wages and employment and for a premium paid on average to the public sector workers.

I contribute to this literature by providing three new robust empirical facts relating the occupational heterogeneity with the determination of the public sector wage differential. The first reflects a negative monotonic relationship between the public sector wage differential and the private sector hourly wages across occupations. The second signals the existence of a public sector wage differential polarization, in which low-skill and low-wage occupations have very high wage premiums, high-skill and high-wage occupations have wage penalties, and the occupations in the middle of the distribution have smaller differentials across sectors. Lastly, the third fact argues that the public sector wage differential is affected by the occupational employment composition across sectors and therefore it is affected by the job polarization structural trend that is occurring in the labor market since 1990. To test the robustness of these results I execute a battery of Oaxaca-Blinder counterfactual decompositions for the average worker. The main conclusion is that the occupational composition is important both for the determination of the average public sector wage differential and for the determination of the public sector labor market share over time.

As it is argued in this chapter, the occupational heterogeneity across workers is

crucial in determining the public sector wage differential, since some occupations have public sector wage penalties (NRC), some occupations have large public sector wage premiums (NRM), and some occupations have mild public sector wage penalties and premiums (RC, RM). This implies that the main challenge for future research comes from modeling the evidence provided here in a dynamic general equilibrium framework. The macroeconomics literature that search for a theoretical workhorse to model the public sector employment is still limited and to my knowledge only Albrecht et al. (2014) tries to account for the effects of heterogeneity across workers in the determination for the public sector employment. They assume the workers are heterogeneous in terms of their human capital and that productivity is match specific, being the distribution of this productivity more favorable as we consider more highly skilled workers in terms of their human capital accumulation. Two key characteristics differentiate the evidence provided here and in their work. First, they focus on human capital accumulation (Education) instead of focusing on the workers' occupational choice. Second, they focus their conclusions on the public sector employment and not on the public sector wage differential.

Appendix A

Appendix 1 to Chapter 2: Competing Labor Share Measures.

A.1 Headline Measure for the Labor Share (BLS)

The headline labor share measure from the BLS looks to the nonfarm business sector and assumes that the average wage for a self-employed worker is the same as the average wage for an employee working on a similar occupation. The associated measurement of the labor share for the nonfarm business sector is

$$\begin{aligned}\lambda_t^{\text{BLS}} &= \left(1 + \frac{\# \text{ hours self-employed}_t}{\# \text{ hours employees}_t}\right) \cdot \frac{\text{Compensation of Employees}_t}{\text{Gross Value Added}_t} \\ &= \left(1 + \frac{H_t^S}{H_t^E}\right) \cdot \frac{W_t \cdot H_t^E}{P_t \cdot Y_t}\end{aligned}$$

where H_t^S is the total number of hours worked by the self-employed workers, H_t^E the total number of hours worked by employees, W_t the average hourly wage earned by employees, and $P_t Y_t$ the nominal gross value added. The gross value added for the nonfarm business sector represents $\approx 75\%$ of the gross value added for the total economy.

That is, the headline measure for the BLS inflates the payroll share to account for the number of hours worked by the self-employed. Elsby et al. (2013) argue that a part of the recent decline in the headline measure of the labor share in the United States is spurious, due to the “labor approach” assumption. For the purposes of my paper, Elsby et al. (2013) state that short-run cyclical movements in the U.S. labor share can be tracked by accounting by the payroll share, which is the measure that I ultimately use.

To understand whether this statement is true, the challenge is to reconstruct the hours worked by the self-employed, as they are not publicly available. To do so, I follow Elsby et al. (2013) and construct a time series for the nonfarm business sector payroll share¹. Then, the share of hours worked by the self-employed with respect to the hours worked by the employees can be obtained as

$$\frac{H_t^S}{H_t^E} = \frac{\ln_t - \text{Payroll Share}_t^{\text{NFB}}}{\text{Payroll Share}_t^{\text{NFB}}}$$

Additionally, I use a time series on total hours worked ($H_t^E + H_t^S$) for the NFB from the BLS’s Productivity and Costs release to get

$$1 + \frac{H_t^S}{H_t^E} = \frac{H_t^E + H_t^S}{H_t^E} = \frac{1}{H_t^S} \cdot \frac{H_t^E + H_t^S}{H_t^E/H_t^S}$$

implying that the total hours worked by the self-employed can be computed as

$$H_t^S = \left(\frac{\frac{H_t^S}{H_t^E}}{1 + \frac{H_t^S}{H_t^E}} \right) \cdot (H_t^E + H_t^S)$$

¹ For more information on the methodology I use, check Table A5 on Elsby et al. (2013) technical appendix. When necessary, annual data is converted to quarterly using a cubic spline for quarterly interpolation.

