UNIVERSITÉ DU QUÉBEC À MONTRÉAL

L'AUGMENTATION DE VOLATILITÉ DES SALAIRES RÉELS ET CHANGEMENTS STRUCTURELS DANS LE MARCHÉ DU TRAVAIL AUX ÉTATS-UNIS

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THE INCREASE IN REAL WAGE VOLATILITY AND STRUCTURAL CHANGES IN THE U.S. LABOR MARKET

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RÉSUMÉ

Cette thèse comprend trois articles qui portent sur les changements dans le marché de travail aux États-Unis, et de leurs effets sur le comportement dynamique des salaires réels moyens en particulier et le cycle économique en général. Le premier article documente de façon détaillée l'augmentation de volatilité relative des salaires réels aux États-Unis qui a eu lieu durant la Grande Modération et propose une explication théorique pour ce phénomène. Le deuxième article se penche sur la divergence marquante au niveau de la tendance et du cycle des deux mesures agrégées les plus populaires de salaire moyen aux États-Unis, et offre des explications pour ces divergences. Finalement, le troisième chapitre tente d'établir un lien théorique entre deux phénomènes qui sont survenus dans le marché du travail lors des trente dernières années, soit l'augmentation de volatilité relative des salaires réels (documentée dans le premier article) et l'augmentation de l'incidence de la rémunération liée à la performance dans l'économie américaine.

Le premier article documente qu'au cours des 25 dernières années, la volatilité du salaire réel horaire moyen a augmenté substantiellement par rapport à la celle du PIB réel aux États-Unis. Utilisant des micro-données provenant du *Current Population Survey* (CPS) nous montrons que cette augmentation est principalement due aux augmentations de volatilités relatives des salaires horaires moyens de différents groupes de travailleurs dans la force de travail et non pas à cause de biais de composition dans celle-ci. Des simulations provenant d'un modèle d'équilibre général dynamique stochastique (DSGE) illustrent qu'il est très peu probable que l'augmentation observée de la volatilité relative des salaires moyens provienne de changements à l'extérieur du marché de travail (e.g. de chocs exogènes moins fréquents ou d'une politique monétaire plus agressive). Par contre, une plus grande flexibilité dans la détermination des salaires, due à la baisse du niveau de syndicalisation et à l'augmentation de l'incidence de la rémunération liée à la performance tels qu'observées dans les données du marché de travail américain, est capable d'expliquer une portion substantielle de l'augmentation de volatilité relative des salaires moyens. Cette plus grande flexibilité dans la détermination des salaires implique aussi une diminution de la volatilité du cycle économique, suggérant ainsi une nouvelle explication à la Grande Modération.

Le deuxième article documente la divergence graduelle, autant en taux de croissance qu'en volatilité cyclique, des deux mesures de salaires moyens les plus utilisées pour l'économie américaine: les revenus horaires moyens provenant du *Labor*

Productivity and Cost (LPC) program and les revenus horaires moyens du *Current Employment Statistics* (CES). Pendant que le salaire horaire LPC augmentait de 70% durant les quatre dernières décennies et devint beaucoup plus volatile au début des années 1980, le salaire horaire CES crû de seulement 20% durant la même période et a vu sa volatilité réduire après le début des années 1980. Nous avons déterminé que la divergence entre les deux mesures de salaire est due à une évolution très différente des revenus moyens par travailleur, et non à cause des heures travaillées (ces dernières évoluent de façon similaires). Nous utilisons ensuite des données sur les salaires provenant du *Current Population Survey* (CPS), des *National Income and Product Accounts* (NIPAs), et de Piketty et Saez (2003) pour tenter de réconcilier la divergence entre les revenus moyens par travailleur. Notre analyse indique que des différences dans la définition des revenus et dans les populations échantillonnées peuvent expliquer une grande partie de la divergence. Notre analyse montre aussi que les différences entre les revenus provenant du CPS et du LPC peuvent être attribuées presqu'entièrement par les revenus des individus très fortunés ainsi qu'aux suppléments aux salaires tels que les contributions des employeurs aux pensions de retraite, qui sont inclus dans LPC mais pas dans CPS. Ce résultat est intéressant en soi étant donné l'utilisation très répandue dans les études utilisant les données en coupes transversales du CPS.

Le troisième article considère un modèle de type du "cycle réel" (RBC) avec des frictions sur le marché du travail où sont introduites deux types de rémunération liée à l'effort. L'idée derrière ceci suit de près les travaux de la littérature microéconomique sur le *performance-pay* (e.g. Lazear, 1986). Dans le modèle, la négociation se fait avant d'observer les chocs à la période t pour les deux types de rémunération, mais l'objet de la négociation est très différente sous chaque type. La première forme de rémunération est une sorte de salaire d'efficience suivant l'intuition derrière le modèle de *shirking* de Shapiro et Stiglitz (1984), tandis que la seconde est apellée *performance-pay* car la négociation se fait autour d'une formule salariale qui lie le salaire à la production du travailleur. L'élément-clé ici est que le travailleur peut ajuster son effort (et donc sa performance) à chaque période étant donné l'état de l'économie. J'utilise le modèle pour simuler un changement dans l'incidence de la paie-à-la-performance tel qu'observé dans le marché du travail américain et j'évalue si ce type de changement structurel peut expliquer simultanément les deux phénomènes documentés ci-haut: la Grande Modération et l'augmentation de volatilité relative des salaires réels moyens. Alors que le modèle implique un salaire moyen plus volatile lorsque l'incidence de la rémunération à la performance est plus élevée, il implique aussi une plus grande volatilité de l'output et une plus grande corrélation entre le salaire réel moyen et l'output, deux résultats contrefactuels à l'expérience vécue par l'économie américaine durant la Grande Modération. Ces résultats posent un grand défi à l'idée qu'une plus grande flexibilité des salaires due à une plus grande incidence de la paie-à-la-performance

peut répliquer les statistiques du cycle économique observées avant et pendant la Grande Modération.

Mot-clés: cycle économique, salaires, volatilité des salaires, Grande Modération, rémunération liée à la performance, marché du travail, modèle d'appariement.

ABSTRACT

This thesis consists of three chapters related to structural changes in the U.S. labor market and their effects on the business cycle behavior of average real wages in particular and macroeconomic variables in general. The first chapter documents in details the increase in real wage volatility during the Great Moderation period and puts forward a theory to explain this new stylized fact. The second chapter looks into the divergence both in terms of trend and business cycle of two of the most popular and readily available average hourly wage series in the U.S., and offers explanations to explain the divergent behavior of the two series. Finally, the third chapter builds on the first and tries to develop a theory linking the increase in wage volatility to the increase incidence of performance-pay schemes in the U.S. economy.

The first chapter documents that over the past 25 years, real average hourly wages in the United States have become substantially more volatile relative to output. Microdata from the Current Population Survey (CPS) is used to show that this increase in relative volatility is predominantly due to increases in the relative volatility of hourly wages across different groups of workers. Compositional changes of the workforce, by contrast, account for only a small fraction of the increase in relative wage volatility. Simulations with a Dynamic Stochastic General Equilibrium (DSGE) model illustrate that the observed increase in relative wage volatility is unlikely to come from changes outside of the labor market (e.g. smaller exogenous shocks or more aggressive monetary policy). By contrast, greater flexibility in wage setting due to deunionization and a shift towards performance-pay contracts as experienced by the U.S. labor market is capable of accounting for a substantial fraction of the observed increase in relative wage volatility. Greater wage flexibility also decreases the magnitude of business cycle fluctuations, suggesting an interesting new explanation for the Great Moderation.

The second chapter documents the gradual divergence in trend growth and business cycle volatility of two popular aggregate hourly wage series for the U.S. economy: average hourly compensation from the Labor Productivity and Cost (LPC) program and average hourly earnings from the Current Employment Statistics (CES). While the LPC wage increased by about 70% over the past four decades and became markedly more volatile starting in the 1980s, the CES wage grew by only about 20% over the same period and experienced a large drop in volatility

post-1980. We establish that the divergence between the two aggregate hourly wage series is due to the different evolution of average labor earnings. Average hours worked, by contrast, evolve very similarly. We then use labor earnings data from the Current Population Survey (CPS), the National Income and Product Accounts (NIPAs), and Piketty and Saez (2003) in an attempt to reconcile the divergence between LPC and CES labor earnings. Our analysis indicates that differences in earnings concept and population coverage can account for a large part of the divergence. Our analysis also shows that earnings differences between the CPS and the LPC can be attributed almost entirely to earnings of high-income individuals and supplements such as employer contributions to pension and health plans, which are included in the LPC but not in the CPS. This result is interesting in its own right given the widespread use of micro earnings data from the CPS in cross-sectional studies.

The third and last chapter considers a real business cycle model with labor search frictions where two types of incentive pay are explicitly introduced following the insights from the micro literature on performance-pay (e.g. Lazear, 1986). While in both schemes workers and firms negotiate ahead of time-t information, the object of the negotiation is different. The first scheme is called an 'efficiency-wage' as it follows closely the intuition of the shirking model by Shapiro and Stiglitz (1984), while the second is called a 'performance-pay' wage as the negotiation occurs over a wage schedule that links the worker's wage to his output. The key feature here is that the worker can then adjust his effort (i.e. performance) level in any period. I simulate a shift towards performance-pay contracts as experienced by the U.S. labor market to assess if it can account simultaneously for two documented business cycle phenomena: the increase in relative wage volatility and the Great Moderation. While the model yields higher wage volatility when performance-pay is more pervasive in the economy, it produces higher volatility of output and higher procyclicality of wages, two results counterfactual to what the U.S. economy has experienced during the Great Moderation. These results pose a challenge to the idea that higher wage flexibility through an increase in performance-pay schemes can account for business cycle statistics observed over the last thirty years.

Keywords: business cycle, wages, wage volatility, Great Moderation, performance pay, labor market, search and matching.

INTRODUCTION

This thesis actually started some years ago when I was an M.A. student at UQAM, when we found one single, puzzling observation: during the Great Moderation, a period of unprecedented macroeconomic stability in the U.S. and in many industrialized countries, the business cycle volatility of real hourly wages in the U.S. has increased significantly such that the relative volatility of real hourly wages to output became 2.5 to 3.5 times larger than before the Great Moderation period. The three chapters all tackle this observation in one way or another, trying to seek what we can understand on the labor market from wage dynamics and vice versa.

The first chapter, coauthored with Andre Kurmann, aims directly at this observation and documents that over the past 25 years, real average hourly wages in the United States have become substantially more volatile relative to output. Micro-data from the Current Population Survey (CPS) is used to show that this increase in relative volatility is predominantly due to increases in the relative volatility of hourly wages across different groups of workers. Compositional changes of the workforce, by contrast, account for only a small fraction of the increase in relative wage volatility. Simulations with a Dynamic Stochastic General Equilibrium (DSGE) model illustrate that the observed increase in relative wage volatility is unlikely to come from changes outside of the labor market (e.g. smaller exogenous shocks or more aggressive monetary policy). By contrast, greater flexibility in wage setting due to deunionization and a shift towards performance-pay contracts as experienced by the U.S. labor market is capable of accounting for a substantial fraction of the observed increase in relative wage volatility. Greater wage flexibility also decreases the magnitude of business cycle fluctuations, suggesting an interesting new explanation for the Great Moderation.

The second chapter (also coauthored with Andre Kurmann) builds on the first chapter as it documents the gradual divergence in trend growth and business cycle volatility of two popular aggregate hourly wage series for the U.S. economy: average hourly compensation from the Labor Productivity and Cost (LPC) program and average hourly earnings from the Current Employment Statistics (CES). While the LPC wage increased by about 70% over the past four decades and became markedly more volatile starting in the 1980s, the CES wage grew by only about 20% over the same period and experienced a large drop in volatility post-1980. We establish that the divergence between the two aggregate hourly wage series is due to the different evolution of average labor earnings. Average hours worked, by contrast, evolve very similarly. We then use labor earnings data from the Current Population Survey (CPS), the National Income and Product Accounts (NIPAs), and Piketty and Saez (2003) in an attempt to reconcile the divergence between LPC and CES labor earnings. Our analysis indicates that differences in earnings concept and population coverage can account for a large part of the divergence. Our analysis also shows that earnings differences between the CPS and the LPC can be attributed almost entirely to earnings of high-income individuals and supplements such as employer contributions to pension and health plans, which are included in the LPC but not in the CPS. This result is interesting in its own right given the widespread use of micro earnings data from the CPS in cross-sectional studies.

Finally, the third chapter aims at first defining a more "serious" theory of performance-pay in general equilibrium and then takes this theory to the data. It considers a real business cycle model with labor search frictions where two types of incentive pay are explicitly introduced following the insights from the micro literature on performance-pay (e.g. Lazear, 1986). While in both schemes workers and firms negotiate ahead of time-t information, the object of the negotiation is different. The first scheme is called an 'efficiency-wage' as it follows closely the intuition of the shirking model by Shapiro and Stiglitz (1984), while the second is called a 'performance-pay' wage as the negotiation occurs over a wage schedule that links the worker's wage to his output. The key feature here is that the worker can then adjust his effort (i.e. performance) level in any period. I simulate a shift towards performance-pay contracts as experienced by the U.S. labor market to asses if it can account simultaneously for two documented business cycle phenomenons: the increase in relative wage volatility and the Great Moderation. While the model yields higher wage volatility when performance-pay is more pervasive in the economy, it produces higher volatility of output and higher procyclicality of wages, two results counterfactual to what the U.S. economy has experienced during the Great Moderation. These results pose a challenge to the idea that higher wage flexibility through an increase in performance-pay schemes can account for business cycle statistics observed over the last thirty years.

