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THE LABOR WEDGE: NEW FACTS BASED ON US MICRODATA*

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Abstract
I document a new set of facts about the labor wedge in the United States. First, while the labor wedge is counter-cyclical, its cross-sectional variation is pro-cyclical. Second, this finding holds regardless of gender, marital status, age, race, education and income rank. In order to show these facts, I develop a simple heterogeneous-agent model, in which productivities are different across individuals. In addition, I show evidence that the variation in the aggregate labor wedge is explained partially (between 16 and 45 percent) by the variation in the aggregate heterogeneous productivities across individuals. Finally, I discuss implications for future related research.

Resumen
En este trabajo, documento un conjunto nuevo de hechos estilizados acerca de las brechas laborales en los Estados Unidos. Primero, las brechas laborales son contracíclicas, y su variación intratemporal es procíclica. Segundo, esta observación se mantiene, aun controlando por género, estado civil, edad, raza, nivel de educación y ránking de ingresos. Para encontrar estos hallazgos, desarrollo un modelo simple de agentes heterogéneos, en los cuales las productividades difieren entre individuos. Además, muestro evidencia que la variación de las brechas laborales agregadas es parcialmente explicada (entre 16 y 45 por ciento) por la variación intratemporal de las productividades heterogéneas agregadas. Finalmente, discuto implicancias para investigación futura.

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1 Introduction

In this paper, I show new empirical findings that the labor wedge - the ratio between the marginal rate of substitution (MRS) and the marginal productivity of labor (MPL) - is countercyclical. In addition, I present evidence that it comoves negatively with its cross-sectional standard deviation. This negative correlation is relatively strong and holds even if we condition the sample by traits and characteristics. Specifically, I establish three facts:

Fact 1: The aggregate labor wedge is countercyclical, and its cross-sectional standard deviation correlates negatively with it (in deviation from trends). This correlation is strong (between -0.56 and -0.75). In particular, the standard deviation of the labor wedge is pro-cyclical.

Fact 2: Fact 1 holds regardless of gender, marital status, age, race, education and income rank.

Fact 3: The variation in the aggregate labor wedge is explained partially by the variation in the aggregate heterogeneous productivity.

In order to establish these facts, I develop a simple heterogeneous-agent model in which productivities differ across individuals. This heterogeneous source of variation allows me to derive an *individual-specific* labor wedge. I use this measure to account for Facts 1 and 2. In addition, I also show that the aggregate labor wedge is a composite of three sources of variation. The first one refers to any distortion in the market (for example taxes and subsidies). The second accounts for the aggregation of heterogeneous productivities. The third is a correction for aggregate hours worked, in terms of aggregate effective hours. This decomposition shows the finding shown in Fact 3.

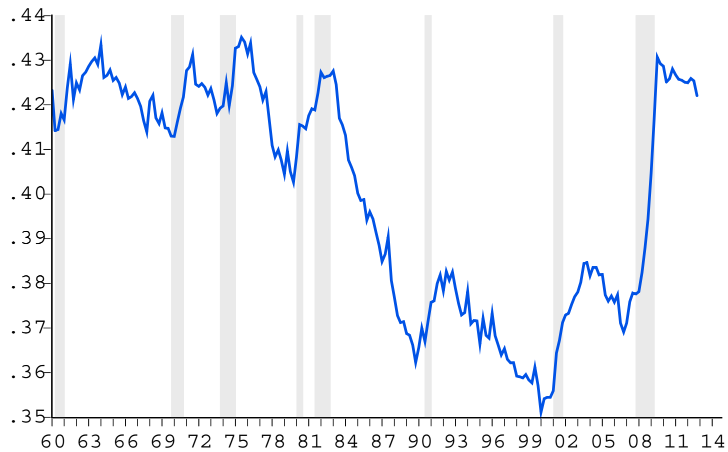
In the last few years, several researchers have shown great interest in both: level and cyclical behavior of the labor wedge. According to the neoclassical theory, after controlling for taxes and subsidies this ratio should be constant. Interestingly, many of these papers have shown that the labor wedge is actually counter-cyclical, that is, that this gap increases in recessions.[1] Figure 1 shows this stylized fact.

Even though many papers have investigated possible explanations of this pattern, I found that none of them have exploited the heterogeneity present in micro data. In order to fill in this gap, this paper documents group-specific labor wedges, and characterizes their behavior throughout the business cycle. Since the literature on this topic using micro data is at most scant, this paper could be a useful source to motivate future research on the topic. In particular, the evidence I show in the present document could be used as a motivation to construct a theory to explain each of this new set of facts.

My paper makes two main contributions. First, I show evidence about the second moment of the labor wedge, and its cyclical behavior. I show that this pattern is robust even

[1] See for example Shimer (2009), Hall (2009), Karabarbounis (2012, 2014) among others

Figure 1: Labor Wedge in the US



Source: Own calculations based on Figure 2 in Shimer (2009). Shaded areas represent NBER recession periods.

within particular sets of groups in the data. The new evidence shown in this paper indicates that the cross-sectional standard deviation of the labor wedge may predict its level depending on current economy conditions, negatively when the standard deviation is high (which coincidentally happens when the economy is in booms), and positively when the opposite happens. This is Fact 1. As I will show in the following sections, regression exercises and causality tests corroborate this finding. Second, this paper shows evidence that the aggregate labor wedge is explained partially by the variation in the (aggregate) heterogeneous component of the labor wedge, composed mainly by the different productivity shocks per individual. This finding is consistent with the idea that when we introduce heterogeneity in the model, aggregation may be driving the results. In other words, the counter-cyclical pattern of the labor wedge may be, at least partially, explained by aggregation issues, and not only by distortions in the labor market.[2]

Fact 2 shows that this pattern is independent of any specific group. There are concerns that the findings shown in this paper are driven by specific groups in the dataset.[3] Fact 2 shows that Fact 1 holds even after conditioning for gender, marital status, education levels, income ranks, and race. Because of this, it may now be possible to predict labor wedges by specific characteristics of the individuals.

[2]Mulligan (2012) argues that about 80% of the variation in the aggregate labor wedge during the Great Recession may be explained by labor market distortions, such as unemployment benefits, food stamps, subsidies, and other safety net policies.

[3]For example, it may be argued that during booms many women drop out of the labor force. Then, the labor wedge pattern is mainly driven by men during the cycle. The same could be said for young workers versus prime age workers; married versus singles; whites versus blacks; or less educated versus college graduates.

For this study, I exploit the Consumer Expenditure Survey (CEX), which is a dataset containing rich information about a representative sample of American expenditure patterns. I take moments from repeated cross-sections starting from the second quarter of 2003 until the first quarter of 2013. It is particularly important for the purpose of this paper to have information on all of the following variables per individual: total consumption, hours worked, and total income. Since there is no other data set containing all this information, at least not that I am aware of, the CEX is the only source of information to assess these findings for the United States. In this paper I show semi-aggregate statistics containing information about key moments (mean and standard deviations), and show how they move through time for different sets of groups. Since this paper is concerned about how the labor wedge behaves during the business cycle, I only show deviation from trends. Therefore, I will not show how large this measure is, but rather I will characterize its cyclical pattern.