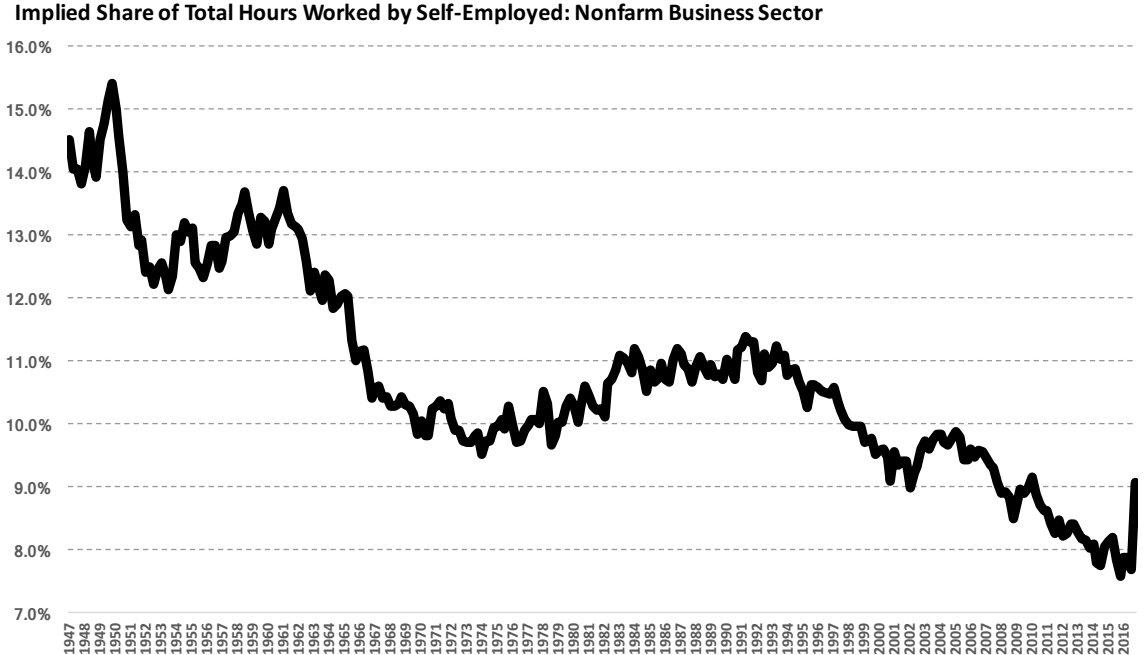


FIGURE A.1: Share of Total Hours Worked by the Self-Employed (NFB)

and the total hours worked by employees is the difference between total hours worked and the hours worked by the self-employed workers. The quarterly time series for the implied share of total hours worker by the self-employed, that is, $H_t^S / (H_t^E + H_t^S)$, is shown in Figure ???. As in Elsby et al. (2013) we notice a large decline in the share of hours worked by the self-employed, from 14.1% in 1947 to 8.1% in 2016. This decline is mostly driven by a stagnation in the number of hours worked by the self-employed, and it occurs in two phases.

The first happens from 1947 to the mid-1970s. In this period, the total number of hours worked by the self-employed remained constant and the total number of hours worked by employees continuously increased, achieving a cumulative increase of 57.7% from 1947 to 1977. This means an increase of 1.86% per year in the number of hours worked by employees. The second phase occurs from the mid-1990s to 2015. Over this time period, the number of hours worked by the self-employed

decreased by 22.2%, while the number of hours worked by employees increased by 12.3%. This implies a decrease of 1.17% per year in the number of hours worked by the self-employed and an increase of 0.64% per year in the number of hours worked by employees. The decline in the share of hours worked by the self-employed has an impact in the fall of the headline measure for the labor share.

After describing the other measures used to compute the labor share, I will study whether the share of hours worked by the self-employment has an impact on the cyclicity of the labor share. I reach the conclusion that it has not, and I find that Elsby et al. (2013) statement that the cyclicity of the labor share can be described by the cyclicity of the payroll share is correct.

A.2 Economy-Wide Labor Share

The economy-wide measure of the labor share is the measure favored by Gomme and Rupert (2004). The main assumption is that the ambiguous income is allocated between labor and capital in the same share as the unambiguous income is allocated between factors of production. Define the unambiguous income in two components. The unambiguous labor income is $P_t \cdot Y_t^{\text{UL}} = \text{Compensation of Employees}_t$ and the unambiguous capital income is $P_t \cdot Y_t^{\text{UK}} = \text{Rental Income}_t + \text{Profits}_t + \text{Net Interest}_t + \text{Depreciation}_t$. The labor share can then be computed as

$$ls_t = \frac{Y_t^{\text{UL}}}{Y_t^{\text{UL}} + Y_t^{\text{UK}}}$$

Under this measure of the labor share, the “ambiguous” income is allocated to labor and capital in the same proportions they represent in the part of national accounting that can be unambiguously assigned to labor and capital. Therefore, the main assumption is that “proprietors” allocate their resources between capital and labor in the same way corporations do, independently of the number of self-employed

workers have their own businesses.

However, one can argue that this measure underestimates the labor share. For this statement to be true, we need to consider a world in which firms allocate resources differently between capital and labor according to their size. Moreover, we need to think on this allocation to be more biased towards labor at smaller sizes and towards capital at larger sizes. Another issue with this measure is that there is a disagreement in the literature on the measurement and economic interpretation of residential housing, which decreases the reliability of this measure. The gross unambiguous income for capital and labor represent $\approx 75\%$ of the gross value added for the total economy.

A.3 Corporate Business Sector Payroll Share

The corporate business sector is defined as the sector encompassing financial and nonfinancial corporations. The corporate business sector does not include any proprietors' income in its gross value added, which constitutes a big advantage when we look to the dynamics of the labor share. It still has an ambiguous income component from the net indirect taxes, but the payroll share will be equal to the labor share, as it is not affected by the statistical imputation of wages from combined capital and labor income earned by sole proprietors and unincorporated enterprises. This advantage overcomes the measurement issues raised by Gollin (2002) and this measure is the one favored by Karabarbounis and Neiman (2014) to compare the labor share across countries.