CHAPTER I

THE GREAT INCREASE IN RELATIVE WAGE VOLATILITY IN THE UNITED STATES

1.1 Introduction

The 25 years prior to the most recent recession were a time of unprecedented macroeconomic stability for the United States. During that period, referred to by many as the 'Great Moderation', the business cycle volatility of output declined by more than 50% and the volatility of many other macroeconomic aggregates fell by similar proportions.[1]

This paper documents that the Great Moderation does not apply to one of the most prominent labor market aggregates: real average hourly wages (or 'hourly wages' for short). Specifically, we document that from 1953-1983 to 1984-2006, the business cycle volatility of hourly wages increased by 15% to 60%, depending on the dataset and filtering method used. As a result, the business cycle volatility of hourly wages *relative* to the volatility of aggregate output became 2.5 to 3.5 times larger over the two sample periods.

The increase in volatility of hourly wages raises several related questions. First,

[1] See for example McConnell and Perez-Quiros (2000) or Stock and Watson (2002).

does this increase apply similarly for different groups of workers? Second, how much of the increase in volatility is due to compositional changes; i.e. a shift of the workforce towards jobs with more volatile wages? Third, to what extent is the increase in volatility related to structural changes in the U.S. labor market? Fourth, how do these labor market changes contribute to our understanding of the Great Moderation?

To answer the first and second question, microdata from the Current Population Survey (CPS) is used to construct hourly wage series for different groups of workers. This data reveals that the increase in *absolute* volatility of hourly wages is larger for male, skilled and salaried workers. Also, there are sizable differences across industries, with absolute volatilities of hourly wages decreasing in some industries. However, these decreases are generally modest and thus, the volatility of hourly wages *relative* to the volatility of output increases substantially for all worker groups considered. We call this phenomenon the 'Great Increase in Relative Wage Volatility'.

Based on the CPS data, a volatility accounting method is developed to quantify how much of the increase in the relative volatility of average hourly wages is due to compositional changes of the workforce towards jobs with more volatile wages and how much is due to increases in the relative volatility of hourly wages across the different worker groups. The main result coming out of this exercise is that the latter accounts for 69% or more of the increase in the relative volatility of average hourly wages. Compositional changes, by contrast, account for at most 12%. This suggests that the increase in relative wage volatility is due to structural changes in the economic environment that affect wage dynamics of different groups of workers in similar ways although to varying degrees.

To address the third and fourth question, the paper develops a Dynamic Stochastic

General Equilibrium (DSGE) model to quantify the effects of two particular structural changes in the U.S. labor market: deunionization and increased incidence of performance-pay. The focus on these two changes is motivated by a combination of empirical observations. First, over the past decades, the U.S. experienced a marked decline in private-sector unionization (e.g. Farber and Western, 2001) and a shift towards performance-pay contracts (e.g. Lemieux et al., 2009a). Second, the comparison of different datasets reveals that the increase in wage volatility is largest for workers who are on average more likely to have experienced deunionization and a shift towards performance-pay. Third, Lemieux et al. (2009b) show that wages are most responsive to local labor market shocks for non-union workers with performance-pay contracts and least responsive for union workers without performance-pay. Exactly the opposite is the case for hours worked. Together, these observations suggest that deunionization and increased incidence of performance-pay result in greater wage flexibility, making wages more and hours (and output) less responsive to business cycle shocks.

Simulations with the DSGE model illustrate that while reasonable changes in the (absolute and relative) importance of exogenous shock processes can have a sizable effect on the *absolute* volatility and cyclicality of wages, their effect on the *relative* volatility of wages is small. By contrast, a decrease the proportion of unionized workers and an increase the incidence of performance-pay contracts as observed in U.S. data leads to greater wage flexibility in equilibrium, accounting for a substantial fraction of the observed increase in relative wage volatility while simultaneously decreasing the magnitude of business cycle fluctuations. This suggests that deunionization and a shift towards performance-pay contracts are at least partially responsible for the observed changes in wage volatility and the Great Moderation.[2]

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[2] Increased wage flexibility does not render the economy immune to large business cycle

The paper contributes to a recent literature on changes in U.S. labor market dynamics. Most notably, Gali and Gambetti (2009) and Stiroh (2009) document that the Great Moderation period is characterized by an increase in the relative volatility of hours worked and a fall in the correlation of labor productivity with output and hours. Gali and Van Rens (2010) argue that a decrease in labor hoarding due to decreased hiring costs accounts for both of these changes in labor market dynamics.[3] Gali and Van Rens (2010) also note the increase in relative wage volatility and show that under certain assumptions about wage setting, a decrease in hiring costs increases wage flexibility.[4] Alternatively, Nucci and Riggi (2011) argue that an increase in the sensitivity of the effort component of wages to current economic conditions, interpreted as a shift towards performance-pay, is capable of accounting for the empirical evidence in Gali and Gambetti (2009). Compared to these studies, the present paper focuses more squarely on wage volatility. In particular, the paper first documents that the increase in relative wage volatility is not due to compositional changes but generalized across the workforce. This result is important because it directs the search for possible explanations towards structural changes that have a similar impact on all workers. Furthermore, the proposed DSGE model explicitly distinguishes between union and non-union workers that either receive performance-pay or not. While the model does not propose a new theory of the equilibrium existence of unions and

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shocks such as the ones experienced during the recent financial crisis. The simulation results suggest, however, that the effects of these large shocks would have been even more severe if wage setting had been as rigid as in the early 1980s.

[3] In related work, Barnichon (2010) documents that the correlation of labor productivity with unemployment has switched from mildly negative to significantly positive. He proposes a combination of changes in the relative importance of business cycle shocks and lower labor search frictions as an explanation.

[4] To our knowledge, the increase in relative wage volatility was first observed in unpublished manuscripts by Champagne (2007) and Gourio (2007).

performance-pay contracts, it can be calibrated with actual data on unionization and performance-pay to provide a *quantitative* assessment of the effects of these two structural changes for U.S. labor market dynamics.[5]

The rest of the paper proceeds as follows. Section 2 documents the increase in volatility of different aggregate hourly wage measures. Section 3 presents changes in relative wage volatility across different worker decompositions and implements the volatility accounting exercise. Section 4 describes the DSGE model and simulates the effects of deunionization and increased incidence of performance-pay. Section 5 concludes.

1.2 Hourly wages during the Great Moderation

This section documents the increase in volatility of average real hourly wages in the United States. First, the construction of the preferred measure of hourly wages is described and the main results are presented. Then, robustness with respect to alternative measures of hourly wages is discussed. For the sake of brevity, the description of the data is kept to a minimum, with an extensive on-line appendix providing more detailed information.

1.2.1 Data

The most comprehensive measure of average hourly wages in the non-farm business sector comes from the Bureau of Labor Statistics' (BLS) Labor Productivity and

[5] A number of other recent papers conjecture that different structural changes in the U.S. labor market have led to greater wage flexibility. Prominent examples are Blanchard and Gali (2007); Davis and Kahn (2008); and Lemieux et al. (2009a,b). Davis and Kahn (2008) conclude that greater wage flexibility *"...offers a unified explanation for the rise in wage and earnings inequality, flat or rising volatility in household consumption, a decline in the job-loss rate, and declines in firm-level and aggregate volatility measures."* However, none of these papers proposes a model that would permit an explicit *quantitative* assessment.

Costs (LPC) program.[6] The measure is computed as total compensation divided by a corresponding series of total hours worked and is available quarterly starting in 1948. Total compensation is comprised of wage and salary disbursements (including executive compensation, commissions, tips and bonuses) plus supplements such as vacation pay or employer contributions to pension and health plans. The wage and salary portion of total compensation is based on the Quarterly Census of Employment and Wages (QCEW), a mandatory employer-based program for all employees covered by unemployment insurance (UI) that spans about 98% of U.S. establishments and jobs. The supplements portion, in turn, is compiled from different sources by the Bureau of Economic Analysis (BEA). To obtain real hourly wages, the LPC measure is deflated by the Personal Consumption Expenditure (PCE) index from the National Income and Products Accounts (NIPA). All results are robust to the use of other deflators. The resulting series is compared to the non-farm business real chain-weighted GDP per capita, which is also computed from the NIPA tables. All series are logged and filtered to extract the business cycle component. Three filtering methods are considered: (i) quarterly first-difference filtering; (ii) Hodrick-Prescott (HP) filtering; and (iii) Bandpass Filtering (BP) as proposed by Christiano and Fitzgerald (2003).

1.2.2 Main results

Table 1.1 shows the standard deviation of output and real hourly wages for the periods 1953:2-1983:4 and 1984:1-2006:4, with standard errors for each estimate provided in brackets.[7] The sample split is motivated by the Great Moderation literature that estimates a break in output volatility in 1984 (e.g. McConnell and Perez-Quiros, 2000). While output volatility decreases by about 50% over the

[6] The analysis is confined to the non-farm business sector because it is unclear how to interpret public-sector wages in a market-based economy such as the one presented in Section

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*p-value*	*Pre-84*	*Post-84*	*Post/Pre-84*
First-Difference							
Output	1.52	0.68	0.45	0.00	1.00	1.00	1.00
	(0.10)	(0.07)					
Wage	0.50	0.68	1.37	0.01	0.33	1.00	3.04
	(0.03)	(0.07)			(0.02)	(0.12)	
Hodrick-Prescott filter							
Output	2.57	1.28	0.50	0.00	1.00	1.00	1.00
	(0.24)	(0.14)					
Wage	0.63	1.02	1.62	0.00	0.24	0.80	3.33
	(0.06)	(0.10)			(0.02)	(0.12)	
Bandpass filter							
Output	2.50	1.16	0.46	0.00	1.00	1.00	1.00
	(0.26)	(0.11)					
Wage	0.62	0.94	1.52	0.00	0.25	0.81	3.24
	(0.07)	(0.10)			(0.02)	(0.13)	

Note : Standard deviations (left panel) and standard deviations relative to standard deviation of output (right panel) are reported for different filtering methods. All w age series are PCE-deflated. 'Post/pre-84' column reports post-84 divided by pre-84 measure of volatility. Total sample extends from 1953:2 to 2006:4 w ith split in 1984:1 using quarterly data for the non-farm business sector. P-values are reported for a test of equality of variances across the tw o subsamples. Standard errors are computed via the delta method from GMM-based estimates and appear in parentheses below estimates.

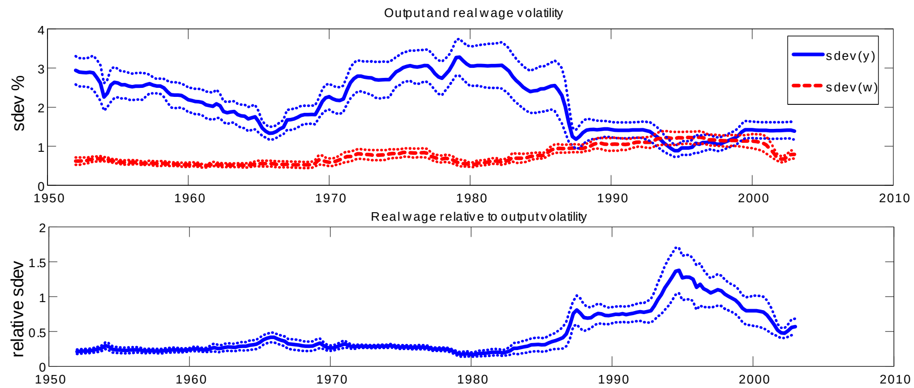
Table 1.1 Changes in volatility

two periods (i.e. the Great Moderation), the volatility of hourly wages increases by 40% to 60% depending on the filtering method. According to the p-value of Levene's (1960) test of equal variance, this increase is highly significant. As the last column of Table 1 shows, the volatility of hourly wages *relative* to the volatility of output therefore increases more than three-fold over the two periods.

Figure 1.1 illustrates this result by plotting the volatility of output and hourly wages over 8-year rolling windows.As the first panel shows, the volatility of output falls precipitously in the 1980s whereas the volatility of hourly wages increases during the 1980s and 1990s. As shown in the second panel, the relative volatility of hourly wages thus increases dramatically from the mid-1980s to the mid-1990s. Thereafter, the relative volatility of hourly wages returns to an intermediate level

4. Results would be very similar for economy-wide hourly wages, however.

[7] The sample starts in 1953:2 to avoid the extreme swings in inflation during the Korean War. Starting the sample in 1948 does not change any of the results. Standard errors are computed via the delta method from GMM-based estimates. See the appendix for details.



Top panel: std(y) and std(w); Lower panel: std(w)/std(y). Eight-year rolling windows; quarterly, HP-filtered data.

Figure 1.1 Standard deviations of output and real hourly wages and relative standard deviation

that remains, however, more than twice as high as the level before the mid-1980s. The two graphs make clear that the increase in *relative* volatility of hourly wages is to a large part driven by the decline in output volatility.

1.2.3 Evidence from alternative hourly wage measures

The hourly wage from the LPC is based on a very broad measure of compensation that includes employer contributions to pension and health plans and gains from exercising certain stock options. Both of these components have grown importantly over the past decades, raising the question of whether they drive the documented increase in wage volatility. The question is particularly relevant for stock options because they are likely to be exercised in upturns when their value is higher than their fair-market value at the time they were granted (i.e. the time when they should have been recorded as compensation).[8] A related but at the same time more general concern is that since the QCEW includes wages and salaries of the quasi-totality of employees, the increase in wage volatility may be due to the emergence of a small fraction of individuals with very large and variable earnings who account for an increasing share of total labor income.[9]

To address the concern about contributions to pensions and health plans, we consider labor earnings data from the NIPA tables that only contains the 'wages and salary' portion from the QCEW. As results reported in the Appendix show, the increase in hourly wage volatility computed from this wages and salary portion is even slightly larger than the one from the LPC that includes supplements. To address the concern about stock options and more generally the role of high-earning individuals, we construct an alternative hourly wage measure from the Current Population Survey (CPS). The CPS is the BLS' monthly household survey and collects, among other information, data on labor earnings and hours worked. Labor earnings in the CPS has two advantages for our purpose. First, tips, commissions and bonuses are counted only if earned and paid in each period. The CPS therefore provides a more conservative source of earnings that ignores irregular compensation, including deferred stock option disbursements. Second, the publicly available earnings data from the CPS is topcoded. Swings in earnings for individuals above the topcode therefore leave the average hourly wage unaffected.[10] A disadvantage of the CPS is that hourly wages can be computed only

[8]Mehran and Tracy (2001) argue that the growth of stock options in the 1990s and their inclusion in compensation at the time of exercise has biased the evolution of compensation upwards. The authors also conjecture that increased use of stock options may render compensation more variable.