The rest of the document is organized as follows. In Section 2, I illustrate conceptually what the labor wedge is. I present the derivation of the labor wedge derived from a simple heterogeneous-agent model, and how it compares with the representative agent one. Section 3 shows the methodology used to document the facts. I also discuss in this section potential drawbacks that may be driving the results, and how I cope with them. Section 4 shows the findings of the paper. In addition, I show why heterogeneity may matter for explaining the aggregate labor wedge. Finally, Section 5 shows the conclusion and a brief discussion about future research related to what is found in this document.

2 Conceptual Underpinnings

The labor wedge, measured as the distance between a representative household's MRS between consumption and leisure and the representative firm's MPL, has been a great object of study in the recent years. In the neoclassical theory, these two mathematical objects should be equal, or at most their distance should be constant explained only by the variation in taxes. There is a growing amount of evidence that this condition is violated empirically. In fact, the labor wedge is counter-cyclical, as shown in Figure 1. Lately, some papers have arisen in the literature in order to explain this behavior. The first intuitive and obvious hypothesis to test empirically is that taxes increase during recessions. McGrattan and Prescott (2007) for example, show that when variation in taxes is included in the labor wedge dynamics, the model fits better to the data. However, the improvement is marginal (Romer and Romer 2007 show that the variation explains at most 18% of the business cycle variance). Still, most economists do not share this explanation as the main driver of the labor wedge pattern. The present work supports this finding by isolating the effect of labor market distortions, which is not observed in my data set, with that of heterogeneity present in the market.

Other authors claim that this pattern may be explained because utility and production functions are misspecified. Shimer (2009) shows that many different and flexible specifications lead to labor wedges with essentially the same cyclical behavior than the regular Cobb-Douglas and additively separable CRRA specifications. I will not be discussing about this issue in the present paper.

A third wave of papers suggest that disutility of working is pro-cyclical. In other words, either there are some kind of chronic laziness in recessions or workers acquire monopoly power during recessions, which makes them work *less* in order to drive up wages (see for example Galí and Rabanal 2004, Smets and Wouters 2007).

In this section, I organize the discussion by briefly presenting a simple model usually seen in this literature, which derives the labor wedge (see for example Shimer (2009) and Karabarbounis (2014)). Then, I will motivate the following sections by changing the model to introduce heterogeneity, and how the individual labor wedge would look like under these circumstances. Facts 1 and 2 are based on the individual labor wedge. Finally, I show the derivation of the aggregate labor wedge, by decomposing it in three terms: labor market distortions, aggregate heterogeneous effects, and a correction for aggregate hours worked.

2.1 The neoclassical model

Households

In this economy, every household is identical, and has the following preferences:

$$U(c,h) = \log c_t + \gamma \log(1 - h_t), \tag{1}$$

where $\gamma > 0$, c_t is consumption, $h_t \in [0,1]$, hours worked. This specification is more restrictive than what others have estimated[4]. I will restrict my specification to this one for the sake of simplicity, especially for the derivation of the aggregate labor wedge for the heterogeneous-agent model presented in the next subsection. The intertemporal budget constraint faced by the household is:

$$a_t + (1 - \tau_h) w_t h_t + T_t = (1 + \tau_c) c_t + (1 + \tau_k) q_{t+1} a_{t+1}, \tag{2}$$

where τ_h, τ_c, τ_k are labor, consumption and capital tax rates, respectively; T_t is a lump-sum transfer; w_t is the hourly wage; a_t are bond holdings; and q_{t+1} is the before-tax price of a bond at time $t+1$.

The problem of the household is to maximize equation (1) subject to (2). The first-order conditions are the following:

$$\begin{aligned} \frac{1}{c_t} &= \lambda(1 + \tau_c) \\ \gamma \frac{1}{h_t} &= \lambda(1 - \tau_h) w_t. \end{aligned}$$

Combining both, and defining $\tau \equiv \frac{\tau_c + \tau_h}{1 + \tau_c}$ (the *relevant* tax rate), we obtain:

$$w_t(1 - \tau) = \gamma \frac{c_t}{h_t}, \tag{3}$$

[4] Shimer (2009) and Karabarbounis (2014) use a more flexible specification, in order to estimate the Frisch elasticity of labor.

which reflects the (inverse) labor supply of the household.

Firms

In this economy, firms are homogeneous. They solve the following problem:

$$\max_{\{k,n\}} \left[A_t k^\alpha n_t^{1-\alpha} - (\delta + r_t)k_t - w_t n_t\right].$$

The first-order conditions for labor demand (n_t) is:

$$w_t = (1-\alpha)\frac{y_t}{n_t}. \tag{4}$$

Imposing labor market clearing: $h_t = n_t$, using equations (4) and (3), and rearranging terms we obtain the labor wedge:

$$\tau = 1 - \left(\frac{\gamma}{1-\alpha}\right)\frac{h_t}{1-h_t}\left(\frac{c_t}{y_t}\right) \tag{5}$$

This equation presents a static relationship between the labor wedge on the left-hand side; with the consumption to income ratio and labor hours on the right-hand side. The cyclical behavior of the labor wedge will finally depend on both: labor hours and the consumption-to-income ratio.

2.2 Heterogeneous-agent model

Households

In this subsection, I introduce a small twist in the model.[5] Suppose there are J different types of consumers. Then, the household problem becomes:

$$\max_{\{c_{jt},h_{jt}\}} \log c_{jt} + \gamma \log(1-h_{jt}), \qquad j \in \{1,2,\ldots,J\} \tag{6}$$

subject to the budget constraint:

$$k_{jt} + (1-\tau_h)w_t z_{jt} h_{jt} + T_{jt} = (1+\tau_c)c_{jt} + (1+\tau_k)q_{t+1}k_{t+1}, \tag{7}$$

where z_{jt} is an *individual-specific* (j) productivity shock during period t. The optimal intratemporal condition is:

$$\gamma\frac{c_{jt}}{1-h_{jt}} = w_t z_{jt}(1-\tau), \tag{8}$$

where w_t is the *average* hourly wage. If the individual productivity is high, z_{jt}, more hours are supplied. Consequently, consumption also differs across individuals. Therefore, the introduction of an idiosyncratic shock generates dispersion in the labor wedge, even though they possess the same utility function. I will later show that this feature may be important for the determination and cyclical pattern of the aggregate labor wedge.

[5] This heterogeneous-agent model is similar to that developed in Cociuba and Ueberfeldt (2012).

Firms

As before, the representative firm uses a standard Cobb-Douglas production function: $Y_t = AK^{\alpha}\widetilde{L}^{1-\alpha}$, where $K \equiv \sum_j k_j$; and $\widetilde{L} \equiv \sum_j z_{jt}h_{jt}N_j$ is the effective labor hours. N_{jt} is the amount of people of type j in time t. The first-order condition for the representative firm is the standard one:

$$w_t = (1-\alpha)\frac{y_t}{\widetilde{h}_t}, \tag{9}$$

where $y \equiv Y/N$, is the production per capita, and $N \equiv \sum_j N_j$ is the total amount of people in this economy. Also, $\tilde{h}_t = \frac{\widetilde{L}}{N}$ is the aggregate effective hours worked per capita.