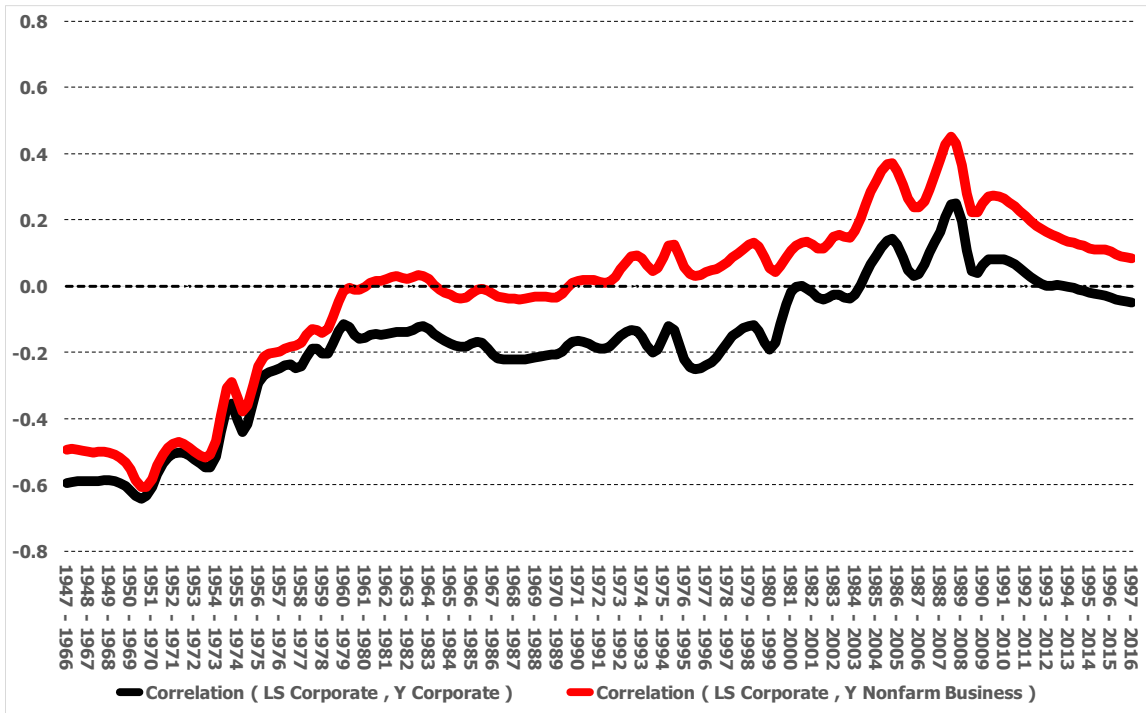
The payroll share for the corporate sector is mildly negatively related (or unrelated) with the real value added for the corporate sector, but it comoves procyclically with the real value added for the noncorporate sector. This may imply that firms and workers bargain the workers' compensation by looking to the aggregate real output, instead of looking only to the real production of the corporate sector. Another

reason may be that the production in the corporate sector has positive externalities in the noncorporate sector, which show up not on the value added for the corporate sector but on the value added for the noncorporate sector. However, these externalities may have a higher intensity on the compensation of employees in the corporate sector and less on other components of the gross value added for this sector.

On the left panel of the Figure A.2 it is plotted the correlation between the payroll share for the corporate sector (LS Corporate) with the real value added for the corporate sector (black line) or with the real value added for the nonfarm business sector (red line). This correlation is plotted for a rolling 20 year window using quarterly data. It is clear that for both series there is a shift in the cyclicity of the labor share for the corporate sector towards procyclicality. Both time-varying correlations move almost in parallel, implying the existence of a stationary bias in these correlations, coming from the non-corporate business sector.

The right panel shows then the time-varying correlation for the payroll share for the corporate sector with the real value added for the corporate sector (black line) or with the non-corporate sector (red line). While the correlation with the real value added for the corporate sector passes from countercyclical to acyclical, the correlation with the real value added for the non-corporate sector passes from acyclical to procyclical. The difference between the two remains relatively constant, with the clear exception for the 20 year rolling windows between 1958-1973 and very briefly for the period in which the Great Recession starts showing up in these time-varying correlations (around 1989-2008). The gross value added for the corporate business sector represents $\approx 55\%$ of the gross domestic product for the total economy.

Comovement with Real Output for Nonfarm Business Sector



Comovement with Real Output for Non-Corporate Business Sector

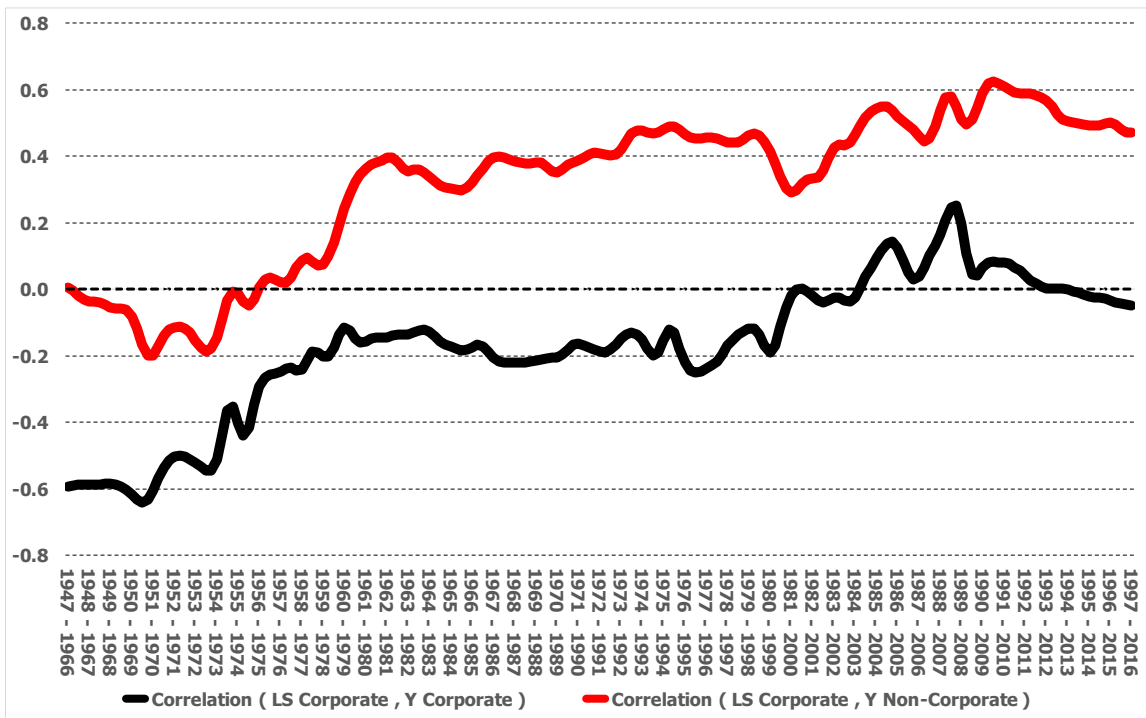


FIGURE A.2: Cyclicity of Payroll Share for Corporate Sector

A.4 Multifactor Productivity Labor Share (BLS)