[9]See Piketty and Saez (2003) on the important increase in labor income share of high-earning individuals.

[10]For hourly-paid workers, the CPS topcodes earnings at \$99.99 per hour, a threshold rarely crossed. For salaried workers, the CPS topcodes weekly earnings at \$999 until 1989;

from 1973 onwards with the introduction of the CPS May supplements, and this only at an annual frequency. Starting in 1979 then, hourly wage information is available monthly from the Outgoing Rotation Groups (ORG) files.[11] Following Lemieux (2006) and others, an annual series of the average hourly wage combining the May supplements for 1973-1978 with annual averages of the monthly ORG files for 1979-2006 is constructed. In order to obtain a non-farm business equivalent, all unemployed; self-employed; individuals under 16 years old; government, agricultural and private household workers; and armed force personnel are removed.[12]

The top panel of Table 1.2 presents the results for hourly wages from the CPS along with the annualized series for output and hourly wages from the LPC.[13]

$1923 between 1989 and 1997; and $2884 from 1998 onwards. For certain years, this puts a substantial share of workers above the topcode. To reduce the risk of spurious volatility induced by topcode adjustments, topcoded earnings are multiplied by a factor of 1.3. While this correction is standard in the labor literature, we also experiment with alternative topcode adjustments and find all results to be robust. See the appendix for details on these and other robustness checks intended to minimize spurious volatility in the post-1984 period.

[11] An interviewed individual appears in the CPS for two periods of four consecutive months, separated by eight months during which the individual is left out of the survey. Before 1979, the earnings questions were asked only once a year (the May supplements). Thereafter, the earnings questions are asked each month to the individuals who are at the end of a four-month rotation (the ORGs). The March supplements of the CPS provides an alternative source of information about (annual) labor earnings. This data would have the advantage that it is available from 1963 onward. However, the March supplements only started to collect information on total hours worked in 1976, which makes it impossible to compute hourly wages before that year. Furthermore, Lemieux (2006) argues that the annual earnings data of the March supplements are subject to measurement errors not present for the weekly earnings data of the CPS May/ORG files. See Lemieux' (2006) paper for a detailed discussion.

[12] For 1973-78, the sample from the May supplements averages 30406 observations per year. From 1979 onwards, the combination of 12 monthly ORG files averages 139230 observations per year. Measurement error should therefore not be an issue. If at all, measurement error is smaller in the post-84 sample, which would lead to an understatement of the increase in wage volatility.

[13] All series in Table 1.2 are HP filtered, with the constant set to 6.25 for annual data as recommended by Ravn and Uhlig (2002). Results are robust to alternative filters.

Both absolute and relative volatilities of the LPC measure increase in similar

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*p-value*	*Pre-84*	*Post-84*	*Post/Pre-84*
Annual							
Ouput	2.90	1.15	0.40	0.00	1.00	1.00	1.00
	(0.19)	(0.13)					
LPC wage	0.60	0.93	1.55	0.14	0.21	0.80	3.89
	(0.08)	(0.09)			(0.04)	(0.13)	
CPS wage	0.63	0.72	1.14	0.57	0.22	0.62	2.86
	(0.06)	(0.12)			(0.03)	(0.15)	
Quarterly							
Output	2.73	1.28	0.47	0.00	1.00	1.00	1.00
	(0.31)	(0.14)					
LPC wage	0.65	1.02	1.58	0.00	0.24	0.80	3.38
	(0.08)	(0.10)			(0.03)	(0.12)	
CES wage (AHE)	1.11	0.45	0.41	0.00	0.41	0.36	0.87
	(0.19)	(0.05)			(0.07)	(0.07)	

Note : Standard deviations (left panel) and standard deviations relative to standard deviation of output (right panel) are reported for HP-filtered data. All w ages are PCE-deflated. 'Post/pre-84' column reports post-84 divided by pre-84 measure of volatility. Total sample extends from 1964 to 2006 for quarterly data and 1973 to 2006 for annual data, both for the non-farm business sector. P-values are reported for a test of equality of variances across the tw o subsamples. Standard errors are computed via the delta method from GMM-based estimates and appear in parentheses below estimates.

Table 1.2 Changes in volatility

proportions as in Table 1.1. Interestingly, for the pre-84 period, the absolute volatility of the CPS measure is almost identical to the volatility of the LPC measure. For the post-84 period, the volatility of the CPS wage also increases but the increase is smaller and insignificant. This comparison suggests that higher wage volatility at the top end of the income distribution – possibly due to the increased importance of irregular compensation, including deferred stock options disbursements – drives part of the increase in *absolute* volatility of the LPC wage. At the same time, the volatility of the CPS wage *relative* to the volatility of output still displays an almost three-fold rise, confirming the main finding from above: while the volatility of output has decreased substantially during the Great Moderation, the volatility of the aggregate hourly wage has remained constant or even increased.

Another popular measure of hourly wages is Average Hourly Earnings (AHE) from the BLS' Current Establishment Survey (CES), which is available monthly and starts in 1964. The lower panel of Table 1.2 presents the results for AHE averaged to quarterly frequency along with the corresponding series for output and LPC hourly wages. The absolute and relative volatility of the LPC wage increase in similar proportions as before. By contrast, the absolute volatility of AHE is higher in the pre-84 period and then declines significantly in the post-84 period, so much that its volatility relative to the volatility of output becomes in fact smaller. This stark difference in hourly wage dynamics is not limited to the business cycle. As Abraham et al. (1998) document in earlier work, AHE also diverges greatly from other hourly wage measures in terms of its trend. For example, whereas the LPC hourly wage increases by about 7% between 1973 and 1993, AHE falls by about 10% over the same period. Given the frequent use of AHE in both academic research and the business press, it is important to investigate this striking difference and explain why the LPC and CPS measures of hourly wages should be preferred.

Conceptually, differences between AHE and the LPC measure of hourly wages can come from either total compensation, total hours or both. Since total hours in the LPC are constructed primarily from CES hours (which underlies AHE), the business cycle components of total hours in the LPC and the CES are almost identical (see appendix). Hence, the divergent business cycle dynamics of AHE and the LPC wage must be due to differences in total compensation. As described above, the LPC wage is mostly based on the QCEW, which is mandatory and covers 98% of all private-sector jobs. By contrast, AHE is constructed from compensation of production and nonsupervisory workers as reported on a voluntary basis by establishments in the CES sample. AHE therefore covers only a subset of the workforce that, according to Abraham et al. (1998), represents approximately 60% of total private-sector compensation. These differences make for a very strong argument in favor of the LPC.

Determining the exact reasons for the divergence of AHE is complicated by many data issues and is therefore pursued in a separate paper (Champagne and Kurmann, 2012). In what follows, the main findings of this investigation are briefly summarized. First, to assess the role played by the lack of representativeness of AHE, Champagne and Kurmann (2012) follow Abraham et al. (1998) and use the occupational information provided in the CPS to recreate an hourly wage series for production and non-supervisory workers from the May/ORG dataset.[14] Abraham et al. (1998) show that this simulated AHE series accounts for about 60% of the above mentioned decline in actual AHE between 1973 and 1993. Champagne and Kurmann (2012) find that the same simulated AHE series almost exactly replicates the higher volatility of actual AHE in the pre-84 period and generates about 35% of the decline in volatility reported in Table 1.2. Hence, the lack of representativeness of AHE seems to play a substantial role for its divergence from other wage measures, not only in terms of trend but also in terms of volatility.

The second issue with AHE examined in Champagne and Kurmann (2013) concerns sampling problems. In particular, the CES sample underwent a substantial expansion from about 160,000 to 400,000 establishments between 1980 and 2006. A large part of this expansion occurred for young and small establishments in service industries, which were severely underrepresented in the 1970s and early 1980s (see Plewes, 1982).[15] The resulting improvement in the sample properties of the CES is likely to have led to spurious changes in AHE, both because measurement

[14]The definition of compensation in the CES and the CPS is very similar. One difference is that CPS compensation includes tips. However, as Abraham et al. (1998) report, tips account for a mere 0.3% of total compensation in 1993.

[15]Employment numbers in the CES are benchmarked to the UI records, which are the source of the QCEW. Earnings and hours are, however, not benchmarked and therefore do not undergo a regular bias correction.

errors for wages in service industries decreased substantially and because small and young firms in service industries hire on average less skilled workers for which hourly wages have become less volatile (see Section 3). Together with the lack of representativeness of AHE, these sampling problems lead us to conclude that the LPC and CPS measures of hourly wages should be unambiguously preferred over AHE.[16]

1.2.4 Other changes in labor market dynamics

Table 1.3 reports changes in business cycle dynamics of other prominent labor market aggregates.The first four rows show relative volatilities for the pre-84 and post-84 period. The relative volatility of both aggregate hours and labor productivity (computed as output divided by total hours) increases, a result first uncovered by Gali and Gambetti (2009). Compared to the more than three-fold increase in the relative volatility of real hourly wages, these changes are, however, modest. The relative volatility of *nominal* hourly wages also increases substantially but not by as much as the relative volatility of real hourly wages.

The last four rows of Table 1.3 report changes in different correlation coefficients. The correlation of labor productivity with both output and hours declines substantially during the Great Moderation, a phenomenon documented by Gali and Gambetti (2009) and Stiroh (2009). A similar decline in cyclicality also applies to real hourly wages. Finally, the correlation of nominal hourly wages with prices turns from strongly positive to almost zero. To our knowledge, this result is new and provides an interesting perspective on the increase in volatility of real hourly wages. Since real hourly wages equal nominal hourly wages divided by the price

[16]Moreover, as shown in the appendix, the increase in relative wage volatility is confirmed by two other hourly wage measures, one from the NBER manufacturing productivity database; and the other from the PELQ database, which combines data from the CPS and the Census.

	Pre-84	*Post-84*	*Relative*
Relative Standard deviations			
$\sigma(n)/\sigma(y)$	0.78	1.15	1.47
	(0.04)	(0.09)	
$\sigma(w)/\sigma(y)$	0.24	0.80	3.33
	(0.02)	(0.12)	
$\sigma(y/n)/\sigma(y)$	0.49	0.59	1.20
	(0.04)	(0.08)	
$\sigma(Wnominal)/\sigma(y)$	0.37	0.80	2.16
	(0.04)	(0.12)	
Correlations			
$\rho(y,w)$	0.37	-0.14	-0.50
	(0.14)	(0.15)	
$\rho(y,y/n)$	0.65	0.01	-0.64
	(0.07)	(0.14)	
$\rho(n,y/n)$	0.21	-0.50	-0.71
	(0.11)	(0.11)	
ρ(Wnominal,P)	0.82	0.26	-0.57
	(0.04)	(0.15)	

Note : The four first rows report the standard deviations relative to standard deviation of output respectively for hours per capita, real average hourly wage, output per hour, and nominal average hourly wage. The next two rows report the correlations between output and respectively the real average hourly wage and output per hour. The last two rows report the correlation between hours and output per hour, and between the nominal average hourly wage and the price level. All series are HP-filtered, and real wages are PCE-deflated. 'Relative' column reports post-84 divided by pre-84 relative standard deviations or the difference between post-84 and pre-84 for correlations. Total sample extends from 1953:2 to 2006:4 using quarterly data for the non-farm business sector. P-values are reported for a test of equality of variances across the two subsamples. Standard errors are computed via the delta method from GMM-based estimates and appear in parentheses below estimates.

Table 1.3 Changes in labor market dynamics

level, changes in the volatility of real hourly wages can be decomposed into changes in the volatility of nominal hourly wages; changes in the volatility of the price level; and changes in (the negative of) the correlation between the two variables.[17] The (absolute) volatility of nominal hourly wages has remained roughly constant and the volatility of the price level has fallen substantially. Hence, the increase in the (absolute) volatility of real hourly wages is to a large part accounted for by the drop in correlation between nominal hourly wages and the price level.

[17] The variance of the business cycle component of log real hourly wages is approximately $var(w) \approx var(w^{nom}) + var(p) - 2corr(w^{nom}, p) \times \sqrt{var(w^{nom})var(p)}$

1.3 A closer look at disaggregated data

The documented increase in the relative volatility of hourly wages raises two important questions. First, did this increase occur across different groups of workers? Second, what is the role played by changes in workforce composition? The answers to these questions provide valuable clues in the search for possible explanations. If, for example, the relative volatility of hourly wages increases in similar proportions for many groups of workers, then this directs us towards changes in the economic environment that affect different labor markets alike. If, to the contrary, the relative volatility of hourly wages remains approximately constant for most groups of workers, then the focus turns to other explanations such as the role played by changes in workforce composition towards jobs with historically more volatile wages.