2.2.1 The Individual Labor Wedge

I now have all the information to derive an individual-specific labor wedge. Suppose there are N individuals in the economy, each of whom is intrinsically different of another individual. Then $N_j = 1$, for all $j \in J$. Using equations (8) and (9), and arranging, I can derive the *individual* labor wedge:

$$\tau_{het} = 1 - \left(\frac{\gamma}{1-\alpha}\right)\frac{\widetilde{h}_t}{1-h_{jt}}\left(\frac{c_{jt}}{y_t}\right)\left(\frac{1}{z_{jt}}\right), \tag{10}$$

where $\widetilde{h}_t \equiv \frac{1}{N}\sum_j^N z_{jt}h_{jt}$. Now notice that if $z_{jt} = z_t \equiv 1$, we have that $c_{jt} = c_t$, $h_{jt} = h_t$, $w_{jt} = w_t$, and naturally, the heterogeneous-agent labor wedge boils down to the representative-agent one. In order to estimate the idiosyncratic productivity, I propose

$$z_{jt} = \frac{w_{jt}}{w_t}.$$

Then, the individual labor wedge in the heterogeneous-agent model is:

$$\tau_{het} = 1 - \left(\frac{\gamma}{1-\alpha}\right)\frac{\widetilde{h}_t}{1-h_{jt}}\left(\frac{c_{jt}}{y_t}\right)\left(\frac{w_t}{w_{jt}}\right), \tag{11}$$

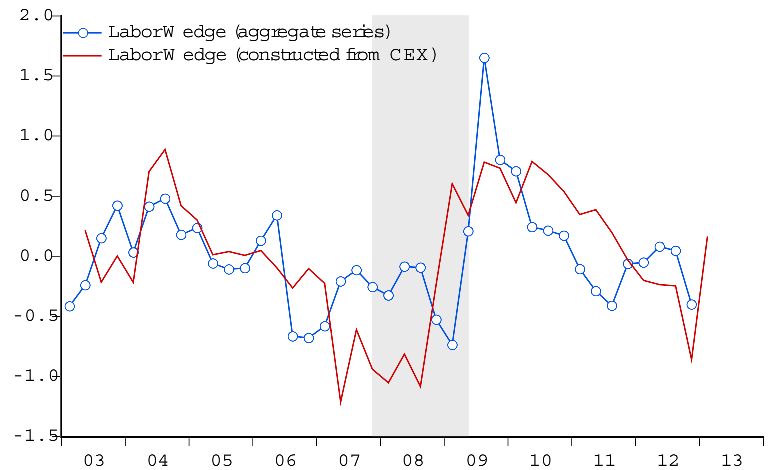
which I calculate using micro data. Section 4 shows these calculations. Specifically, I will focus on two moments: mean and standard deviation.

3 Methodology and Data

The main purpose of this paper is to document cyclical movements of the labor wedge, using micro data. In this section I lay out the empirical definitions, methodology and data.

As shown in equation (5), labor hours, total income and consumption per consumer unit are crucial to undertake this study. While hours and income are usually found in most household surveys, total consumption (or expenditures) are scant. For this reason, I exploit the CEX, a representative survey for the American spending behavior for families. I possess quarterly data starting from the second quarter of 2003 until the first quarter of 2013. In order to calculate individual labor wedges, I make the following working assumptions. First, I only take into account working individuals, that is, those who reported positive hours *usually* worked. Since I first want to validate my aggregate measure of labor wedge with the standard aggregate variable, I consider hours worked of those who actually worked (present in the employment force). Second, the variable for income I use is total income before taxes. The after-taxes measure contains many missing values, which is an issue for the representativeness of the final sample. However, both series are very close to each other. Even though I do not show them in the present document, they are available upon request. Third, the consumption variable does not include durable goods. I subtract them from total consumption, as durable expenditure does not necessarily follow business cycle frequency. In particular, I subtract housing, healthcare and education expenditures.

Figure 2: Labor Wedge in the US: Comparison between Aggregate Series and own calculation using CEX



Source: Author's calculations based on equation (8) in Shimer (2009), with parameter $\varepsilon = 4$. Cyclical component using Hodrick-Prescott filter with parameter 1600. Shaded area represents NBER 2008-09 recession period.

Fourth, I assume (nondurable) expenditures are spent in equal parts between all working persons in every household. Because the relevant unit in the CEX are families, there is no way to observe spending behavior per individual inside the households.[6] The final product is a labor wedge per working person inside each consumption unit. Since the CEX has quarterly frequency, all series were seasonally adjusted using standard Arima-X12 methods. Figure 2 shows the aggregate labor wedge for both aggregate series (constructed using data from

[6]The CEX survey uses as the relevant individual the so-called consumer unit, which consists of any of the following: (i) members of the same household related by blood, marriage, adoption or other legal arrangement, (ii) a person living alone (or with others) who is financially independent; or (iii) two or more people living together who share incomes to make financial spending decisions jointly. For a more technical definition see BLS (2010)

the CPS, with the same methodology as in Shimer 2009), and the aggregate labor wedge using the CEX. It is visually clear that both variable resemble, and tell the same story in business cycle frequencies. The labor wedge is countercyclical (in deviations from trend). Their simple correlation is 0.47.

Having explained the treatment of the data set, I will now proceed to explain what is next in the paper. I first calculate individual labor wedges according to equation (10). I calculate the standard deviation of the cross section, which reflects the dispersion across all individual who belong to a given group for a given period of time. The labor wedge per group is calculated as a weighted average of all labor wedges that belong to that group. Then, all series are smoothed using a Hodrick-Prescott filter with parameter 1600. I present graphs, correlations, regressions and Granger causality tests. I also regress labor wedges (in deviations from trend) against a constant and the cross-sectional standard deviation. In addition, I present the same regression taking first differences in order to see if there is a noncyclical pattern that is explaining some of the labor wedge variation. As it will be shown later, I find strong evidence that standard deviation of the labor wedge predicts it, not only in levels, but also in first differences. In addition, I also show Granger causality tests, which confirm the predictability of standard deviation on labor wedges. I must emphasize, however, that these exercises do not show economic causality, but merely interesting correlations among them. The final idea is to motivate further research to explain the facts presented in this document.

Finally, I assume the following parameters for the labor wedge calculations. $\alpha = 1/3$, which is conventional in macroeconomics; $\gamma = 1$ is assumed as well. I do not show calculations for different parameters for γ, as it should not affect cyclical patterns, which is mainly the scope of this paper. An important parameter is the Frisch elasticity of labor, which still is no present in this study. The Frisch elasticity of labor (ε) is relevant to account for the responsiveness of hours worked to productivity shocks. Microeconomists consider that ε is generally less than one, and clearly closer to zero. On the other hand, macroeconomists in general coincide in that $\varepsilon = 1$ is relatively low. Shimer (2009), for example, shows exercises in which the response of hours in different countries (Germany, France and US) yields a theoretical value for ε closer to 4. In the same study he shows that the business cycle pattern of the labor wedge does not depend much on this parameter. Even though this parameter is an important part of the story on how to account for labor wedge changes, I will restrict it only for Fact 1 below. There are two reasons to support this decision. First, as I will show soon, parameter ε is not a very relevant source of information to account for the *cyclical pattern* of the labor wedge. Although the amplitude of the cycle is affected by this elasticity, the general pattern remains the same. Second, Fact 3 shows the aggregate labor wedge as a function of a (closed form) expression which is composed partially by an aggregate composite of heterogeneous productivities. Since I want to show a simple expression to account for heterogeneity in aggregate terms, I will restrict the utility function for the sake of clarity in the exposition.