This labor share series uses the asset basis approach from Kravis (1959), augmented with a measurement of the user cost of capital advocated by Jorgenson (1963). The main assumption is that returns to capital (captured by its user cost) are the same for the capital used by employees and by the self-employed. This measure is used by Fernald (2014) to construct his real-time growth accounting data set. The BLS Multifactor Productivity (MFP) data infers self-employment labor income in a very similar way, although this data is only available at an annual frequency. To transform the available data into a quarterly time series, I use a cubic spline for quarterly interpolation.

Appendix B

Appendix 2 to Chapter 2: Construction of Variables for the Nonfarm Business Sector.

I construct the nonfarm business sector variables by following Elsbey et al. (2013). All data is taken from the National Income and Product Accounts (NIPA) published by the Bureau of Economic Analysis (BEA). I will refer to variables coming from $x:y$, where x is the number of the corresponding NIPA table and y the number of the row in that NIPA table. The quarterly gross value added for nonfarm business sector is taken from 1.3.5:3. The quarterly compensation of employees for total economy is taken from 1.10:2. The quarterly compensation of employees for the government sector is taken from 3.10.5:4. The compensation of employees for Households and Nonprofit Institutions Serving Households is only available as annual data and it is taken from 1.13:43 (Households) and 1.13:50 (NISH). These variables are then summed to get the aggregate series. To obtain a quarterly time series, I apply to this annual variable a cubic spline for quarterly interpolation. The midpoint for the annual data is assumed to be on the third quarter (Q3) of each year. Since the

annual data is only available from 1948 onwards, I adjust the quarterly series for periods 1947Q1 to 1948Q2 using the quarterly growth rate for the gross value added for the Households and NISH sector, taken from 1.3.5:5. The compensation for the farm sector employees is only available at an annual frequency and is obtained from 7.3.5:18. I use the same methodology as for the previous time series by applying a cubic spline for quarterly interpolation. I also apply a cubic spline for quarterly interpolation to the annual gross value added data for the farm sector, taken from 7.3.5:15. This quarterly splined series differs from the quarterly gross value added series for the farm sector taken from 1.3.5:4. I build the ratio of the quarterly series measured from 1.3.5:4 (py-farm) to the quarterly splined series from 7.3.5:15 (py-farm-spline). Finally, I adjust the splined quarterly compensation for the farm sector by multiplying it by this ratio. Having put together this information, I construct the compensation of employees for the nonfarm business sector by subtracting to the compensation of employees for the total economy, the compensation of employees for the government, household and NISH, and farm sectors. Finally, the payroll share for the nonfarm business sector is the ratio between the compensation of employees for the nonfarm business sector and the gross value added for the nonfarm business sector.

Appendix C

Appendix 3 to Chapter 2: Construction of Industry Level Data

I define the industries for the U.S. economy in terms of the North America Industry Classification System (NAICS) definitions for industries. I look to the industries of Mining; Construction; Manufacturing; Transportation and Warehousing; Public Utilities; Information; Wholesale and Retail Trade; Finance and Insurance; Real Estate; Professional and Business Services; Leisure and Hospitality; Educational Services; Health Care and Social Assistance; and Other Services. The cross-walk between the NAICS industries using the available SIC data from the Bureau of Economic Analysis (BEA) is described on Table C.1.

The value added share for manufacturing decreased from 34.13% in 1947 to 13.98% in 2015 and the value added share in the wholesale and retail trade sector fell from 23.33% in 1947 to 13.85% in 2015. The value added share for professional and business services increased from 1.83% in 1947 to 14.22% in 2015 and the value added share for financial activities increased from 3.13% in 1947 to 8.33% in 2015. Other significant changes in the value added shares happened for health care and

Table C.1: Industry Definitions, Cross-Walk Table with SIC, and Value Added Shares for 1947 and 2015.

Nonfarm Private Sector: Industries	NAICS	SIC 72	SIC 87	VA Share (1947)	VA Share (2015)	Change (in p.p.)
Mining	21	10-14	10-14	3.58%	2.11%	- 1.47
Construction	23	15-17	15-17	4.72%	4.72%	- 0.00
Manufacturing	31-33	20-39	20-39	34.13%	13.98%	-20.15
Transportation and Warehousing	48-49	40-42, 44-47	40-42, 44-47	7.20%	3.50%	- 3.70
Public Utilities	22	49	49	1.97%	1.83%	- 0.14
Information	51	48, 78	48, 78	2.51%	5.41%	2.90
Wholesale and Retail Trade	42, 44-45	50-59	50-59	23.33%	13.85%	- 9.48
Finance and Insurance	52	60-64, 67	60-64, 67	3.13%	8.33%	5.20
Real Estate	53	65-66	65-66	9.54%	15.22%	5.69
Professional and Business Services	54-56	73, 81, 84, 89	73, 81, 84, 87, 89	1.83%	14.22%	12.39
Leisure and Hospitality	71	70, 79	70, 79	1.43%	4.57%	3.14
Educational Services	61	82	82	0.38%	1.30%	0.92
Health Care and Social Assistance	62	80, 83	80, 83	1.99%	8.37%	6.38
Other Services	81	72, 75, 76, 86, 88	72, 75, 76, 86, 88	4.25%	2.59%	- 1.67

social activities, with an increase in 6.38 percentage points from 1.99% in 1947 to 8.37% in 2015, for real estate with an increase in 5.69 percentage points from 9.54% to 15.22%, and for transportation and warehousing with a decline in 3.70 percentage points, from 7.20% in 1947 to 3.50% in 2015.