1.3.1 Wage volatility across different decompositions

Information in the CPS May/ORG dataset can be used to decompose the workforce into groups with different characteristics. Following Krusell et al. (2000), we choose education as one of the characteristics, with a 'skilled worker' being someone with a college degree (bachelor) or more, and an 'unskilled worker' being someone with less than a college degree. On top of education, we distinguish in rotating order by gender, age, compensation status (hourly paid or salaried), and industry affiliation. This yields four different decompositions: (i) gender / education; (ii) age / education; (iii) compensation status / education; and (iv) industry affiliation / education.[18] For each decomposition, we compute the average hourly wage; filter the series to extract the business cycle component; and compute the

[18] The appendix reports an additional decomposition with respect to gender and occupation, which yields similar results as the decomposition for gender and education.

volatility both in absolute terms and relative to the volatility of aggregate output for the pre-1984 and the post-1984 periods.[19]

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*p-value*	*Pre-84*	*Post-84*	*Post/Pre-84*
Education / Gender							
Male unskilled	0.71	0.83	1.16	0.55	0.25	0.72	2.92
	(0.08)	(0.16)			(0.03)	(0.17)	
Male skilled	0.41	1.11	2.71	0.10	0.14	0.96	6.80
	(0.04)	(0.23)			(0.01)	(0.26)	
Female unskilled	0.78	0.73	0.94	0.90	0.27	0.63	2.35
	(0.12)	(0.13)			(0.05)	(0.15)	
Female skilled	1.47	0.84	0.57	0.11	0.51	0.73	1.43
	(0.31)	(0.10)			(0.13)	(0.14)	
Education / Age							
16-29 Unskilled	0.98	1.00	1.02	0.85	0.34	0.87	2.56
	(0.14)	(0.16)			(0.05)	(0.18)	
16-29 Skilled	1.13	1.45	1.28	0.32	0.39	1.26	3.23
	(0.17)	(0.22)			(0.07)	(0.24)	
30-59 Unskilled	0.80	0.76	0.95	0.93	0.28	0.66	2.37
	(0.09)	(0.16)			(0.04)	(0.17)	
30-59 Skilled	0.75	0.94	1.25	0.46	0.26	0.82	3.15
	(0.17)	(0.17)			(0.07)	(0.21)	
60-70 Unskilled	1.35	0.97	0.72	0.15	0.47	0.85	1.81
	(0.20)	(0.08)			(0.08)	(0.12)	
60-70 Skilled	2.65	1.63	0.62	0.03	0.92	1.42	1.55
	(0.48)	(0.19)			(0.20)	(0.26)	
Education / Compensation status							
Hourly, unskilled	0.96	0.89	0.92	0.60	0.33	0.77	2.32
	(0.17)	(0.16)			(0.07)	(0.18)	
Hourly, skilled	1.48	1.48	1.00	0.61	0.51	1.28	2.51
	(0.22)	(0.29)			(0.10)	(0.34)	
Salaried, unskilled	1.21	0.85	0.70	0.24	0.42	0.74	1.76
	(0.21)	(0.08)			(0.07)	(0.12)	
Salaried, skilled	0.44	0.91	2.09	0.14	0.15	0.79	5.24
	(0.04)	(0.19)			(0.01)	(0.22)	

Note: Standard deviations (left panel) and relative standard deviations to standard deviation of output (right panel) are reported for different labor force decompositions. All wage series are PCE-deflated and HP-filtered. 'Post/pre-84' column reports post-84 divided by pre-84 measure of volatility. Total sample extends from 1973 to 2006 with split in 1984 using annual data for the non-farm business sector. P-values are reported for a test of equality of variances across the two subsamples. Standard errors are computed via the delta method from GMM-based estimates and appear in parentheses below estimates.

Table 1.4 Changes in average hourly wage volatility

[19] In light of the prominent role that performance-pay and unionization play in the model of Section 4, it would be interesting to decompose the workforce along these two dimensions as well. Unfortunately, the CPS does not contain information to distinguish between regular pay and performance-pay. Moreover, while the CPS does contain a union indicator, this information is missing for 1982; and for 1979 to 1981, the number of individuals in the CPS May with both wage and union information is only about one quarter of the regular sample and not representative of the U.S. workforce. Since the years 1979-1983 are very important for the determination of wage volatility in the pre-84 period, this makes it impossible to compute reliable results for a union / non-union decomposition. As discussed below, the Panel Study of Income Dynamics (PSID) would be an alternative source of individual earnings data that contains information on unionization and performance-pay. However, the PSID covers a much smaller cross-section, which would make cell sizes for certain decompositions too small to be reliable. Moreover, annual data with information on both earnings and performance-pay extends only from 1976 to 1996.

Gender / education decomposition. As the first panel of Table 1.4 shows, the absolute volatility of hourly wages increases strongly for skilled males, stays approximately constant for unskilled males and females, and drops for skilled females. Relative to the volatility of output, the volatility of hourly wages increases substantially across all groups. Most notable is the more than six-fold increase for skilled male workers.

Age / education decomposition. Following Jaimovich and Siu (2008), we create three age groups: 16-29 year olds ('young workers'); 30-59 year olds ('middle-age workers'); and 60-70 year olds ('old workers'). As the second panel of Table 1.4 shows, the absolute volatility of hourly wages increases for both young and middle-aged skilled workers; remains approximately constant for young and middle-aged unskilled workers; and declines for old workers. Similar to the previous decomposition, the relative volatility of hourly wages increases substantially for all groups, especially for the young and middle-aged skilled workers.

Compensation status / education decomposition. As the third panel of Table 1.4 shows, the absolute volatility of hourly wages remains constant or falls slightly for all but the salaried skilled group, for which the volatility doubles. The relative volatility of hourly wages increases again markedly for all worker groups but is most pronounced for the salaried skilled group.

Industry / education decomposition. The industry decomposition contains ten private sectors.[20]As Table 1.5 shows, the absolute volatility of hourly wages increases for unskilled workers employed in manufacturing and other services as well as for skilled workers in wholesale trade and finance, insurance and real estate

[20]See appendix for industry classification. For this decomposition, the sample stops in 2002 because the industry reclassification in 2003 (from SIC to NAICS) makes matching of some 3-digit industries difficult.

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Pre/Post-84*	*p-value*	*Pre-84*	*Post-84*	*Pre/Post-84*
Education / Industry							
MiningOilGas unskilled	2.40	1.71	0.71	0.16	0.83	1.53	1.85
	(0.32)	(0.30)			(0.15)	(0.34)	
Construction unskilled	1.33	0.96	0.72	0.17	0.46	0.86	1.87
	(0.15)	(0.14)			(0.07)	(0.11)	
Manuf-Durables unskilled	0.81	1.04	1.27	0.49	0.28	0.93	3.30
	(0.10)	(0.25)			(0.04)	(0.24)	
Manuf-NonDurables unskilled	0.78	1.23	1.57	0.32	0.27	1.10	4.07
	(0.08)	(0.30)			(0.03)	(0.31)	
Transportation&Utilities unskilled	1.13	0.87	0.77	0.39	0.39	0.78	2.00
	(0.16)	(0.13)			(0.07)	(0.19)	
Communications unskilled	2.22	1.29	0.58	0.02	0.77	1.15	1.51
	(0.19)	(0.13)			(0.11)	(0.23)	
Wholesale Trade unskilled	1.18	0.89	0.75	0.11	0.41	0.79	1.95
	(0.10)	(0.09)			(0.05)	(0.12)	
Retail Trade unskilled	1.11	1.01	0.91	0.83	0.38	0.90	2.35
	(0.18)	(0.26)			(0.08)	(0.27)	
FIRE unskilled	1.26	1.01	0.80	0.49	0.43	0.90	2.08
	(0.25)	(0.11)			(0.08)	(0.18)	
Other services unskilled	0.56	0.68	1.21	0.51	0.19	0.61	3.15
	(0.05)	(0.15)			(0.02)	(0.18)	
MiningOilGas skilled	5.31	3.86	0.73	0.38	1.83	3.45	1.88
	(0.97)	(0.89)			(0.33)	(1.07)	
Construction skilled	2.38	1.88	0.79	0.35	0.82	1.68	2.05
	(0.27)	(0.37)			(0.12)	(0.46)	
Manuf-Durables skilled	1.26	1.24	0.98	0.99	0.44	1.11	2.53
	(0.11)	(0.24)			(0.05)	(0.31)	
Manuf-NonDurables skilled	1.53	1.18	0.77	0.21	0.53	1.05	1.99
	(0.15)	(0.07)			(0.07)	(0.15)	
Transportation&Utilities skilled	2.74	2.26	0.83	0.46	0.94	2.02	2.14
	(0.44)	(0.19)			(0.17)	(0.37)	
Communcations skilled	4.76	2.17	0.46	0.16	1.64	1.94	1.18
	(1.37)	(0.24)			(0.53)	(0.42)	
Wholesale Trade skilled	1.02	1.47	1.44	0.26	0.35	1.31	3.73
	(0.15)	(0.25)			(0.07)	(0.37)	
Retail Trade skilled	3.04	1.90	0.63	0.04	1.05	1.70	1.62
	(0.29)	(0.22)			(0.10)	(0.26)	
FIRE skilled	0.89	1.25	1.40	0.29	0.31	1.11	3.63
	(0.23)	(0.20)			(0.09)	(0.27)	
Other services skilled	1.52	1.13	0.74	0.19	0.52	1.01	1.92
	(0.15)	(0.22)			(0.07)	(0.29)	

Note : Standard deviations (left panel) and relative standard deviations to standard deviation of output (right panel) are reported for the education/industry decomposition. All wage series are PCE-deflated and HP-filtered. 'Post/pre-84' column reports post-84 divided by pre-84 measure of volatility. Total sample extends from 1973 to 2002 with split in 1984 using annual data for the non-farm business sector. P-values are reported for a test of equality of variances across the two subsamples. Standard errors are computed via the delta method from GMM-based estimates and appear in parentheses below estimates.

Table 1.5 Changes in average hourly wage volatility

(FIRE). For all other groups, the absolute volatility of the hourly wage decreases. Compared to the decline in output volatility, these decreases in volatility remain modest, however. The increase in the relative volatility of wages therefore remains pervasive.

We take away two stylized facts from these decompositions. First, there is substantial heterogeneity in how the absolute volatility of hourly wages of different worker groups changes over time. The largest increases in volatility occur for skilled workers that are either male, young or middle-aged or salaried. Many other groups, especially in the industry / education decomposition, experience a decline in wage volatility. Second, the decrease in wage volatility for these latter groups is generally modest relative to the decrease in the volatility of output. Hence, the volatility of hourly wages *relative* to the volatility of output increases substantially for almost all worker groups. This phenomenon is what is called in the introduction 'The Great Increase in Relative Wage Volatility'.

1.3.2 Volatility accounting

While the increase in relative wage volatility is pervasive across worker groups, it might still be the case that a substantial part of the increase in the relative volatility of aggregate hourly wages is driven by changes in workforce composition towards jobs for which hourly wages are historically more volatile. To assess this question, we develop a volatility accounting method that allows us to quantify how much of the increase in the relative volatility of aggregate hourly wages is due to changes in workforce composition and how much is due to increases in the relative volatility of hourly wages across the different worker groups.

By definition, the aggregate hourly wage w_t equals the sum of average hourly wages $w_{i,t}$ across worker groups i of some decomposition (e.g. gender / education), weighted by the respective hours shares $h_{i,t} = H_{i,t}/H_t$; i.e. $w_t = \sum_i w_{i,t}h_{i,t}$. Next, let $x_{i,t} \equiv w_{i,t}h_{i,t}$ be the 'wage component of group i' and express the growth rate of the aggregate hourly wage as

$$\Delta \log w_t \approx \frac{w_t - w_{t-1}}{w_{t-1}} = \sum_i \frac{x_{i,t-1}}{w_{t-1}} \frac{x_{i,t} - x_{i,t-1}}{x_{i,t-1}} \approx \sum_i s_{i,t-1} \Delta \log x_{i,t}, \tag{1.1}$$

where $s_{i,t-1} = x_{i,t-1}/w_{t-1} = (w_{i,t-1}H_{i.t-1}) / (w_{t-1}H_{t-1})$ denotes the 'wage share' of worker group i; i.e. the weight with which growth in group i's wage component affects aggregate hourly wage growth. Since the wage shares of the different worker groups evolve slowly over time, approximate $s_{i,t-1}$ by its average for the subsample under consideration (e.g. the pre-84 period); i.e. $s_{i,t-1} \approx \bar{s}_i$. Numerical checks for the different decompositions shows that the error induced by this approximation is negligible. The change in the relative variance of aggregate hourly wage growth between some subsample a and another subsample b (e.g. between the pre-84 period and the post-84) can thus be expressed as[21]

$$\frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)} \approx \sum_i \sum_j \bar{s}_i(b)\bar{s}_j(b)\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \sum_i \sum_j \bar{s}_i(a)\bar{s}_j(a)\frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}. \quad (1.2)$$

By adding and subtracting different elements on the right-hand-side, this equation can be expanded as

$$\begin{aligned} \frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)} \quad &\approx \quad \sum_i \sum_j \left[\bar{s}_i(b)\bar{s}_j(b) - \bar{s}_i(a)\bar{s}_j(a)\right] \left[\frac{\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} + \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}}{2}\right] \quad (1.3) \\ &+ \sum_i \sum_j \left[\frac{\bar{s}_i(b)\bar{s}_j(b) + \bar{s}_i(a)\bar{s}_j(a)}{2}\right] \left[\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}\right]. \end{aligned}$$

The first line on the right-hand-side represents the effect of changes in workforce composition on the relative variance of aggregate hourly wages, *weighted by the average covariances of the wage components* x_i *over the two subsamples.* The second line captures the effect of changes in the covariances of the different wage components on the relative variance of aggregate hourly wages, *weighted by the average wage shares* $\bar{s}_i$ *over the two subsamples.*[22] Since by definition $\Delta \log x_{i,t} =$

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[21]While the focus is on accounting for changes in *relative* volatility of aggregate hourly wages, the same exercise could be performed for changes in *absolute* volatility. As documented in Section 2, however, the increase in absolute volatility of aggregate hourly wages in the CPS is modest at most. Decomposing this small increase in volatility into its different sources would not be very informative.