4 The Facts

Fact 1: *The aggregate labor wedge is countercyclical, and its cross-sectional standard deviation correlates negatively with it (in deviation from trends). In particular, the standard deviation of the labor wedge is pro-cyclical.*

Before going ahead, I present three different specifications that I use to account for Fact 1. Suppose the utility function of a consumer j is the following:[7]

$$\log c_{jt} - \frac{\gamma\varepsilon}{1+\varepsilon} h_{jt}^{\frac{1+\varepsilon}{\varepsilon}}. \tag{12}$$

The consumer's problem is to maximize (12) subject to (7). Solving the model as I did in Section 2, the (heterogeneous-agent) labor wedge becomes:

$$\tau_{het} = 1 - \left(\frac{\gamma}{1-\alpha}\right)\left(\frac{c_{jt}}{y_t}\right)\widetilde{h}_t h_{jt}^{\frac{1}{\varepsilon}}\left(\frac{1}{z_{jt}}\right), \tag{13}$$

where y_t and $\widetilde{h}_t$ are defined as in Section 2. The advantage of this labor wedge is that I have an extra parameter to calibrate: ε. For the purpose of this paper, and only to account for Fact 1, I will consider two values for ε: 1 and 4.[8]. The specifications studied in this section are the following:

$$\tau_1 = 1 - \left(\frac{\gamma}{1-\alpha}\right)\frac{\widetilde{h}_t}{1-h_{jt}}\left(\frac{c_{jt}}{y_t}\right)\left(\frac{1}{z_{jt}}\right) \tag{14}$$

$$\tau_2 = 1 - \left(\frac{\gamma}{1-\alpha}\right)\widetilde{h}_t h_{jt}\left(\frac{c_{jt}}{y_t}\right)\left(\frac{1}{z_{jt}}\right) \tag{15}$$

$$\tau_3 = 1 - \left(\frac{\gamma}{1-\alpha}\right)\widetilde{h}_t h_{jt}^{\frac{1}{4}}\left(\frac{c_{jt}}{y_t}\right)\left(\frac{1}{z_{jt}}\right) \tag{16}$$

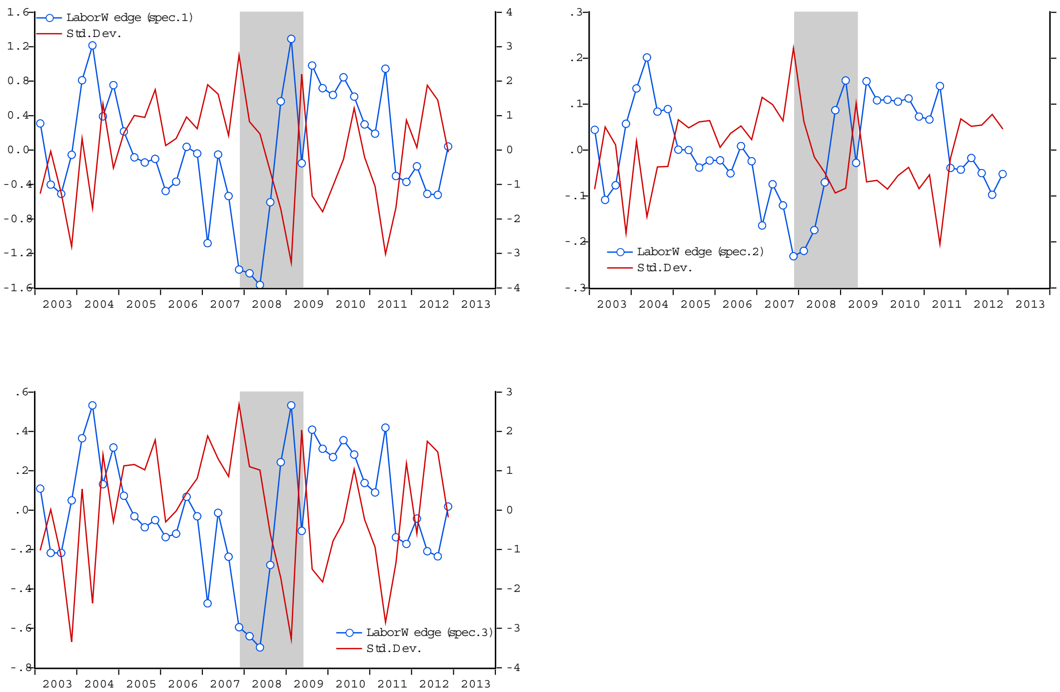
Figure 3 shows graphically the cyclicality of these three measures. Fact 1 is visually clear when we observe Figure 3. The data used in this paper allows me to account for one recession period (the Great Recession 2008-09). Two findings are clear from this graph. First, the labor wedge, as defined in equation (10), is counter-cyclical for the three specifications. Second, the standard deviation is comoves negatively with the mean of the labor wedge. Finally, during the Great Recession, the standard deviation was pro-cyclical. Table 1 shows simple correlations, t-stats and p-values. Fact 1 is confirmed not only by visual inspection, but also for the statistical significance. Simple correlation is around -0.6, with a rounding p-value of 0.001. See these results in Table 1.

This finding is consistent with what many authors have found before: hours worked during recessions decrease (see for example Chang and Kim (2007)). Then, the labor wedge

[7] I now use the specification used in Shimer (2009), adding heterogeneity in the model.

[8] Chang et al. (2014) argue that a Frisch elasticity of 1 is reasonable. I add $\varepsilon = 4$, to account for a more extreme case.

Figure 3: Fact 1: Aggregate Labor Wedge and its Cross-Sectional Standard Deviation



Source: Author's calculations. The three specifications are shown in equations (14), (15), and (16). All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600. Shaded area represents NBER 2008-09 recession period.

mechanically approximates to one (its maximum value). It is important to recall, however, that I only take into account hours worked of those who actually worked (that is hours of work are strictly greater than zero). Consequently, we would expect to have an even greater effect on labor wedge volatility, if we included all members of the labor force.

Table 1: Fact 1 - Correlation between Labor Wedge and its Cross-Sectional Standard Deviation

Underlying Model	Simple Correlation	t-statistic	p-value
Specification 1	-0.562798	-4.197127	0.0002
Specification 2	-0.754951	-7.096615	0.0000
Specification 3	-0.600316	-4.627119	0.0000

Source: Author's calculations. The three specifications are shown in equations (14), (15), and (16). Simple correlations between aggregate labor wedges and their standard deviations. All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

In order to confirm the results of this visual inspection, I also perform regressions of the following form:

$$\widehat{\tau}_t = \beta_0 + \beta_1 sd(\widehat{\tau}_t) + \epsilon_t \quad (17)$$
$$\Delta\widehat{\tau}_t = \pi_0 + \pi_1 \Delta sd(\widehat{\tau}_t) + \upsilon_t, \quad (18)$$

where the 'hats' over the variables denote deviations from trends, $sd(\cdot)$ denotes the cross-sectional standard deviations, and Δ denotes first differences of the variables. The purpose of this exercise is twofold. First, I want to quantify the effect of an increase in the variability of labor wedge on its level. This effect is shown from β_1. Second, I use first difference to evaluate whether this effect is only affected the cyclical pattern. If the estimated parameter for π_1 is statistically significant, then there is something beside the business cycle fashion of the standard deviation that is explaining the labor wedge. The results are shown in Table 2.