To avoid structural breaks in the time series for each industry, due to differences in the industrial classification, and because I am interested in the cyclicity for the value added and payroll shares for each industry, I construct a consistent time-series over time by using both information from the SIC industries and the NAICS industries. Since both classifications have some years in common, 1987 between SIC 72 and SIC 87, and 1997 between SIC 87 and NAICS, I use the information on those years to filter out the differences in the levels of the series over time. The assumption behind is that industries constructed with the cross-walk defined by Table C.1 have the same cyclicity. The industry-level data from the BEA is taken from the NIPA tables 6.2 to 6.9.

Figure C.1 shows the shift in the cyclicity of the labor share for the nonfarm private sector data using the industry-level data from the BEA. Figures 2.4, C.2 and C.3 shows the cyclicity of the labor share for the industries spanning the nonfarm private sector. The key sectors considered in the text are manufacturing, wholesale

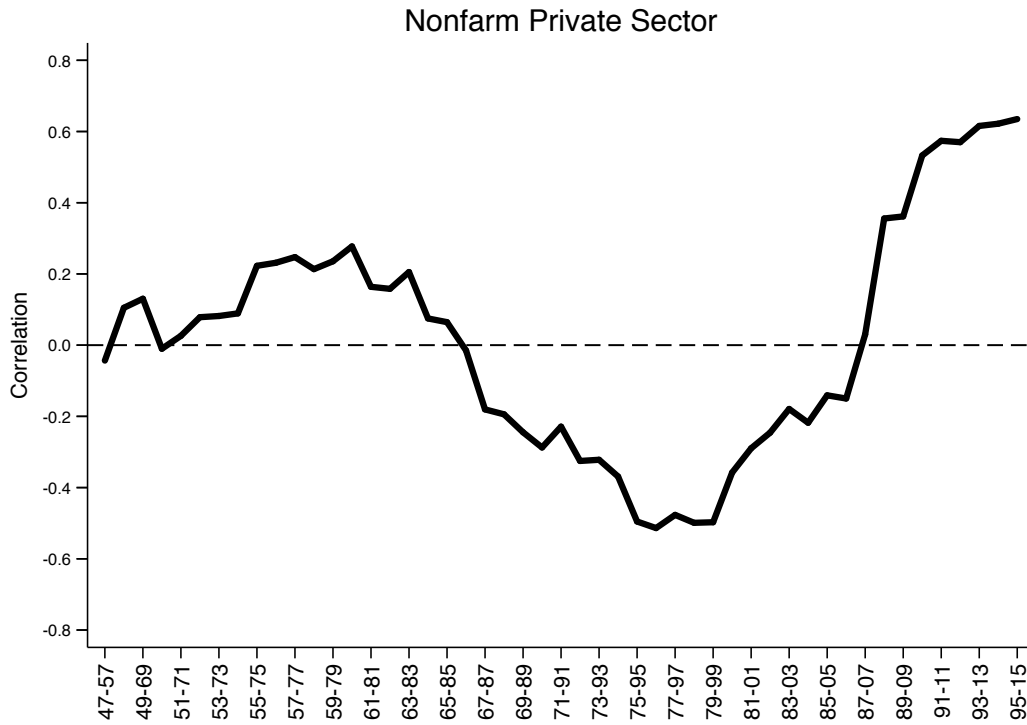


FIGURE C.1: Shift in the Cyclicality of the Labor Share: Nonfarm Private Sector

and retail trade, financial activities, and professional and business services, and the cyclicality of their sectoral labor share is represented in Figure 2.4. Other sectors that contribute to the shift in the cyclicality of the labor share are Real Estate, Information, Educational Services, and Health Care and Social Assistance, and are represented in Figure C.2. Finally, the sectors that do not follow the aggregate pattern are represented in Figure C.3. These are mining, construction, utilities, transportation, leisure and hospitality, and other services. These sectors represent 23.2% and 19.3% of the Value Added for the Nonfarm Private Sector in 1947 and 2015, respectively.

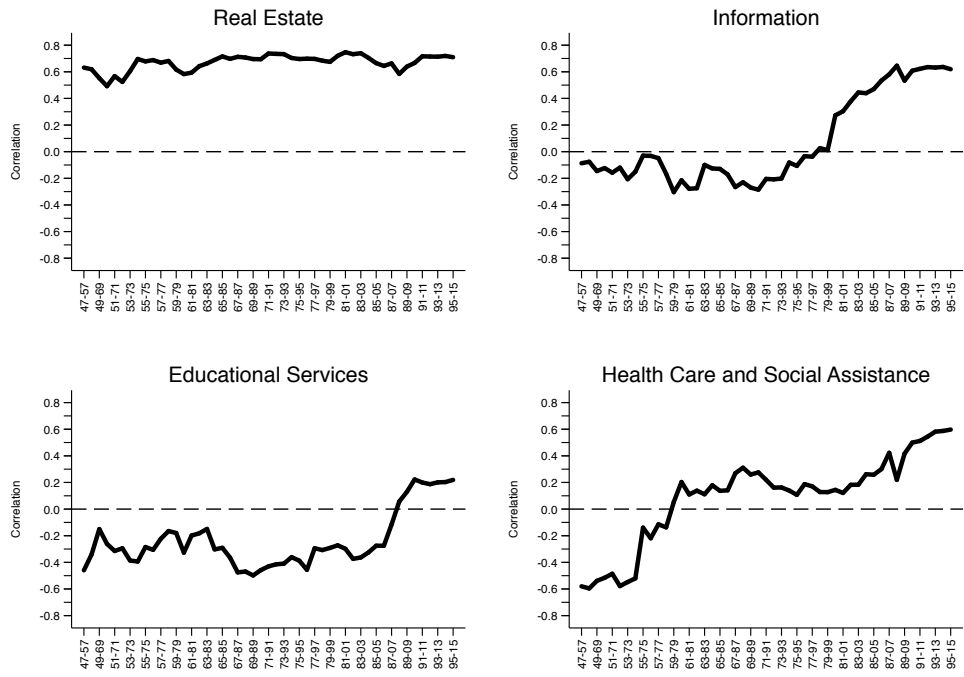


FIGURE C.2: Other Sectors Contributing to a Procyclical Labor Share in the Last Three Decades