[22]While this choice of 'average base period' for the weighting is arbitrary, none of the results would change if averages over the first subsample or the second subsample were used as weights instead.

$\Delta \log w_{i,t} + \Delta \log h_{i,t}$, the changes in the different covariances can be decomposed further. For example, for $i = j$ (such that $\sigma_{x_i x_j} = \sigma^2_{x_i}$)

$$\frac{\sigma^2_{x_i}(b)}{\sigma^2_y(b)} - \frac{\sigma^2_{x_i}(a)}{\sigma^2_y(a)} = \left(\frac{\sigma^2_{w_i}(b)}{\sigma^2_y(b)} - \frac{\sigma^2_{w_i}(a)}{\sigma^2_y(a)}\right) + \left(\frac{\sigma^2_{h_i}(b)}{\sigma^2_y(b)} - \frac{\sigma^2_{h_i}(a)}{\sigma^2_y(a)}\right) + 2\left[\rho(w_i(b), h_i(b))\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma^2_y(b)} - \rho(w_i(a), h_i(a))\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma^2_y(a)}\right], \tag{1.4}$$

where $\rho(w_i(a), h_i(a))$ denotes the correlation coefficient between w_i and h_i for subsample a and so forth. Expressions (1.3) and (1.4) make clear that changes in the relative variance of average hourly wage growth can be decomposed into four different sources: (i) changes in average wage shares (i.e. the effect of compositional changes); (ii) changes in the relative variance of hourly wage growth of the different groups; (iii) changes in the relative variance of hours share growth of the different groups; and (iv) changes in the different correlation coefficients. The appendix provides an explicit formula of this decomposition.

Table 1.6 reports the results of the volatility accounting exercise for each of the decompositions analyzed above.[23]The second line shows that changes in wage shares play only a modest role, contributing at most 12% to the increase in the relative variance of average hourly wages. Changes in the relative variance of hourly wages of the different worker groups, by contrast, explain 69% or more of the increase in the relative variance of average hourly wages. The rest is accounted for by changes in the relative variance of hours shares and changes in the different correlation coefficients. This shows that the widespread increase in the relative volatility of hourly wages across different worker groups is the main source of the increase in the relative volatility of average hourly wages. The absence of

[23]All results pertain to HP-filtered data. This introduces an additional approximation error since the decomposition in (1.1) is based on growth rates. This error turns out to be minimal, however.

Decomposition	Education/ Gender	Education/ Age/	Education/ Comp. Status	Education/ Industry(22)
CPS wage	100.00%	100.00%	100.00%	100.00%
Changing s_i	6.08%	6.49%	12.28%	6.73%
Changing σ(hourly wages)²	77.94%	71.05%	70.28%	69.06%
Changing σ(hours shares)²	-6.30%	-6.40%	-2.64%	-4.88%
Changing correlations	22.28%	28.86%	20.09%	29.09%

Note : Contributions to changes in relative volatility of real average hourly wage across different labor force decomposition. The first row reports the change in real average hourly wage volatility for a given decomposition, while the next four report contributions of changes in (respectively) wage shares, volatilities of real average hourly wages, volatilities of hours' shares, and various correlations. Wages are PCE-deflated and all series are HP-filtered. "Compensation status" stands for hourly-paid or salaried workers. Total sample extends from 1973 to 2006 (Except for Industry(22)/Education, which stops in 2002) with split in 1984 using annual data for the non farm business sector.

Table 1.6 Relative volatility accounting across different decompositions

sizable effects from structural changes in workforce composition directs the search for possible explanations towards changes in the economic environment that have similar effects on wage setting in different labor markets.[24] At the same time, some worker groups experience a larger increase in relative wage volatility than others, which suggests that these structural changes do not occur to the same extent for everyone.

1.4 Wage volatility in general equilibrium

This section develops a DSGE model to quantitatively assess two possible explanations for the increase in relative wage volatility. First, the model is used to assess the role of the 'good luck hypothesis', i.e. a decrease in the importance of

[24]Since the CPS does not follow individual workers over time, we cannot rule out that compositional effects play a role *within* worker groups. Starting with Gottschalk and Moffitt (1994), however, a number of papers using panel data show that labor income has on average become considerably more volatile across individual workers as well. Recent evidence based on PSID data by Dynan et al. (2008) and Jensen and Shore (2008) indicate that this increase in labor income volatility has remained approximately constant for most individuals but has increased greatly for individuals who already had volatile earnings in the past. Since the volatility of output fell by more than 50% during the same time period, this means that the *relative* volatility of labor income must have increased substantially on an individual level as well.

exogenous shocks that many studies credit as the main driver of the Great Moderation (e.g. Stock and Watson, 2002). Second, the model is used to explore the effects of two structural changes in the labor market: deunionization and increased incidence of performance-pay.[25]

The focus on these two particular structural changes is motivated by a combination of empirical observations. First, the U.S. labor market experienced a marked decline in unionization and a shift towards performance-pay contracts that approximately coincides with the documented increase in wage volatility. Figure 1.2 illustrates these developments. The left panel plots the proportion of non-

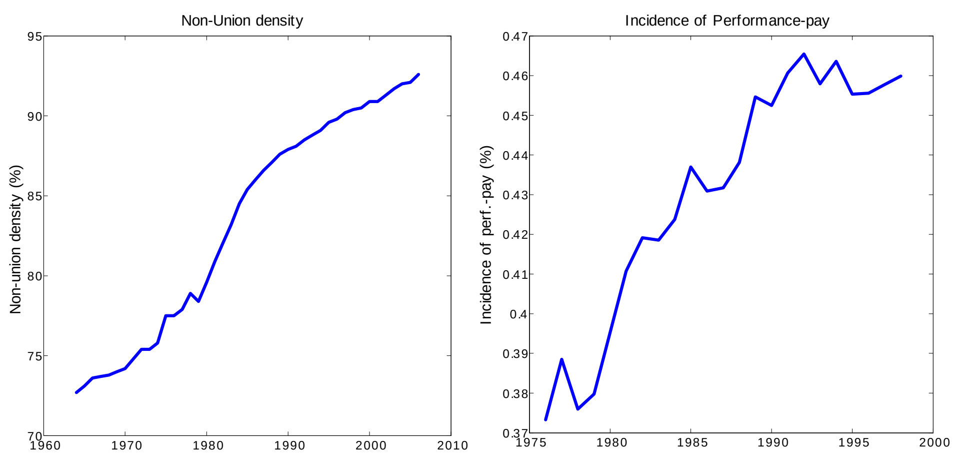

Figure 1.2 Evolution of non-union density (left panel) from nonfarm business workers and incidence of performance-pay (right panel) in the U.S.

union workers in the non-farm business sector, computed from data in Hirsch et

[25] The papers by Gali and Van Rens (2010) and Nucci and Riggi (2011) discussed in the introduction also argue for deunionization and increased performance-pay, respectively, as possible driving forces behind the changes in labor market dynamics. Their models and calibration strategies are quite different from what follows.

al. (2001) and Hirsch and Macpherson (2010).[26] The right panel plots a measure of the incidence of performance-pay from Lemieux et al. (2009a), defined as the proportion of male household heads in the PSID whose compensation during an employment relationship includes a performance pay component (bonus, commission, or piece-rate). As the plots show, both deunionization and the shift towards performance-pay accelerate in the early 1980s and then continue to rise, although at a lower pace, during the 1990s.[27]

Second, in Lemieux et al.'s (2009a) sample of male household heads, performance-pay is more frequent for skilled individuals in salaried positions that are employed in industries such as wholesale trade and FIRE. But these are exactly the worker groups in Tables 1.4 and 1.5 above for which wage volatility increased most.[28] Conversely, the comparison between the estimates in Hirsch and Macpherson (2010) and our results in Table 1.5 indicates that the industries for which union coverage remains high (e.g. communications) are generally also the industries for which

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[26] Union workers are defined as workers covered by a collective bargaining agreement. For the years 1977-2006, union coverage is obtained directly from CPS estimates by Hirsch and Macpherson (2010; updated regularly at http://www.unionstats.com). For the years 1964-1976, union coverage is constructed by taking Hirsch et al.'s (2001) estimates of union membership for the entire U.S. economy from the BLS publication Directory of National Unions and Employee Associations and the CPS May supplements and assuming that the ratio of union coverage in the non-farm business sector to union membership in the entire economy between 1964 and 1976 is the same as in 1977. This probably implies too conservative of an estimate of union coverage before 1977. For 1982, where no union information is available, a linear interpolation with data from 1981 and 1983 is performed.

[27] As argued in the calibration section below, Lemieux et al.'s (2009a) PSID measure of performance-pay is likely to underestimate the true increase in performance-pay contracts. Other studies documenting the increase in performance-pay contracts in the U.S. are Mitchell et al. (1990), Prendergast (1999) and Cunat and Guadalupe (2009).

[28] Since most workers at the top end of the income distribution are skilled males in salaried positions, this result ties in nicely with the finding in Section 2 that the CPS wage, which is based on a more restrictive earnings concept and topcoded high-income salaries, displays a smaller increase in volatility in the post-84 period than the LPC wage.

wage volatility fell most.[29]

Third, based on the same PSID dataset as in Lemieux et al. (2009a), Lemieux et al. (2009b) find that wages of non-union workers with performance-pay contracts are most responsive to local labor market shocks and least responsive for union workers without performance-pay. Exactly the opposite is the case for hours worked, suggesting that wages play an allocative role over the business cycle.

Taken together, these observations suggest that deunionization and the shift towards performance-pay result in greater wage flexibility, making wages more and hours (and output) less responsive to business cycle shocks.

1.4.1 Model

The model contains many elements that are standard in the DSGE literature. As in Erceg et al. (2000), workers are assumed to supply differentiated labor services and set nominal wages according to a given contract rule. Based on these wages, firms then choose the optimal combination of labor services to minimize labor costs. The key novelty here is that this wage setting assumption is extended so as to distinguish between union and non-union workers who are hired either on performance-pay or non-performance-pay contracts. This allows us to perform a disciplined quantitative exercise on the effects of deunionization and increased incidence of performance-pay.

The economy is populated by three types of agents: a continuum of infinitely-lived firms; a continuum of infinitely-lived workers; and a government that determines

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[29] Interestingly, the only group in Hirsch and MacPherson (2010) for which unionization increased (to over 40%) during the post-84 period are public sector workers. Additional analysis with our CPS data shows that wage volatility for these workers fell more than for any other group listed in Table 1.5.

monetary and fiscal policy. Firms produce output Y_t with labor N_t and capital K_t using technology

$$Y_t = A_t N_t^{1-\alpha} K_t^{\alpha}, \tag{1.5}$$

where A_t is an exogenous productivity shock common to all firms. Workers supply differentiated labor services and are employed either in the union sector or the non-union sector. Labor input N_t that firms use for production is a composite made up of union labor N_t^u and non-union labor N_t^{nu} according to

$$N_t = \left[s^u (N_t^u)^{\frac{\mu-1}{\mu}} + s^{nu} (N_t^{nu})^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \tag{1.6}$$

where s^u and $s^{nu} \equiv 1 - s^u$ are fixed weights that pin down the average wage shares of the union sector and the non-union sector; and $\mu > 1$ is the elasticity of substitution determining the extent to which firms can switch between union and non-union labor over the business cycle. Union and non-union labor are themselves Dixit-Stiglitz aggregates of differentiated labor services $N_t^u(i)$ and $N_t^{nu}(i)$ that workers i in the union and non-union sector, respectively, supply; i.e.

$$N_t^l = \left[\int_0^1 N_t^l(i)^{\frac{\mu^l-1}{\mu^l}} di \right]^{\frac{\mu^l}{\mu^l-1}} \quad \text{for } l \in \{u, nu\}. \tag{1.7}$$

The elasticities $\mu^u > 1$ and $\mu^{nu} > 1$ determine the extent to which union workers and non-union workers, respectively, are substitutable among each other. Given nominal wages $W_t^u(i)$ and $W_t^{nu}(i)$, firms demand labor $N_t^u(i)$ and $N_t^{nu}(i)$ for union and non-union workers i to minimize labor costs subject to (1.6) and (1.7).

Nominal wages are set by workers depending on whether they receive performance-pay or not. Let the fraction of workers in the union- and non-union sector with performance-pay be p^u and p^{nu}, respectively. The defining feature of a performance-pay contract is that part or all of compensation is linked to observed output by the worker (see Lemieux et al., 2009b for an illustrative model and a review of the literature).[30] In the context of our model, this feature is taken to mean that in order to remain incentive compatible, the nominal wage $W_t^{l,p}(i)$ of a performance-pay worker adjusts with time t information to equal the worker's marginal rate of substitution times the optimal markup the worker commands because of the imperfect substitutability of its labor service.

For the remaining workers without performance-pay, nominal wages are set in advance of time t information according to a variant of Erceg et al. (2000). In the union sector, the fraction of non-performance-pay workers that get to reoptimize their nominal wage for next period is $1-\xi^u$. In the non-union sector, the equivalent fraction is $1-\xi^{nu}$. For all other non-performance pay workers (a fraction ξ^u in the union sector and a fraction ξ^{nu} in the non-union sector), wages are indexed to the steady state growth rate of consumption γ and partially to realized gross inflation Π_{t-1}; i.e. their nominal wage adjusts according to $W_t^{l,np}(i) = \gamma \Pi_{t-1}^{\omega} W_{t-1}^{l,np}(i)$ with ω denoting the inflation indexing factor. The solution to this optimization problem is provided in the appendix.