Table 2: Fact 1 - Regressions from equations (17) and (18)

Dependent Variable: $\widehat{\tau}$			
Underlying Model		*R-squared*	*N*
In Levels			40
Specification 1	-0.267780	0.316742	
Specification 2	-0.046536	0.569951	
Specification 3	-0.120574	0.360380	
First Differences			39
Specification 1	-0.207576	0.340409	
Specification 2	-0.030790	0.489540	
Specification 3	-0.091178	0.384197	

Source: Author's calculations. All regressions corrected for Newey-West variance-covariance matrix. All parameters are statistically significant at 1% confidence level. I consider two values for ε: 1, and 4. All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

Table 2 shows two results. First, it confirms what was already clear. There is a negative relation between the labor wedge and its standard deviation. Inspecting for different specifications, I find that all the parameters estimated for β_1 in equation (17) are significant at one percent of confidence. The impact of an increase in one percent of $sd(\widehat{\tau})$ over its trend is between 5 and 27% decrease of labor wedge from its trend, depending on the specifications, and the Frisch elasticity. If the Frisch labor elasticity is higher, the impact (in absolute value) is higher. This latter result is intuitive as hours adjust much faster with a higher elasticity, and hence, the labor wedge is impacted harder. Second, the aforementioned effect remains, even after I correct for the cycle. In order to check this, I estimate equation (18) to see if the effect of $sd(\widehat{\tau})$ is only due to a cyclical trends. The results are shown in the second panel of Table 2. Again, the effects are all negative and statistically significant at 1% confidence level. The takeaway of this exercise is that there is something beside the business cycle effect that is affecting the labor wedge.

Finally, I perform standard Granger causality tests. The objective of this exercise is not to show economic causality, but rather a statistical predictability of the labor wedge, based on a VAR structure with two lags. Results for the Granger causality tests are shown in Table 3. The null hypothesis that $sd(\widehat{\tau})$ *does not Granger cause* $\widehat{\tau}$, is always rejected at conventional confidence levels. That is, I find that the cross-sectional standard deviation *predicts* the labor wedge. This is generally true, even after controlling for the cycle. As before, I take first differences and perform Granger causality tests. With no exception, all tests reject the null hypothesis at 5 per cent confidence level.

Table 3: Fact 1 - Grange causality tests

Underlying Model	F-statistic
In Levels	
Specification 1	4.04004**
Specification 2	4.78234**
Specification 3	3.93037**
First Differences	
Specification 1	3.85542**
Specification 2	4.28939**
Specification 3	3.81064**

Source: Author's calculations. Null Hypothesis: $sd(\widehat{\tau})$ *does not cause* $\widehat{\tau}$. *, **, and ***, denote statistical significance at 10%, 5% and 1% confidence level, respectively. I consider two values for ε: 1, and 4. All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

Summing up, Fact 1 shows that the mean of individual labor wedges are countercyclical, as it is widely documented in the literature. The cross-sectional standard deviation, however, is pro-cyclical. In particular, these two series are strongly negatively correlated. This pattern is robust to different parameterizations of the Frisch labor elasticity (ε), and to a different and restrictive consumer preferences.

One might ask now if these patterns are driven by specific subgroups of the labor force. For example, suppose one group is propense to enter the labor market during booms, and drop out of it during recessions. If this group is sufficiently diverse, then the cross-sectional variation of my measure of the labor wedge should increase during booms, and decrease during recessions. This observation led me to investigate whether Fact 1 is robust to these movements. After performing different exercises, I arrived to the next Fact.

Fact 2: *Fact 1 holds regardless of gender, marital status, age, race, education and income rank.*

Fact 2 demonstrates that the aggregate trend found in Fact 1 is robust even if we condition by these individual characteristics. This evidence contradicts what other authors have hypothesized about labor wedge aggregation and its variation over time. For example, Cociuba, and Ueberfeldt (2012) argue that the trend in the labor wedge in the US may be driven by gender productivity gap. If this hypothesis is true, then labor wedges conditional on gender should look different than the aggregate labor wedge. The same may be argued for married and single people, young versus prime age workers, blacks versus whites, low versus highly educated workers and poor versus wealthy individuals.

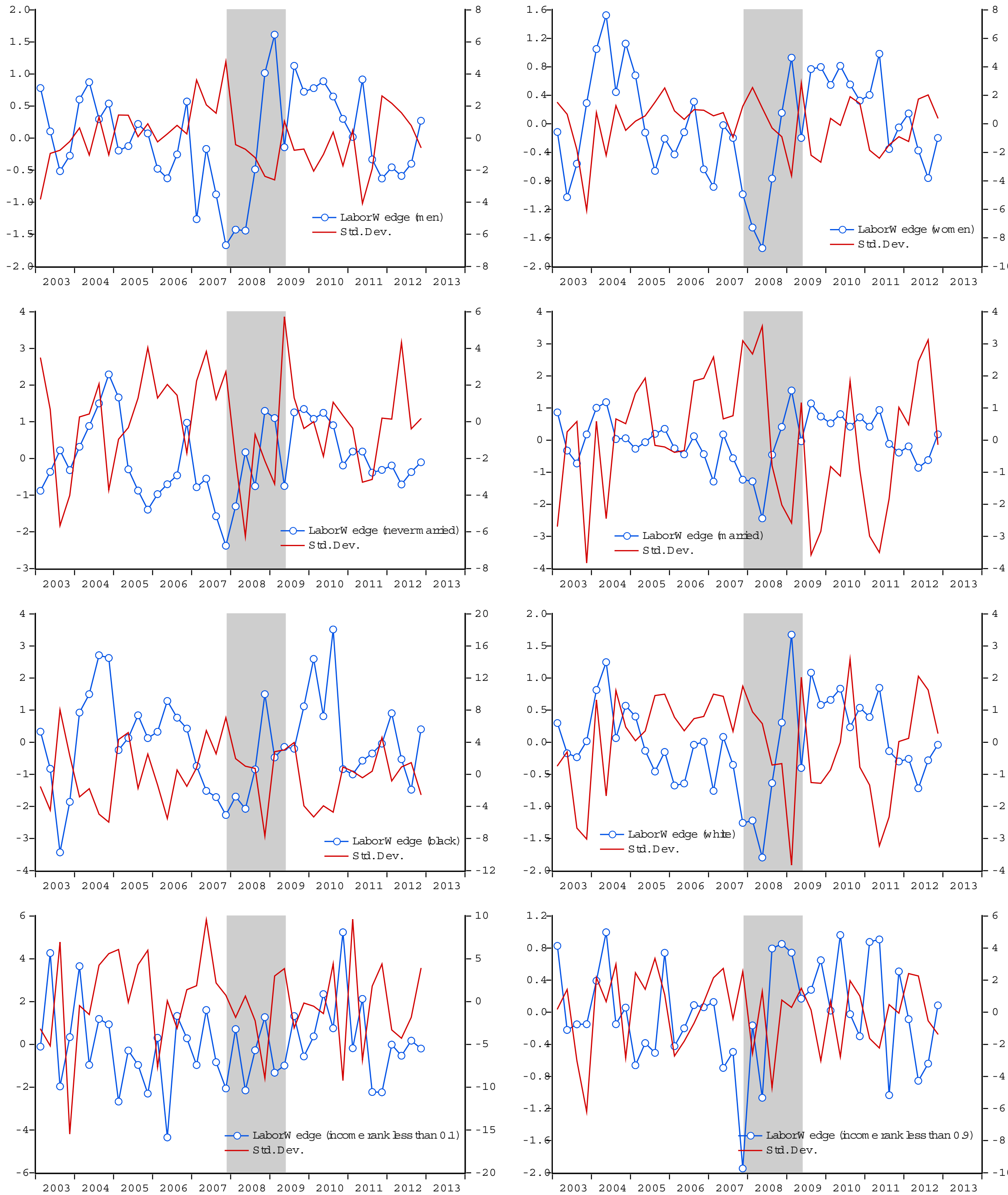
For the rest of the paper, I will only show graphs for labor wedges derived from specification 1 above (equation (14)). Of course, I can provide the calculations upon request. Figures 4 and 5 show labor wedges and their standard deviations, conditional on gender, marital status, race, wealth, age and education level. We can visually notice that the pattern documented in Fact 1 generally remains when we condition the calculations.