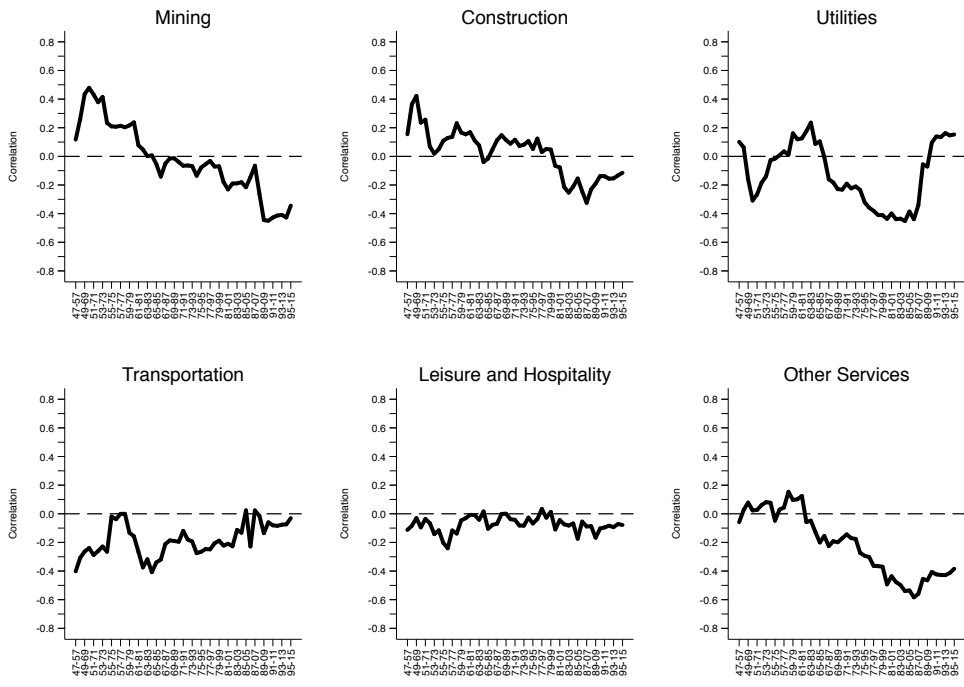


FIGURE C.3: Sectors Without a Clear Shift in the Cyclicity of the Labor Share.

Appendix D

Appendix 1 to Chapter 3: Model Calibration

The calibration of the model is similar to the one used by Galí and van Rens (2017). The discount factor is set to $\beta = 0.99$. It is assumed a log utility over consumption, $\eta = 1$. The frictionless employment-population ratio is assumed to be equal to 70%, implying $\gamma = 1.24$. $\alpha = 1/3$ defines the steady state capital share. $\xi = 0.299$ sets effort equal to one in the frictionless version of the model. δ is calibrated to 0.35 to match pre-mid-1980s data, but in experiments I shift it around to 0.2 (post-mid-1980s data) and to 0.01 (“frictionless” model). The workers’ bargaining power is set to 0.5. ϕ is set to zero so that effort is in utility units. I set $\psi = 0.3$. $g^F(E) = [\kappa/(1 + \mu)] \cdot E^{1+\mu}$ are the hiring costs, in which $\mu = 1.5$ sets these adjustment costs to be convex, and $\kappa = 3.18825$ aims for the cost of frictions to be 3% of output in the calibrated version of the model. Finally, $\rho_A = \rho_Z = 0.97$ allow us to look to persistent shocks, and the volatilities of these shocks ($\sigma_A = 0.01954$, $\sigma_Z = 0.02424$) set the standard deviation of output to be roughly 3%.

Bibliography

- Abraham, K. G., J. R. Spletzer, and J. C. Stewart (1999). Why do different wage series tell different stories? *American Economic Review* 89(2), 34–39.
- Acemoglu, D., P. Aghion, and G. Violante (2001). Deunionization, technical change and inequality. *Carnegie-Rochester Conference Series on Public Policy* 55.
- Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, Volume 4, pp. 1043–1171. Elsevier.
- Albrecht, J., M. Robayo-Abril, and S. Vroman (2015). Public-sector employment in an equilibrium search and matching model. *The Economic Journal*.
- Alexopoulos, M. (2004). Unemployment and the business cycle. *Journal of Monetary Economics* 51.
- Andolfatto, D. (1996). Business cycles and labor-market search. *American Economic Review* 86.
- Ardagna, S. (2001). Fiscal policy composition, public debt, and economic activity. *Public Choice* 109(3-4), 301–325.
- Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2017). The fall of the labor share and the rise of superstar firms. *Working Paper*.
- Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics* 118(4), 1279–1333.
- Bargain, O. and B. Melly (2008). Public sector pay gap in france: new evidence using panel data.
- Barkai, S. (2017). Declining labor and capital shares. *Working Paper*.
- Barnichon, R. (2010). Productivity and unemployment over the business cycle. *Journal of Monetary Economics* 57.