Several comments are in order about this formalization of wage setting. First, as in existing New Keynesian DSGE literature, the model abstracts from the deeper frictions that give rise to staggered wage reoptimization. Likewise, the performance-pay contract is not derived from an explicit principal-agent or hold-up problem as in Lemieux et al. (2009b); and the forces leading to unionization are not explicitly modeled. While very interesting, such a richer environment would exceed the objective of our model, which is to quantify the general equilibrium effects of changes in unionization and the incidence of performance-pay, everything

[30] In Lemieux et al. (2009b), performance-pay contracts arise endogenously if the costs of overcoming informational frictions are sufficiently small. Otherwise, firms and workers find it optimal not to measure performance and enter a fixed-wage contract.

else constant. Second, firms in the model have the right-to-manage; i.e. they can freely decide on labor input given a set wage. This assumption is consistent with most U.S. labor market contracts (see Malcomson, 1999) and the empirical results in Lemieux et al. (2009b) suggest that firms indeed adjust hours most for workers with the least flexible wages. Third, workers without performance-pay contracts in our model are typically not on their labor supply curve. Given the markup they command in the labor market, their wage remains, however, above the marginal rate of substitution; i.e. the wage more than compensates for the disutility from working.

The rest of the model is standard. The exposition is therefore kept to a minimum and the reader is referred to the appendix for details. Given labor income, worker i chooses consumption, investment in physical capital and nominal one-period bonds to maximize

$$\mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t Z_{t-1} \left[\log C_t - \frac{N_t(i)^{1+\phi}}{1+\phi} \right] \tag{1.8}$$

subject to the budget constraint

$$C_t + K_{t+1} - (1-\delta)K_t + \frac{B_{t+1}}{R_t^n P_t} + T_t \leq \frac{W_t(i) N_t(i)}{P_t} + R_t^K K_t + \frac{B_t}{P_t} + D_t + \digamma_t(i). \tag{1.9}$$

$\mathbf{E}_0$ denotes the expectations operator; β the discount factor; Z_{t-1} an exogenous preference shock common to all workers; C_t a composite consumption good; $N_t(i)$ hours worked; $K_{t+1} - (1-\delta)K_t$ investment in physical capital; B_t nominal bond holdings; T_t lump-sum taxes; D_t dividends from a perfectly diversified portfolio of claims to firms; $\digamma_t(i)$ the net return from a state-contingent insurance mechanism; $W_t(i)$ the nominal wage rate; R_t^K the real net rental rate of capital; R_t^n the gross nominal bond return; and P_t the aggregate price level. Labor income $W_t(i)N_t(i)$ is worker-specific due to the labor market frictions described above. As in Erceg et al. (2000), the net return $\digamma_t(i)$ is such that workers remain identical with respect to their consumption and savings decisions. As a result, C_t, K_t and B_t are not worker-specific.

Firms' production in (1.5) yields differentiated intermediate goods that are sold to a wholesaler who then turns them into a final composite using a CES aggregator. The demand for each intermediate good depends on the relative price that firms reoptimize with some constant Calvo probability.

The government, finally, conducts monetary policy according to the following interest rate rule

$$R_t^n = (R_{t-1}^n)^{\rho} \left(P_t/P_{t-1}\right)^{(1-\rho)\theta_\pi} \left(Y_t/Y_{t-1}\right)^{(1-\rho)\theta_y}; \tag{1.10}$$

and limits fiscal policy to a constant spending rule that is fully financed by lump-sum taxes.

1.4.2 Calibration

The model is calibrated to quarterly U.S. data. The structural parameters are partitioned into two groups. The first group contains the parameters not directly related to wage setting. These parameters are kept unchanged in the different simulations and are calibrated as shown in the first panel of Table 1.7.The values of α, β, γ, δ and ϕ are standard. The steady-state government spending-output ratio $T/Y = 0.15$ implies an average consumption-output ratio of 0.63 in line with the data. The slope parameter κ on marginal cost in the New Keynesian Phillips curve (NKPC) that results from the above described Calvo pricing setup lies in the range of estimates reported by different empirical studies on the NKPC. The monetary policy parameters, finally, are also in line with estimates found in the literature. The particular values are chosen so that, conditional on the calibration

Standard parameters									
α	β	γ	δ	$1/\phi$	T/Y	κ	ρ	θ_π	θ_y
0.33	0.99	0.005	0.025	1	0.15	0.05	0.8	2	0.3

Wage setting parameters									
	W^uN^u/WN	p^u	p^{nu}	$1/(1-\xi^u)$	$1/(1-\xi^{nu})$	ω	μ^u	μ^{nu}	μ
pre-1984	0.30	0.17	0.34	12	6	0.5	3.1	6	10
post-1984	0.13	0.32	0.64	12	6	0.5	3.1	6	10

Shock processes						
	$\rho(a)$	$\sigma(\varepsilon_a)$	$\rho(\Delta z)$	$\sigma(\varepsilon_{\Delta z})$	$\sigma(a)$	$\sigma(\Delta z)$
pre-1984	0.9788	0.0094	0.7956	0.0033	0.0549	0.0054
post-1984	0.9738	0.0057	0.8951	0.0020	0.0172	0.0046

Note: Upper panel reports calibration for standard parameters values in New-keynesian DSGE models. Middle panel reports parameter values for wage setting in model. Bottom panel reports estimates for the technological and preference shock processes.

Table 1.7 Model calibration

of all other parameters and shock processes below, the model matches the pre-84 volatility of H-P filtered output and comes close to the correlation coefficients of labor productivity with output and hours in Table 1.3.

The second group of model parameters is directly related to wage setting. The wage share of union workers $W^uN^u/(WN)$, which pins down the parameter s^u in (1.6), and the fractions of union and non-union workers receiving performance-pay are calibrated separately for the pre-84 and the post-84 period. Changes in these values are used to quantify the effects of deunionization and increased incidence of performance-pay. The other parameters are calibrated over the entire sample and are kept unchanged in the simulations. The second panel of Table 7 reports the different values. The wage share of union workers is calibrated to 0.30 for the pre-84 period and 0.13 for the post-84 period. These values are obtained by decomposing $W^uN^u/(WN) = W^u/W \times H^u/H \times E^u/E$ and using CPS data from Hirsch and Macpherson (2010) and our own estimates to calibrate the different components.[31]

[31]Specifically, the ratio W^u/W is related to the union wage premium W^u/W^{nu} by $W/W^u = 1 + 1/(W^u/W^{nu})$. Using estimates in Hirsch and Macpherson (2010, Table 2a),

The fractions of union and non-union workers receiving performance-pay, p^u and p^{nu}, are more challenging to calibrate as no direct measure of performance-pay is available in the CPS. Lemieux et al.'s (2009a) measure plotted in Figure 1.2 can be used as a starting point. However, their sample only covers 1976 to 1998 and their measure explicitly excludes any performance-pay related to overtime work. Since performance-pay was presumably even less common before 1976 and overtime work increased substantially during the 1980s and 1990s (e.g. Kuhn and Lozano, 2008), Lemieux et al.'s (2009a) measure is likely to substantially underestimate the true increase in the incidence of performance-pay. Extrapolating based on the available information in Lemieux et al. (2009a), we thus calibrate p^u and p^{nu} to 0.17 and 0.34 for the pre-84 period; and 0.32 and 0.64 for the post-84 period.[32]

The remaining parameters in Table 1.7 are calibrated as follows. The fraction of non-reoptimizing union workers ξ^u is set such that the average contract duration for union workers is 12 quarters, as reported in Rich and Tracy (2004). According to their estimates, this average remained surprisingly constant over their entire

the average union premium in the private-sector is estimated to be 1.23 for the pre-84 period and 1.24 for the post-84 period. The union wage premium is therefore set to $W^u/W^{nu} = 1.235$ for the entire sample. The ratio H^u/H denotes average hours per union worker relative to average hours over all workers. In the CPS May/ORG data, this ratio averages approximately one for both the pre-84 and the post-84 period. The ratio is therefore set to $H^u/H = 1$ for the entire sample. Finally, E^u/E denotes the the proportion of workers covered by a union bargaining agreement. Using the numbers reported in Figure 1.2, union coverage averages 0.25 for the pre-84 period and 0.11 for the post-84 period. Hence, the fall in the wage share of union workers over time is entirely driven by the fall in union coverage. Since estimates of union coverage estimates only go back to 1964 and was likely to be higher before then, the value of 0.25 for the pre-84 period should be considered as conservatively low.

[32] Specifically, the tables in Lemieux et al. (2009a) indicate that performance-pay contracts are about half as likely for union workers as for non-union workers and that the average incidence of performance-pay in the mid 1970s was about 35%. Assuming that the average incidence of performance-pay was 30% for the pre-84 period and 60% for the post-84 period, average union density rates and the information that performance-pay is half as likely for union workers can then be used to compute the values for p^u and p^{nu}. The assumption that the proportion of performance-pay contracts approximately doubled is consistent with survey information from Fortune 1000 companies (see Lemieux et al., 2009a).

sample under consideration (1970-1995). For non-union workers, the corresponding fraction ξ^{nu} is set such that the average contract duration is 6 quarters, which is approximately consistent with recent estimates of nominal wage stickiness based on quarterly data by Barattieri et al. (2010). The inflation indexation factor ω for non-reoptimized wages of 0.5 roughly equals the average proportion of workers receiving cost-of-living adjustments (COLA) in the sample under consideration (see e.g. Hofmann et al., 2010). The elasticities μ^u and μ^{nu} translate into steady-state markups of 48% and 20% for union and non-union workers, respectively, implying an average union wage premium of 23.5% in line with the above numbers from Hirsch and Macpherson (2010). Finally, the elasticity μ is set such that, in combination with the other wage setting parameters, union hours worked are about 50% more volatile than non-union hours worked, consistent with evidence from our quarterly CPS ORG sample for 1984-2006. All of the results are robust to reasonable changes in ω, μ^u, μ^{nu} and μ.

For the calibration of the two shocks, the logarithms of the technology shock and the preference shock are assumed to follow independent AR(1) processes

$$\begin{aligned} a_t &= \rho_a a_{t-1} + \varepsilon_{at} \ \text{ with } \varepsilon_{at} \ iid \ (0, \sigma^2_{\varepsilon_a}) \\ \Delta z_t &= \rho_{\Delta z} \Delta z_{t-1} + \varepsilon_{\Delta zt} \quad \text{with } \varepsilon_{\Delta zt} \ iid \ (0, \sigma^2_{\varepsilon_{\Delta z}}), \end{aligned}$$

where $a_t = \log A_t$ and $z_t = \log Z_t$. The parameters for each process are estimated separately for the subsamples 1953:2-1983:4 and 1984:1-2006:4. For the technology shock process, a quarterly measure of total factor productivity constructed by Basu et al. (2006) that controls for variable factor utilization is used. This measure is converted into logarithms, a linear trend consistent with the model is subtracted; and ρ_a and σ_{ε_a} are estimated by ordinary least squares (OLS). For the preference shock process, Δz_t is measured as the residual from the Euler equation for nominal bond investment $\Delta z_t = E_t \log(C_{t+1}/C_t) - [\log R_t^n - E_t \log(P_{t+1}/P_t)]$ (see appendix for derivation).[33] The nominal short-rate in this equation is measured by the 3-month treasury bill rate. Expectations of future consumption growth and inflation are estimated from a bivariate VAR in the two variables, with consumption being measured by real chain-weighted per capita expenditures of non-durables and services and inflation being measured by the growth rate of the GDP deflator.[34] As for total factor productivity, a linear trend is subtracted from the obtained series of Δz_t and $\rho_{\Delta z}$ and $\sigma_{\varepsilon_{\Delta z}}$ are estimated by OLS. The point estimates for the pre-1984 and the post-1984 period are provided in the third panel of Table 1.7.[35] The innovations to both shock processes become less volatile in the post-1984 period. This drop in volatility is, however, much less pronounced for the innovation to the preference shock. Furthermore, the preference shock becomes more persistent. As a result, the volatility of the preference shock drops much less and becomes about three times more important relative to the volatility of the technology shock.

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[33] Alternatively, Δz_t could be measured as the residual from the Euler equation for investment in physical capital. There are two reasons to prefer the bond Euler equation. First, the rental rate of capital in the investment Euler equation has to be inferred from macroeconomic quantities using the firm's capital demand condition. Both the real marginal cost and capital stocks, which appear in this condition, are difficult to measure. Second, the investment Euler equation may be affected by investment-specific technology shocks. Primiceri et al. (2006) argue that such investment-specific shocks neutralize a large part of preference shocks, implying a substantially smoother series for Δz_t. None of these issues apply to the bond Euler equation.

[34] Based on Schwarz' Bayesian Information Criterion (BIC), a lag length of five is selected. Results are robust to alternative lag specifications.

[35] For both sub-periods, the correlation between the innovations is negligible (0.11 and -0.03, respectively). Hence, the assumption that the two shock processes are independent is valid.

1.4.3 Simulations

The model is first simulated with all parameters set to their pre-84 values. Second, the shock process calibration is changed to the post-84 estimates so as to assess role played by the 'good luck hypothesis'. Third, $\frac{W^u N^u}{WN}$, p^u and p^{nu} are changed to their post-84 values while keeping the shock processes at their pre-1984 estimates to evaluate the effects of deunionization and higher incidence of performance-pay. Fourth, both the shock processes and $\frac{W^u N^u}{WN}$, p^u and p^{nu} are set to their post-84 values to obtain the joint effect of all changes.