Table 4: Fact 2 - Correlation between Labor Wedge and its Cross-Sectional Standard Deviation: Analysis by subgroups

Subgroup	**Simple Correlation**	**t-statistic**	**p-value**
Men	-0.626958	-4.960934	0.000
Women	-0.460388	-3.196984	0.000
Single	-0.427814	-2.917709	0.0059
Married	-0.753020	-7.054632	0.000
Black	-0.765475	-7.333264	0.000
White	-0.513236	-3.686351	0.0007
Income rank <0.1	-0.418800	-2.842989	0.0072
Income rank >0.9	-0.349166	-2.296972	0.0272
Young (<25 years old)	-0.618748	-4.855231	0.000
Adult (between 25 and 65 y.o.)	-0.623566	-4.916937	0.000
Old (Older than 65 y.o.)	-0.798005	-8.162666	0.000
Less than High School	-0.320324	-2.084446	0.0439
High School and Associate Degree	-0.394173	-2.643904	0.0118
College Degree or more	-0.781193	-7.713713	0.000

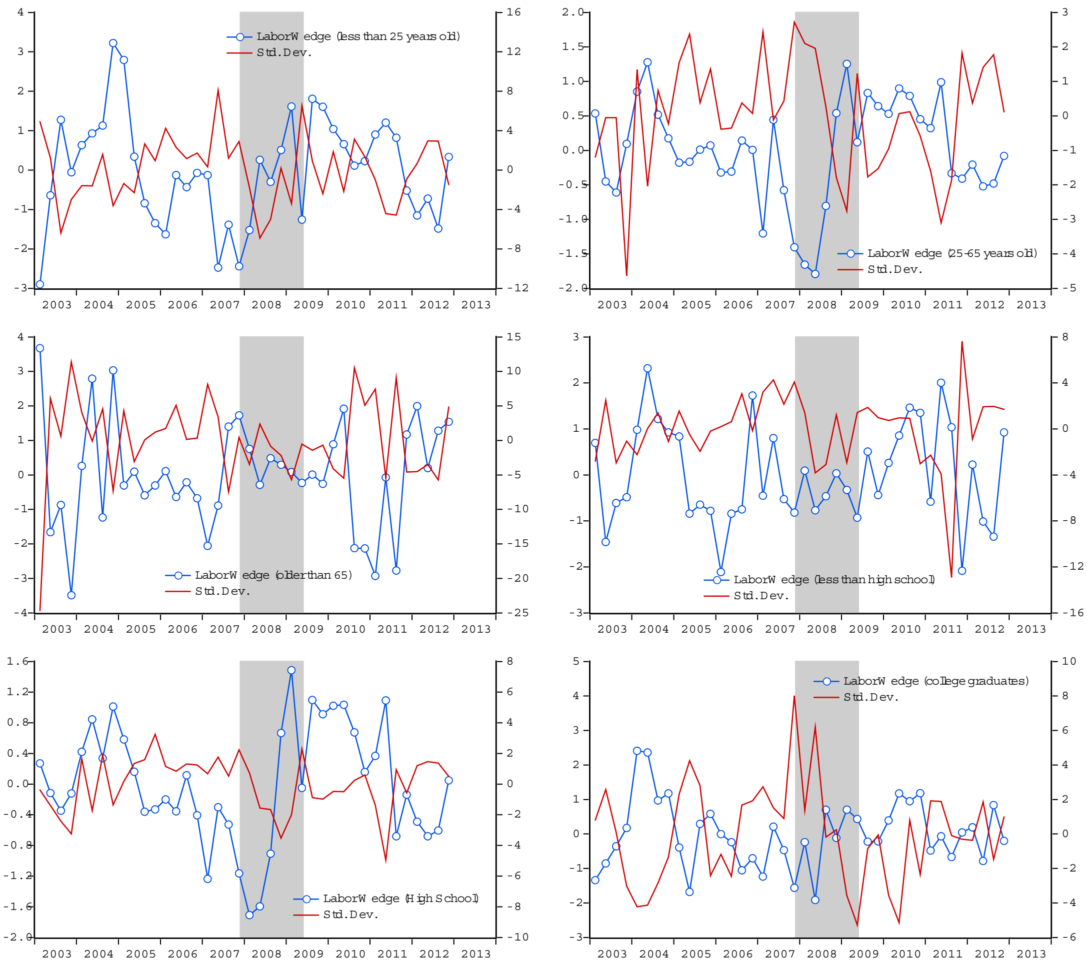
Source: Author's calculations. I only show specification 1 (equation (14)). Simple correlations between group-specific labor wedges and their standard deviations. All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

Figure 4: Fact 2: Conditional Labor Wedges and their Cross-Sectional Standard Deviations



Source: Author's calculations. I only show specification 1 (equation (14)). All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600. Shaded area represents NBER 2008-09 recession period.

Figure 5: Fact 2: Conditional Labor Wedges and their Cross-Sectional Standard Deviations (continuation)



Source: Author's calculations. I only show specification 1 (equation (14)). All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600. Shaded area represents NBER 2008-09 recession period.