- Basu, S., J. Fernald, and M. Kimball (2006). Are technology improvements contractionary? *American Economic Review* 96.
- Bellante, D. and A. N. Link (1981). Are public sector workers more risk averse than private sector workers? *ILR Review* 34(3), 408–412.
- Bender, K. A. and J. S. Heywood (2010). Comparing public and private sector compensation over 20 years. *Washington, DC: Center for State and Local Government Excellence and National Institute on Retirement Security*.
- Bewerunge, P., H. S. Rosen, et al. (2012). Wages, pensions, and public-private sector compensation differentials. *Griswold Center for Economic Policy Studies Working Paper 227*.
- Bjelland, M., B. Fallick, J. Haltiwanger, and E. McEntarfer (2011). Employer-to-employer flows in the united states: Estimates using linked employer-employee data. *Journal of Business & Economic Statistics* 29.
- Blanchard, O. and P. Portugal (2001). What hides behind an unemployment rate: comparing portuguese and us labor markets. *American Economic Review* 91(1), 187–207.
- Blanchard, O. J. and D. Quah (1989). The dynamic effects of aggregate demand and supply disturbances. *American Economic Review* 79.
- Blanchard, O. J. and M. W. Watson (1986). Are business cycles all alike? In R. Gordon (Ed.), *American Business Cycle: Continuity and Change*. National Bureau of Economic Research, Inc.
- Blau, F. and L. Kahn (1999). Institutions and laws in the labor market. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*. Elsevier.
- Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, 436–455.
- Blundell, R., A. Gosling, H. Ichimura, and C. Meghir (2007). Changes in the distribution of male and female wages accounting for employment composition using bounds. *Econometrica* 75(2), 323–363.
- Boldrin, M. and M. Horvath (1995). Labor contracts and business cycles. *Journal of Political Economy* 103.
- Bowlus, A. J. and C. Robinson (2012). Human capital prices, productivity, and growth. *American Economic Review* 102(7), 3483–3515.
- Burda, M. C. and J. Hunt (2011). What explains the german labor market miracle in the great recession? Technical report, National bureau of economic research.

- Burnside, C. and M. Eichenbaum (1996). Factor-hoarding and the propagation of business-cycle shocks. *American Economic Review* 86.
- Burnside, C., M. Eichenbaum, and J. D. Fisher (2004). Fiscal shocks and their consequences. *Journal of Economic theory* 115(1), 89–117.
- Burnside, C., M. Eichenbaum, and S. Rebelo (1993). Labor hoarding and the business cycle. *Journal of Political Economy* 101.
- Burnside, C., M. Eichenbaum, and S. Rebelo (1995). Capital utilization and returns to scale. In B. S. Bernanke and J. J. Rotemberg (Eds.), *NBER Macroeconomics Annual 1995, Volume 10*. MIT Press.
- Cavallo, M. (2005). Government employment expenditure and the effects of fiscal policy shocks. Federal Reserve Bank of San Francisco.
- Champagne, J. and A. Kurmann (2013). The great increase in relative volatility of real wages in the united states. *Journal of Monetary Economics* 60.
- Choi, S. and J.-V. Ríos-Rull (2009). Understanding the dynamics of the labor share: the role of non-competitive factor prices. *Annals of Economics and Statistics* 95-96.
- Christiano, L. J. and T. J. Fitzgerald (2003). The band pass filter. *International Economic Review* 44.
- Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review* 104.
- Cortes, G. M., N. Jaimovich, C. J. Nekarda, and H. E. Siu (2014). The micro and macro of disappearing routine jobs: A flows approach. Technical report, National Bureau of Economic Research.
- Davis, S. J., R. J. Faberman, and J. C. Haltiwanger (2013). The establishment-level behavior of vacancies and hiring. *The Quarterly Journal of Economics* 128(2), 581–622.
- Davis, S. J. and J. Haltiwanger (2014). Labor market fluidity and economic performance. *NBER Working Paper, No. 20479*.
- Eden, M. and P. Gaggl (2017). On the welfare implications of automation. *Working Paper*.
- Elsby, M. W. L., B. Hobijn, and A. Şahin (2013). The decline of the u.s. labor share. *Brookings Papers on Economic Activity Fall 2013*.
- Fernald, J. (2014). A quarterly, utilization-adjusted series on total factor productivity. *FRBSF Working Paper 2012-19*.

- Fortin, N., T. Lemieux, and S. Firpo (2011). Decomposition methods in economics. In *Handbook of labor economics*, Volume 4, pp. 1–102. Elsevier.
- Francis, N. and V. A. Ramey (2009). Measures of per capita hours and their implications for the technology-hours debate. *Journal of Money, credit and Banking* 41(6), 1071–1097.
- Galí, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review* 89.
- Galí, J. and L. Gambetti (2009). On the sources of the great moderation. *American Economic Journal: Macroeconomics* 1.
- Galí, J. and T. van Rens (2017). The vanishing procyclicality of labor productivity. *Working Paper*.
- Garín, J., M. Pries, and E. Sims (Forthcoming). The relative importance of aggregate and sectoral shocks and the changing nature of economic fluctuations. *American Economic Journal: Macroeconomics*.
- Gollin, D. (2002). Getting income shares right. *Journal of Political Economy* 110.
- Gomme, P. and J. Greenwood (1995). On the cyclical allocation of risk. *Journal of Economic Dynamics and Control* 19.
- Gomme, P. and P. Rupert (2004). Measuring labor’s share of income. *Federal Reserve Bank of Cleveland, Policy Discussion Paper no. 04-07*.
- Goos, M. and A. Manning (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics* 89(1), 118–133.
- Goos, M., A. Manning, and A. Salomons (2009). Job polarization in Europe. *American economic review* 99(2), 58–63.
- Gordon, R. J. (2010). Revisiting U.S. productivity growth over the past century with a view of the future. *NBER Working Paper, No. 15834*.
- Gregory, R. G. and J. Borland (1999). Recent developments in public sector labor markets. *Handbook of labor economics* 3, 3573–3630.
- Grossman, G., E. Helpman, E. Oberfield, and T. Sampson (2017). The productivity slowdown and the declining labor share: A neoclassical exploration. *NBER Working Paper, No. 23853*.
- Groves, T. and J. Ledyard (1977). Optimal allocation of public goods: A solution to the “free rider” problem. *Econometrica: Journal of the Econometric Society*, 783–809.