	US Data			**Simulation 1**	**Simulation 2**		**Simulation 3**		**Simulation 4**	
				Pre-84 calibration,	*Pre-84 calibration,*		*Post-84 calibration,*		*Post-84 calibration,*	
	Pre-84	*Post-84*	*Relative*	*Pre-84 shock*	*Post-84 shock*	*Relative*	*Pre-84 shock*	*Relative*	*Post-84 shock*	*Relative*
$\sigma(y)$	2.57	1.28	0.50	2.55	1.65	0.65	2.12	0.83	1.39	0.55
$\sigma(n)/\sigma(y)$	0.78	1.15	1.47	0.86	0.93	1.08	0.73	0.84	0.83	0.96
$\sigma(w)/\sigma(y)$	0.24	0.80	3.33	0.26	0.25	0.97	0.40	1.56	0.43	1.67
$\sigma(y/n)/\sigma(y)$	0.49	0.59	1.20	0.32	0.33	1.02	0.44	1.36	0.43	1.33
$\sigma(Wnominal)/\sigma(y)$	0.37	0.80	2.16	0.29	0.28	0.97	0.42	1.45	0.45	1.53
$\rho(y,w)$	0.37	-0.14	-0.50	0.64	0.65	0.02	0.78	0.14	0.74	0.11
$\rho(y,y/n)$	0.65	0.01	-0.64	0.55	0.36	-0.19	0.76	0.20	0.57	0.02
$\rho(n,y/n)$	0.21	-0.50	-0.71	0.27	0.03	-0.23	0.44	0.17	0.17	-0.09
$\rho(nomW,P)$	0.82	0.26	-0.57	0.63	0.50	-0.13	0.41	-0.22	0.28	-0.35

Note : The first five rows report respectively the standard deviation of output and relative standard deviations relative to standard deviation of output for respectively hours per capita, real average hourly wage, output per hour, and nominal average hourly wage. The next two rows report the correlation between output and respectively the real average hourly wage and output per hour. The last two rows report the correlation between hours and output per hour, and between the nominal average hourly wage and the price level. The 'Relative' column denotes the Post/Pre-84 ratios for standard deviations and the Post-Pre-84 differences for correlations. All series are HP-filtered and the real wage series is PCE-deflated. U.S. data: Total sample extends from 1953:2 to 2006:4 with split in 1984:1 using quarterly data for the non-farm business sector.

Table 1.8 Model simulations

Baseline calibration. The first three columns of Table 1.8 reproduce the U.S. data moments in Table 1.3. Simulation 1 displays the second moments generated by the model for the baseline pre-84 calibration. Despite its relative simplicity, the model does a good job matching the volatilities of the different labor market variables. The model also generates a reasonably high correlation between nominal wages and prices but overpredicts the correlation of wages with output.

Smaller shocks. Simulation 2 in Table 1.8 shows the results of changing the calibration of the two shock processes to their post-1984 estimates while keeping all other parameters at their baseline values. The smaller volatilities for the two shock processes lead to a substantial fall in output volatility of about 35% as well as a fall in the cyclicality of labor productivity. At the same time, the smaller shock volatilities in the post-1984 period also generate a substantial fall in the volatility of wages with the result that the relative volatility of wages decreases slightly. Hence, while the 'good luck hypothesis' on its own can account for a substantial part of the Great Moderation, it fails to account for the increase in the relative volatility of wages in the data.

To understand these results, it is useful to think of the labor market in our model as consisting of a standard downward-sloping aggregate labor demand and an upward-sloping wage setting curve that combines the optimal wage conditions of the different workers.[36] A temporary technology shock primarily shifts labor demand along the wage setting curve. A temporary preference shock, by affecting current consumption, primarily shifts the wage setting curve along labor demand. Smaller shocks change the size of these shifts, thus affecting the *absolute magnitude* of adjustments in wages and hours. However, since the slopes of the two curves are unchanged, the *relative magnitude* of adjustments in the real wage and hours remains approximately constant. Furthermore, changes in the relative importance of the two shocks can have important effects on the cyclicality of wages and labor productivity. Technology shocks imply that both wages and labor productivity co-move with hours whereas preference shocks imply exactly the opposite. Hence, when preference shocks become relatively more important, the correlation of wages and labor productivity with hours (and thus output) falls and may even become negative. The same intuition suggests that similar conclusions apply for other

[36] The appendix contains a detailed description of the labor market with linearized wage setting conditions for each worker group. These conditions can be combined to obtain an expression for the aggregate wage as a function of the aggregate marginal rate of substitution that is called here the wage setting curve.

exogenous shocks that primarily shift either the wage setting curve (e.g. labor supply shocks, government spending shocks) or labor demand (e.g. monetary policy shocks). This conjecture is confirmed by a variety of robustness exercises in the appendix. Likewise, structural changes outside the labor market (i.e. changes that do not directly affect the nature of wage setting or labor demand) are unlikely to affect relative wage volatility. For example, a change in the responsiveness of monetary policy to inflation, which is often advanced as a contributor to the Great Moderation, would have only a modest effect on the relative volatility of wages since this does not affect the shape of either wage setting curve or labor demand but only by how much they shift in response to shocks (through changes in wage and price markups).

Deunionization and increased incidence of performance-pay. The calibration of the shock processes is now reset to the pre-1984 estimates and instead, the wage share of union workers and the fractions of performance-pay contracts for union and non-union workers is changed to the post-84 calibration. As Simulation 3 in Table 1.8 shows, the result is an increase in the relative volatility of wages by about 55% and a reduction in the volatility of output by more than 15%. At the same time, while the correlation between nominal wages and prices drops, the cyclicality of labor productivity and wages increase counterfactually.

To understand the mechanisms behind these results, return to the intuition from above. In a labor market with widespread unionization and little performance-pay, the wage setting curve is relatively flat. A positive technology shock in such a situation leads to a relatively small change in wages but a large change in labor and output. As unionization declines and performance-pay becomes more widespread, wage setting increasingly depends on the marginal rate of substitution and the wage setting curve steepens. The same positive technology shock therefore implies a larger equilibrium response of wages relative to the equilibrium response of hours. Furthermore, the comovement of wages with output increases because the wage is now more dependent on the current state of the economy. In turn, the change in consumption after a preference shock has a relatively small income effect if unionization is widespread and there is little performance-pay. Wages therefore adjust relatively little. Instead, when there is little unionization and performance-pay is widespread, the income effect of the preference shock is more important. This leads to larger shifts in the wage setting curve, making wages more countercyclical in response to preference shocks and labor productivity less procyclical.

Deunionization, increased incidence of performance-pay and smaller shocks. Finally, the effects of simultaneously changing the union wage share, the incidence of performance-pay, and the shock processes to their post-84 calibration values is assessed. As Simulation 4 in Table 1.8 shows, this decreases the volatility of output by about 45% and increases the relative volatility of wages by over 65%. The combination of 'good luck hypothesis' and greater wage flexibility through deunionization and increased incidence of performance-pay therefore accounts for almost the entire drop in output volatility during the Great Moderation and simultaneously generates a substantial increase in relative wage volatility. The model also generates a decrease in the correlations of labor productivity with hours and nominal wages with prices relative to the baseline pre-84 calibration (i.e. Simulation 1). The decrease in correlation of labor productivity with hours is, however, considerably smaller than in the data and the correlation of labor productivity with output barely moves. Moreover, the cyclicality of wages displays a counterfactual increase. Given the small number of shocks in our model, this failure to replicate the different changes in correlations should not come as a surprise. As discussed above, any additional shock affecting the marginal rate of substitution (e.g. a labor supply shock) that gains in importance relative to the technology shock in the post-84 period would decrease the cyclicality of labor productivity and wages, thus improving the model performance.

In sum, we consider this simulation exercise an instructive and partially successful first step towards a *quantitative* explanation of the great increase in relative volatility of wages. While the increase in relative wage volatility due to deunionization and a shift towards performance-pay remains below what is observed in the data, the exercise highlights how any structural change in the labor market that leads to greater wage flexibility (i.e. wage setting that becomes more sensitive to the marginal rate of substitution) increases the relative volatility of wages and simultaneously reduces business cycle fluctuations.

1.5 Conclusion

During the Great Moderation period, the relative volatility of hourly wages increased by a factor of 2.5 to 3.5. A large part of this increase in relative wage volatility is due to the fact that while output volatility fell by about 60%, the volatility of hourly wages remained approximately constant or even increased. CPS microdata reveals that this relative stability in wage volatility applies for many different groups of workers. As a result, the increase in the relative volatility of hourly wages is predominantly due to the increase in relative wage volatility for different groups of workers. Compositional changes of the workforce, by contrast, account for no more than 13% of the increase in the relative volatility of hourly wages.

These findings represent a challenge for macroeconomic modeling in general and explanations of the Great Moderation in particular. Simulations with a DSGE model show that reasonable changes in the volatility of exogenous shocks can have a substantial impact on the *absolute* volatility and cyclicality of wages but that these changes on their own have only a small impact on *relative* wage volatility. Hence, the 'good luck hypothesis' that many studies credit as the main driver of the Great Moderation cannot explain the observed large increase in relative wage volatility. Similarly, structural changes outside of the labor market are unlikely to have a large effect on relative wage volatility. This puts the labor market front and center. Motivated by empirical observations, the nominal wage setting component of the New Keynesian literature is extended to allow for a distinction between unions and performance-pay contracts. For calibrations in line with the degree of deunionization and increased incidence of performance-pay experienced by the U.S. labor market, the thus extended model generates a substantial increase in relative wage volatility and simultaneously helps to account for part of the Great Moderation.

Our model simulations represent one of the first attempts to provide a *quantitative* assessment – based on calibrations with actual U.S. labor market data – of the business cycle effects of structural changes in the U.S. labor market that occurred during the Great Moderation. While deunionization and increased incidence of performance-pay in our model imply a substantial increase in relative wage volatility, much remains to be explained. Given the stylized formalization of unions and performance-pay in our model, this should not come as a surprise. In particular, it is likely that union behavior itself and the nature of performance-pay contracts has changed over the past decades. Building a model that accounts for these changes and can be calibrated from available data remains a challenge for future work.

CHAPTER II

RECONCILING THE DIVERGENCE IN AGGREGATE U.S. WAGE SERIES

2.1 Introduction

The evolution of average hourly wages is a key indicator for economic analysis. In the U.S., two of the most popular and most readily available measures of average hourly wages for the non-farm business sector are average hourly compensation from the Labor Productivity and Costs (LPC) program and average hourly earnings from the Current Employment Statistics (CES).[1] This paper documents that over the past four decades, the two measures diverged substantially both in terms of trend growth and business cycle volatility. In particular:

1. While the LPC wage grew consistently over time and stands today about 70% higher in real terms than in 1970, the CES wage decreased by almost 10% between the mid-1970s and the mid-1990s and increased by only 20% total over the past four decades.

2. While the volatility of the LPC wage increased by 35% to 45% since the early 1980s, the volatility of the CES wage dropped by about 50%. Since

[1] Both data sources come from the Bureau of Labor Statistics (BLS).

> the volatility of output declined by 40% to 50% since the early 1980s (i.e. the Great Moderation), the *relative* volatility of average hourly wages increased two- to threefold according to the LPC and but remained roughly unchanged according to the CES.

The main objective of the paper is to reconcile this divergence in trend and business cycle volatility of the LPC wage and the CES wage. Since each series is constructed by dividing an average labor earnings measure with an average hours measure, we start by decomposing the total divergence into differences coming from the earnings side and the hours side. We find that the divergence between the LPC wage and the CES wage – both in terms of trend growth and business cycle volatility – is driven by the different evolution of average labor earnings. Average hours worked, by contrast, evolve very similarly.

Next, we use data from a third source, the Current Population Survey (CPS), to examine potential reasons for the different evolution of average earnings from the LPC and the CES. Following Abraham, Spletzer and Stewart (1998) and Lemieux (2006), the CPS earnings series is constructed by combining information from the annual May supplements for 1973-1978 with information from the monthly outgoing rotation groups (ORG) from 1979 onward. The resulting CPS May/ORG extracts – referred to as 'CPS data' from hereon – represent a relatively long, consistent earnings series that, on the one hand, is based on a very similar earnings concept as the one used in the CES and, on the other hand, allows us to cover the same worker population as in the LPC.[2] The CPS data therefore allows us to separately quantify how much of the difference between LPC earnings and

[2] Alternatively, we could have used earnings data from the March CPS supplements. As discussed below, the CPS May/ORG extracts have some advantages over the March CPS supplements for our purpose; but we plan to incorporate March CPS earnings information in subsequent versions of the paper. Other interesting earnings information for the U.S. economy is contained in the ECI/ECEC database or the PSID database.

CES earnings is due to (i) differences in earnings concept; and (ii) differences in population coverage. Furthermore, the comparison of CPS earnings with LPC and CES earnings is interesting in its own right because the micro-data of the CPS is publicly available and its earnings series has been widely used in cross-sectional studies on U.S. labor market characteristics.[3]

Analysis of the CPS data yields several interesting results. First, we document that the evolution of average earnings from the CPS falls in between the evolution of LPC earnings and CES earnings, both in terms of trend growth and changes in business cycle volatility. Given the shared characteristics of the CPS earnings data with both the LPC and the CES data, this result suggests that the divergence between LPC and CES earnings has indeed multiple sources.

Second, using information from the National Income and Product Accounts (NIPAs) about the wage and salaries portion of earnings in the LPC as well as labor income share data for high-earning individuals computed by Piketty and Saez (2003), we show that differences in earnings concept account for almost all of the differences between CPS and LPC earnings. In particular, LPC earnings include supplements such as employer contributions to pension and health plans as well as earnings of high-income individuals (including gains from exercising certain stock options) whereas CPS earnings do not. Once these components of earnings are controlled for, LPC earnings and CPS earnings evolve very similarly. The CPS data therefore provides a reliable measure of wages and salaries that is representative of a very large part of the U.S. workforce.

Third, based on information from the publicly available micro-data of the CPS, we find that differences in worker population coverage can account for a substantial

[3]See Bound and Johnson (1992); Katz and Murphy (1992); or Lemieux (2006) among many others.

part of the divergence in trend growth and volatility between CPS earnings and CES earnings. However, the sources of the remaining differences remain an open question. We conjecture that compositional changes in the CES due to a major sample expansion occurring between the early 1980s and the late 1990s represent one of the most plausible candidates.