Table 5: Fact 2 - Regressions from equations (17) and (18)

Dependent Variable: $\widehat{\tau}$			
Subgroup		*R-squared*	*N*
In Levels			40
Men	-0.262223^{***}	0.393077	
Women	-0.182575^{***}	0.211957	
Single	-0.163579^{***}	0.183025	
Married	-0.292516^{***}	0.567040	
Black	-0.299810^{***}	0.585952	
White	-0.230343^{***}	0.263411	
Income rank <0.1	-0.152007^{***}	0.175394	
Income rank >0.9	-0.101484^{*}	0.121917	
Young (<25 years old)	-0.253260^{***}	0.382849	
Adult (between 25 and 65 y.o.)	-0.279965^{***}	0.388834	
Old (Older than 65 y.o.)	-0.200551^{***}	0.636812	
Less than High School	-0.106665^{***}	0.102608	
High School and Associate Degree	-0.170782^{***}	0.155372	
College Degree or more	-0.261292^{***}	0.610262	
First Differences			39
Men	-0.224845^{***}	0.394244	
Women	-0.124412^{**}	0.216652	
Single	-0.171050^{***}	0.374920	
Married	-0.225347^{***}	0.414634	
Black	-0.227394^{***}	0.550586	
White	-0.223063^{***}	0.365103	
Income rank <0.1	-0.186633^{***}	0.286287	
Income rank >0.9	-0.134865^{**}	0.263349	
Young (<25 years old)	-0.233667^{***}	0.535982	
Adult (between 25 and 65 y.o.)	-0.164361^{**}	0.260898	
Old (Older than 65 y.o.)	-0.207137^{***}	0.724937	
Less than High School	-0.126165^{***}	0.184119	
High School and Associate Degree	-0.168365^{***}	0.294339	
College Degree or more	-0.236490^{***}	0.501861	

Source: Author's calculations. All regressions corrected for Newey-West variance-covariance matrix. All parameters are statistically significant at 1% confidence level. I only show specification 1 (equation (14)). All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

In addition to the visual evidence, I present correlations, regressions and Granger causality tests. Table 4 shows the results for simple correlations. All correlations per subgroup are high and statistically significant. This table only confirms what already was visually clear from Figures 4 and 5. Labor wedges and cross-sectional variability comoves negatively. In

Table 6: Fact 2 - Grange causality tests

Subgroup	F-statistic
In Levels	
Men	2.96604*
Women	1.03328
Single	2.49739*
Married	0.99730
Black	0.46988
White	5.18222***
Income rank <0.1	0.15215
Income rank >0.9	3.34067***
Young (<25 years old)	3.32700**
Adult (between 25 and 65 y.o.)	1.54079
Old (Older than 65 y.o.)	0.09877
Less than High School	2.57425*
High School and Associate Degree	1.59129
College Degree or more	1.40393
First Differences	
Men	2.44445
Women	1.97658
Single	1.95574
Married	2.12092
Black	0.14474
White	6.08931***
Income rank <0.1	0.43187
Income rank >0.9	2.54438*
Young (<25 years old)	2.44576
Adult (between 25 and 65 y.o.)	1.28427
Old (Older than 65 y.o.)	0.49300
Less than High School	2.26154
High School and Associate Degree	1.28929
College Degree or more	2.70948*

Source: Author's calculations. Null Hypothesis: $sd(\widehat{\tau})$ *does not cause* $\widehat{\tau}$. *, **, and ***, denote statistical significance at 10%, 5% and 1% confidence level, respectively. I only show specification 1 (equation (14)). All variables are in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

addition, I also show regressions (in levels and differences) as shown in Fact 1. Table 5 show the regressions. Both levels and first-difference regressions show a strong negative relation. As before, this evidence suggests that the standard deviation may predict the mean of individual labor wedges in a sense other than the cyclical pattern. Finally, I show Granger causality tests in Table 6. In general, these tests are inconclusive and we cannot say that for each subgroup $sd(\widehat{\tau})$ predicts labor wedge. However, with all other evidence shown, we can confidently affirm that Fact 1 holds, even when we condition on different subgroups of the population.

Next section will show the third and last fact documented. The aggregate labor wedge may be predicted by the aggregation of idiosyncratic productivities.

Fact 3: *The variation in the aggregate labor wedge is explained partially by the variation in the aggregate heterogeneous productivities.*

In the last few years, the literature has been studying whether heterogeneity in the data may explain some of the movements in the labor wedge. For example, Chang and Kim (2007) derive a model with heterogeneous agents who exhibited indivisible labor supply and liquidity constraints. In this paper they showed that more than 75% of the variation in the aggregate labor wedge arouse endogenously. Unfortunately for them, Takahashi (2014) shows that this result is due to a computational typo in their code. Cociuba and Ueberfeldt (2012) also develop a heterogeneous-agent model to account for the gender wage gap and its implication on the aggregate labor wedge. In this section, I will aggregate the individual labor wedges derived in Section 2, in order to obtain a tractable expression of the aggregate labor wedge. The advantage of this methodology is that I can distinguish the labor market distortion from the aggregation issue in presence of heterogeneous agents.

In order to decompose the aggregate labor wedge in the data, I first derive it as a function of three elements: labor market distortions, aggregation of heterogeneous productivities, and a correction for aggregate labor hours.

4.1 The Aggregate (Heterogeneous-Agent) Labor Wedge

The aggregate labor wedge can be obtained by equating the MRS and MPL of the whole economy. For this, use equations (8) and (9) and aggregate them over all individuals. I obtained the following expression:

$$\gamma \frac{c_t}{1-h_t} = (1-\tau)\left[\frac{1}{N}\sum_{j=1}^{J} z_{jt}\left(\frac{1-h_{jt}}{1-h_t}\right)\right]\left(\frac{h_t}{\widetilde{h}_t}\right)(1-\alpha)\frac{y_t}{h_t}, \tag{19}$$

where I define $h_t \equiv \frac{1}{N}\sum_j h_{jt}$, the *average* hours worked per person, and $c_t \equiv \frac{1}{N}\sum c_{jt}$, which is the *average* consumption per capita. Finally, using equation (19), we can define the aggregate labor wedge, $\widetilde{\tau}$ as:

$$\begin{aligned}\widetilde{\tau} &\equiv 1-\left(\frac{\gamma}{1-\alpha}\right)\left(\frac{c_t}{y_t}\right)\frac{h_t}{1-h_t} \\ &= \underbrace{\tau}_{\text{labor market distortions}} \quad \underbrace{\left[\frac{1}{N}\sum_{j=1}^{N} z_{jt}\left(\frac{1-h_{jt}}{1-h_t}\right)\right]}_{\text{aggregate of heterogeneous productivities}} \quad \underbrace{\left(\frac{h_t}{\widetilde{h}_t}\right)}_{\text{correction for aggregate labor hours}} \quad .\end{aligned}$$

Taking logs on both sides I obtain:

$$\log \widetilde{\tau} = \log \tau + \log \varphi_t + \log \left(\frac{h_t}{\widetilde{h}_t} \right) \tag{20}$$

where $\varphi_t = \left[\frac{1}{N} \sum_{j=1}^{J} z_{jt} \left(\frac{1-h_{jt}}{1-h_t} \right) \right]$ represents the aggregate of heterogeneous productivities.

Table 7: Fact 3 - Regression Analysis

Specifications: equations	(21)	(22)	(22)	(23)
φ_t	0.885***	1.880***	0.940***	0.777***
N	40	40	40	39
R-squared	0.208	0.453	0.283	0.159
Adjusted R-squared	0.188	0.438	0.264	0.135
Wald Test ($H_o : \alpha = 1$, p-values)	0.617	0.059	0.828	0.496

Source: Author's calculations. *, **, and ***, denote statistical significance at 10%, 5% and 1% confidence level, respectively. Specification (21) is in deviations from trend, using the cyclical component of the Hodrick-Prescott filter with parameter 1600.