- Hall, R. (2003). Wage determination and employment fluctuations. *NBER Working Paper 9967*.
- Hall, R. (2007). How much do we understand about the modern recession? *Brookings Papers on Economic Activity 2*.
- Hamilton, J. D. (2017). Why you should never use the hodrick-prescott filter. *The Review of Economics and Statistics Forthcoming*.
- Hansen, G. D. and E. C. Prescott (2005). Capacity constraints, asymmetries, and the business cycle. *Review of Economic Dynamics 8*.
- Hodrick, R. J. and E. C. Prescott (1997). Postwar us business cycles: an empirical investigation. *Journal of Money, credit, and Banking*, 1–16.
- Hyatt, H. and J. Spletzer (2013). The recent decline in employment dynamics. *Center for Economic Studies Working Paper No. 13-03*.
- Jaimovich, N. and H. E. Siu (2012). The trend is the cycle: Job polarization and jobless recoveries. Technical report, National Bureau of Economic Research.
- Jorgenson, D. (1963). Capital theory and investment behavior. *American Economic Review 53*.
- Kaldor, N. (1957). A model of economic growth. *The Economic Journal 67*.
- Karabarbounis, L. (2014). The labor wedge: Mrs vs. mpn. *Review of Economic Dynamics 17*.
- Karabarbounis, L. and B. Neiman (2014). The global decline of the labor share. *Quarterly Journal of Economics 129*.
- Katz, L. F. and A. B. Krueger (1992). *Public sector pay flexibility: labour market and budgetary considerations*. Organisation for Economic Co-operation and Development.
- Katz, L. F. and A. B. Krueger (2012). Changes in the structure of wages in the public and private sectors. In *35th anniversary retrospective*, pp. 721–756. Emerald Group Publishing Limited.
- Kehrig, M. and N. Vincent (2017). Growing productivity without growing wages: The micro-level anatomy of the aggregate labor share decline. *ERID Working Paper No. 244*.
- Koh, D. and R. Santaeulàlia-Llopis (2017). Countercyclical elasticity of substitution. *Working Paper*.

- Kravis, I. B. (1959). Relative income shares in fact and theory. *American Economic Review* 49.
- Lommerud, K. E. and O. R. Meland, Frode asnd Straume (2009). Can deunionization lead to international outsourcing? *Journal of International Economics*.
- Lorenzoni, G. (2009). A theory of demand shocks. *American Economic Review* 99.
- Machado, J. A. and J. Mata (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of applied Econometrics* 20(4), 445–465.
- MacLeod, W. B. and J. M. Malcomson (1993). Investments, holdup, and the form of market contracts. *American Economic Review* 83.
- Martinez, J. Automation, growth and factor shares.
- McConnell, M. M. and G. Perez-Quiros (2000). Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review* 90.
- McGrattan, E. R. and E. C. Prescott (2012). The labor productivity puzzle. In L. Ohanian, J. Taylor, and I. Wright (Eds.), *Government Policies and the Delayed Economic Recovery*. Hoover Institution Press.
- Melly, B. (2005). Public-private sector wage differentials in germany: Evidence from quantile regression. *Empirical Economics* 30(2), 505–520.
- Molloy, R., C. L. Smith, R. Trezzi, and A. Wozniak (2016). Understanding declining fluidity in the u.s. labor market. *Brookings Papers on Economic Activity Spring 2016*.
- Na, S. (2017). The labor share fluctuation. *Working Paper*.
- Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, 693–709.
- OECD. Public sector compensation in times of austerity.
- Poterba, J. M. and K. S. Rueben (1994). The distribution of public sector wage premia: new evidence using quantile regression methods. Technical report, National Bureau of Economic Research.
- Quadrini, V. and A. Trigari (2007). Public employment and the business cycle. *The Scandinavian Journal of Economics* 109(4), 723–742.
- Ravn, M. O. and H. Uhlig (2002). On adjusting the hodrick-prescott filter for the frequency of observations. *Review of economics and statistics* 84(2), 371–376.

- Ríos-Rull, J.-V. and R. Santaaulàlia-Llopis (2010). Redistributive shocks and productivity shocks. *Journal of Monetary Economics* 57.
- Rognlie, M. (2015). Deciphering the fall and rise in the net capital share: Accumulation or scarcity? *Brookings Papers on Economic Activity Spring 2015*.
- Solow, R. M. (1958). A skeptical note on the constancy of relative shares. *American Economic Review* 48.
- Stiroh, K. J. (2009). Volatility accounting: A production perspective on increased economic stability. *Journal of the European Economic Association* 7.
- Stock, J. H. and M. W. Watson (2002). Has the business cycle changed and why? *NBER Macroeconomics Annual*.
- Thomas, J. and T. Worrall (1988). Self-enforcing wage contracts. *Review of Economic Studies* 55.

Biography

Vasco Gomes Lopes de Castro Botelho was born October 2, 1988 in Lisbon, Portugal. He graduated from Nova School of Business and Economics in 2009 with a B.Sc. in Economics. He started the Research Masters in Economics at Nova School of Business and Economics and won the 2012 Fundação Amélia de Mello Prize. He started his Ph.D. at Duke University in 2012 and earned his M.A. at Duke in 2017. Vasco earned his Ph.D. in Economics from Duke University in May 2018.