This simple exercise shows that the labor wedge not only depends on labor market distortions, represented by the effective tax rate τ, but also on relative productivities among groups (φ_t). In this sense, the aggregation may be relevant in the accounting of the labor wedge. In particular, if φ_t is countercyclical, the aggregate labor wedge, $\widetilde{\tau}$, follows this pattern as well. In this section I show evidence that the aggregate component of heterogeneous productivities partially drives the results of the aggregate labor wedge in the United States.

The exercise I present in this section is to estimate four constrained versions of equation (20):

$$\begin{aligned}
gap\left[\log \widetilde{\tau}_t - \log \left(\frac{h_t}{\widetilde{h}_t} \right)\right] &= \alpha_0 + \alpha_1 gap\left[\log \varphi_t\right] + \upsilon_{1t} && (21)\\
\log \widetilde{\tau}_t - \log \left(\frac{h_t}{\widetilde{h}_t} \right) &= \alpha_0 + \alpha_1 \log \varphi_t + \upsilon_{2t} && (22)\\
\log \widetilde{\tau}_t - \log \left(\frac{h_t}{\widetilde{h}_t} \right) &= \alpha_0 + \alpha_1 \log \varphi_t + \alpha_2 \times t + \upsilon_{3t} && (23)\\
d\log \widetilde{\tau}_t - d\log \left(\frac{h_t}{\widetilde{h}_t} \right) &= \alpha_0 + \alpha_1 d\log \varphi_t + \upsilon_{4t}, && (24)
\end{aligned}$$

where $gap(\cdot)$ refers to a deviation from trend using a Hodrick-Prescott filter. This exercise has two objectives: first, obtaining the R-squared (or the Adjusted R-squared), and second, estimate the value of parameter α_1. The former seeks to measure how much of the variation in the left-hand side is explained by the variation in the (nonconstant) explanatory variable. This way, I will estimate the contribution of the variation of φ_t on the variation of the aggregate labor wedge. The latter seeks to check if there is a relatively large misspecification. According to (20), parameter α_1 should (theoretically) be equal to one. One important problem is that $\log \tau_t$ is an omitted variable in this set of regressions. Labor market distortions (τ_t) is an unobservable variable in my data set, so estimation of parameter α_1 is expected to be biased. Although this is inconvenient for obtaining a good estimate of α_1, this exercise is still useful to fulfill the first objective.

The results are shown in Table 7. The R-squared lie between 16 and 45 per cent. This finding sheds light in that heterogeneity might be a useful source of cyclical influence in the labor wedge, consistent with what was discussed in Facts 1 and 2. Using different specifications, I find that φ_t possesses relevant information that correlates with the aggregate labor wedge. In particular, the Wald tests does not reject the null hypothesis that $\alpha_1 = 1$, except in specification (22), where the *p-value* is close to 5%. Since the levels of the labor wedge were affecting the estimation of specification (22), I control for trend, in order to isolate the effects of φ_t. The result of this correction is shown in specification (23) in Table 7. Finally, I also correct for the trend taking first differences (specification (24)) to see if φ_t still contributes to variations in the aggregate labor wedge. In this last equation, I also obtain a significant parameter for α_1, statistically close to one, and an R-squared close to 16%.

Summing up, the aggregate labor wedge correlates positively with the aggregate of idiosyncratic productivities, φ_t, and it is robust to various specifications. Even though the estimates are biased (due to a relevant omitted variable), the parameters are positive, statistically significant, and close to one (the theoretical number derived in Section 4.1).

5 Concluding Remarks

In this paper, I have documented a new set of facts about the labor wedge in the United States. Using a simple heterogeneous-agent model, I derive individual-specific labor wedges. I corroborate what other researchers have shown: the aggregate labor wedge (the mean of individual labor wedges) is counter-cyclical. The novel contribution of this study is that the aggregate labor wedge correlates negatively with its cross sectional standard deviation. Using the Consumer Expenditure Survey, I show that the standard deviation of the individual labor wedges exhibits a correlation about -0.6 with its mean, and it is statistically significant. In particular, I show that the standard deviation is pro-cyclical. I check this finding with regressions and grange causality tests. This pattern holds even when I condition on gender, marital status, age, race, education and income rank. Finally, I derive the aggregate labor wedge as a function of three components: an unobservable labor market distortion, an aggregate of idiosyncratic labor wedges (φ_t), and a correction for aggregate labor hours. Using different specifications, I find that φ_t partially explains the variation in aggregate labor wedges (between 16% and 45%). All findings in this paper are consistent with the idea that heterogeneity matters when accounting for aggregate labor market fluctuations. These results may be useful to motivate future research on the topic.

6 References

Aiyagari, S. R. (1994). *Uninsured idiosyncratic risk and aggregate saving.* The Quarterly Journal of Economics, 109(3), 659-684.

Bureau of Labor Statistics (2010) *Consumer Expenditure Survey - Glossary.* Retrieved October 6.

Chang, Yongsung, and Sun-Bin Kim (2007). *Heterogeneity and aggregation: Implications for labor-market fluctuations.* The American Economic Review 1939-1956.

Chang, Yongsung, Sun-Bin Kim, Kyooho Kwon, Richard Rogerson, (2014). *Individual and Aggregate Labor Supply in a Heterogeneous Agent Economy with Intensive and Extensive Margins*, RCER Working Papers 583, University of Rochester - Center for Economic Research (RCER).

Cociuba, Simona, and Alexander Ueberfeldt (2012). *Heterogeneity and Long-Run Changes in US Hours and the Labor Wedge.* No. 20124. University of Western Ontario, CIBC Centre for Human Capital and Productivity.

Galí, J., & Rabanal, P. (2005). *Technology Shocks and Aggregate Fluctuations: How Well Does the Real Business Cycle Model Fit Postwar US Data?.* In NBER Macroeconomics Annual 2004, Volume 19 (pp. 225-318). MIT Press.

Hall, R. E. (2009). *Reconciling cyclical movements in the marginal value of time and the marginal product of labor.* Journal of political Economy, 117(2), 281-323.

Karabarbounis, Loukas 2014. *The Labor Wedge: MRS vs. MPN*, Review of Economic Dynamics, Elsevier for the Society for Economic Dynamics, vol. 17(2), April.

Karabarbounis, Loukas (2012), *Home Production, Labor Wedges, and International Real Business Cycles.* NBER Working Paper No. 18366. September

McGrattan, Ellen R. & Prescott, Edward C. 2010, . *Unmeasured Investment and the Puzzling US Boom in the 1990s,* American Economic Journal: Macroeconomics, American Economic Association, vol. 2(4), pages 88-123, October.

Mulligan, Casey B. (2012) *The redistribution recession: How labor market distortions contracted the economy.* Oxford University Press.

Romer, C. D., & Romer, D. H. (2009). *A narrative analysis of postwar tax changes.* Unpublished paper, University of California, Berkeley (June).

Shimer, Robert. (2009). *Convergence in Macroeconomics: The Labor Wedge.* American Economic Journal: Macroeconomics, 1(1): 280-97.

Smets, F., & Wouters, R. (2007). *Shocks and frictions in US business cycles: A Bayesian DSGE approach.* The American Economic Review, 97(3), 586-606.

Takahashi, Shuhei (2014). *Heterogeneity and Aggregation: Implications for Labor-Market Fluctuations: Comment.* The American Economic Review 104.4 : 1446-1460.

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