We are not the first to document differences in average hourly wages for the U.S. economy. In particular, Abraham, Spletzer and Stewart (1998) analyze in detail the differences in trend growth of the three labor earnings series studied here. While our paper builds heavily on their analysis, we make three distinct contributions. First, we extend the sample analyzed by Abraham, Spletzer and Stewart (1998) by almost 20 years to show that the three wage series continued to diverge in the 1990s and the 2000s and that several of the reasons for the divergence discussed in their paper continue to be important. Second, Abraham, Spletzer and Stewart (1998) only consider the divergence in trend growth whereas we also document the divergence in business cycle volatilities and show that the sources for this divergence are, to some extent, the same as the ones for the divergence in trends. Third, our analysis reveals that the difference in earnings concept can account for almost all of the divergence between LPC and CPS earnings, which is an important result given the widespread use of the CPS earnings data.

Our paper also builds on earlier work by Gali and Van Rens (2010) and Champagne and Kurmann (2013) who document the divergence in business cycle volatility of the CES wage relative to LPC and CPS wages. Compared to these two studies, we provide a detailed analysis for the reasons behind this divergence.[4]

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[4] There is also an extensive survey by Abraham and Haltiwanger (1995) on the correlation of hourly wages with the business cycle. Their focus is mostly on the sensitivity of results to the measurement of nominal wages, nominal prices, and cyclical conditions. Our focus, by contrast, is on the volatility of real hourly wages. In the interest of completeness, we also show some results for the correlation of our hourly wage series with the business cycle and how this

Finally, while our findings are suggestive of important structural changes in the U.S. labor market, it is important to stress that the analysis of these changes, however important, is not the focus of the paper. Instead, the primary contribution of the paper is to provide a detailed account of the divergence in different popular aggregate hourly wage series so as to obtain better guidance on which wage series to use for the analysis of different aspects of the U.S. labor market.

The remainder of the paper proceeds as follows. Section 2 describes the different data series and documents the divergence in aggregate hourly wages. Section 3 examines different potential explanations. Section 4 concludes.

2.2 Divergent average wages: data and facts

We begin with a description of the different data sources. Additional details are available in the appendix. Then we document the divergent evolution of the average hourly wage series in terms of trend, business cycle volatility and business cycle correlation. For ease of exposition, we directly report for average hourly wages, average earnings per worker and average hours per worker from the LPC, the CES and from the CPS May/ORG data.

2.2.1 Data

The Labor Productivity and Costs (LPC) database reports a variety of labor market variables for the non-farm business sector available quarterly starting in 1948. Its weekly earnings measure has two components: 'wages and salaries'; and 'supplements'. The 'wages and salaries' component is based on the Quarterly Census of Employment and Wages (QCEW) – also known as the BLS' ES-202 program

correlation changed over time. Similar results are reported in Gali and Van Rens (2010) and Champagne and Kurmann (2013).

– a mandatory employer-based program for all employees covered by unemployment insurance (UI) that spans about 98% of U.S. establishments and jobs. Wage and salary disbursements are very comprehensive and include executive compensation, commissions, tips, bonuses and gains from exercising non-qualified stock options. The 'supplements' component is based on estimates by the Bureau of Economic Analysis and consists of vacation pay, employer contributions to pension and health plans, and employer contributions for government social insurance. Average weekly hours in the LPC are based primarily on hours from the Current Employment Statistics (CES) survey (see below), supplemented by hours from the Current Population Survey (CPS) for workers not covered by the CES. The hourly wage series computed from these average earnings and hours measures ('LPC wage' for short) is very comprehensive, both in terms of earnings concept and population coverage.

The second source of earnings and hours comes from the Current Employment Statistics (CES), which is a monthly survey starting in 1964 and is administered on a voluntary basis. The sample was significantly expanded during the 1980s and 1990s and currently covers about 140,000 private-sector firms representing almost 500,000 establishments. The historical CES earnings only covers production and nonsupervisory workers and comprises regular wage and salary disbursements as well as overtime, commissions and bonuses but only if paid each pay period.[5] Tips, irregular bonuses, gains from exercising stock options, and supplements are excluded. The hourly wage series computed from the CES measures of earnings and hours ('CES wage' for short) is therefore more restrictive than the LPC wage, both in terms of earnings concept and population coverage.

The third source of earnings and hours comes from the Current Population Sur-

[5]Starting in 2006, the CES started collecting data for all workers. We use this information below.

vey (CPS), which is a monthly household survey of about 60,000 individuals that can be weighted to make them representative of the U.S. Census. Information on earnings and hours are available from different extracts of the CPS. As in Abraham, Spletzer and Stewart (1998), Lemieux (2006), and Champagne and Kurmann (2013), we use information from the annual CPS May supplements from 1973 to 1978 together with information from the monthly outgoing rotation groups (ORG) from 1979 onwards to construct annual series of earnings and hours for private-sector workers.[6] CPS earnings are comprised of wages and salaries, including overtime, tips and commissions (OTC) and bonuses if earned and paid in each period.[7] Irregular bonuses, gains from exercising stock options and supplemental benefits are excluded. Furthermore, earnings are topcoded. For hourly-paid workers, the CPS topcodes earnings at $99.99 per hour, a threshold rarely crossed. For salaried workers, the CPS topcodes weekly earnings at $999 until 1989; $1923 between 1989 and 1997; and $2884 from 1998 onwards. For certain years, this puts a substantial share of workers above the topcode. To reduce the risk of

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[6] An interviewed individual appears in the CPS for two periods of four consecutive months, separated by eight months during which the individual is left out of the survey. Before 1979, earnings questions were asked only in March and May of each year (the March and May supplements). Thereafter, an earnings question is asked each month for individuals who are at the end of a four-month rotation (the ORG extracts). This information is collected each year by the NBER into a single merged ORG file, available on the NBER website. For the years between 1973 and 78, the May supplements yield an average of 30,406 observations per year. From 1979 onwards, the merged ORG files yield an average of 139,230 observations per year. Prior to 1979, we prefer the May supplements to the March supplements because the earnings question in the May supplements is consistent with the one in the ORG files; and because the March supplements only contain information on total hours worked starting in 1976. Furthermore, Lemieux (2006) argues that the earnings data from the March supplements are subject to other measurement errors not present in the CPS May/ORG files. See his paper for discussion.

[7] CPS respondents are first asked if they are salaried or paid by the hour. In the first case they report earnings on a weekly basis, in the latter caes on an hourly basis. Salaried workers report all regular earnings including overtime, tips and commissions (OTC) if earned and paid in each period. Hourly-paid workers are asked to only report their regular hourly wage rate. In 1994, a new, separate question about OTC earnings was added for hourly-paid workers. As in Abraham, Spletzer and Stewart (1998), we do not use this additional OTC information for hourly workers for the baseline results. We use this information, however, in Section 3.

breaks in the earnings' trend or spurious volatility induced by irregular topcode adjustments, we multiply topcoded earnings by a constant factor of 1.3 before averaging across individuals. While this constant-factor adjustment is standard in the labor literature, we also experiment with more sophisticated topcode adjustments (see the discussion in Section 3 and the appendix for details). Consistent with the LPC wage and the CES wage, the 'CPS wage' is computed as average weekly earnings divided by average weekly hours. Compared to the two other data sources, the CPS wage is similar to the CES wage in terms of its earnings concept but provides coverage representative of the non-farm business workforce of the US economy, as the LPC wage.[8] We exploit this 'in-between' characteristic of the CPS wage relative to the LPC wage and the CES wage for much of our analysis.

All three earnings measures and therefore all three hourly wage series are deflated using the Personal Consumption Expenditure (PCE) index from the National Income and Products Accounts (NIPAs).[9]

2.2.2 Trends

Figure 2.1 plots the evolution of the three average real hourly wage series (all in natural logs). Three observations stand out. First, in the early 1970s, the LPC wage is already about 35% higher than the CES wage and the CPS wage. Second, the LPC wage grows at a substantially higher rate over the sample, ending up

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[8] As opposed to CPS earnings, CES earnings do not include tips. According to Abraham, Stewart and Spletzer (1998), however, tips represented only a very small part of total earnings. It is therefore unlikely that tips play a major role in explaining the divergence of the CES wage.

[9] As Abraham and Haltiwanger (1995) point out, there is controversy about the price index that should be used to deflate wages. While the choice of deflator may be important for the determination of the real wage *level* at any given point in time, our conclusions about the divergence in the three series is not affected by the use of alternative deflators.

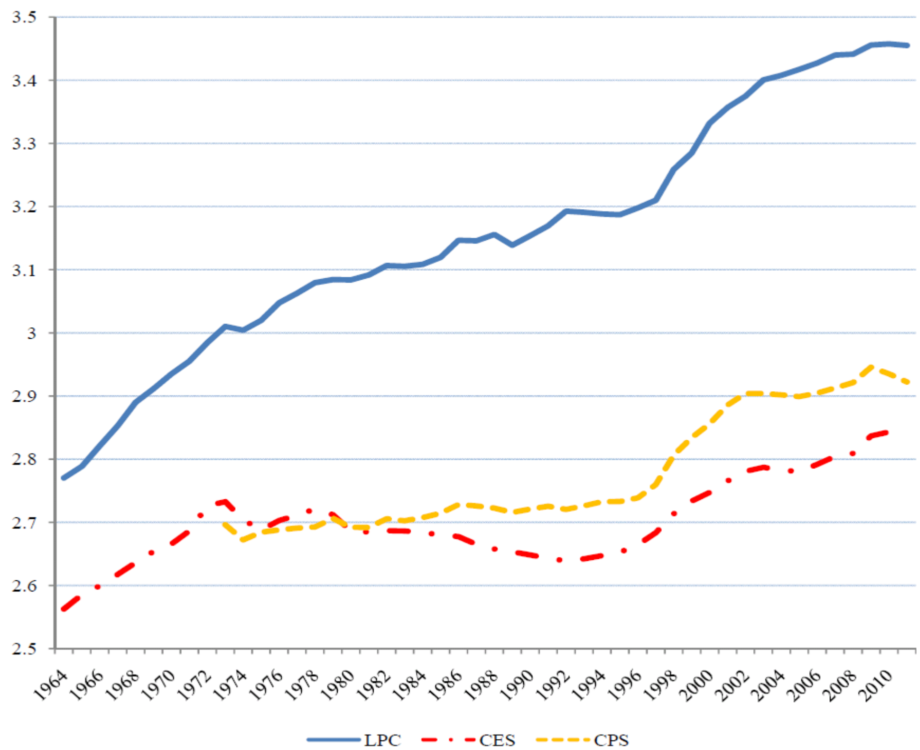

Figure 2.1 Real hourly wages (2005 dollars)

86% and 67% higher than the CES wage and the CPS wage, respectively, in 2009. Third, while the CPS wage grows consistently throughout the sample, the CES wage experiences a prolonged decline between the mid 1970s and the early 1990s.

2.2.3 Business cycle volatilities

To compute business cycle statistics, we take logarithms of the different hourly wage series and extract the business cycle component using the Hodrick-Prescott (H-P) filter.[10] Then, we compute standard deviations of each series for the pre-

[10]The H-P filter constant is set to 1600 for quarterly data and 6.25 for annual data as recommended by Ravn and Uhlig (2002). Results are robust to alternative filtering methods.

1984 period and the post-1984 period. The break in 1984 is motivated by the Great Moderation literature that estimates a significant change in output volatility around 1984 (e.g. McConnell and Perez-Quiros, 2000).

The first panel of Table 2.1 reports standard deviations for quarterly series of the LPC wage and the CES wage for the subsamples 1964:1-1983:4 and 1984:1-2011:4, with standard errors provided in brackets.[11] The second panel of Table 2.1 reports the same standard deviations using annualized data for the samples 1973-1983 and 1984-2011 together with standard deviations for the CPS wage. Both tables also show the corresponding standard deviation of non-farm business chain-weighted GDP as a benchmark and report the ratio of the standard deviation of the different wage series to the standard deviation of GDP (denoted relative standard deviation).

There is a clear divergence in business cycle volatility for the three hourly wage series. While the volatility of the LPC wage increases by 35% to 45% between the pre-84 period and the post-84 period, the volatility of the CPS wage increases only by about 20% and the volatility of the CES wage drops by about 50%. Since the volatility of output drops by 40% to 50% between the two periods (i.e. the Great Moderation), the relative volatility of hourly wages increases two- to threefold according to the LPC and the CPS but remains roughly unchanged according to the CES. Furthermore, the LPC wage and the CPS wage are equally volatile in the pre-84 period, whereas the volatility of the CES wage is substantially higher during that period.

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[11] Standard errors are computed via the delta method from GMM-based estimates. See the appendix for details.

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
Quarterly data						
Output	2.73	1.62	0.59	1.00	1.00	1.00
	(0.31)	(0.23)				
LPC wage	0.68	0.97	1.43	0.25	0.60	2.41
	(0.08)	(0.09)		(0.03)	(0.11)	
CES wage	1.13	0.57	0.50	0.41	0.35	0.85
	(0.20)	(0.07)		(0.07)	(0.04)	
Annual data						
Output	2.91	1.46	0.50	1.00	1.00	1.00
	(0.19)	(0.25)				
LPC wage	0.64	0.85	1.33	0.22	0.58	2.65
	(0.08)	(0.10)		(0.04)	(0.15)	
CPS wage	0.64	0.76	1.19	0.22	0.52	2.37
	(0.09)	(0.10)		(0.03)	(0.10)	
CES wage	1.01	0.50	0.49	0.35	0.34	0.98
	(0.15)	(0.07)		(0.05)	(0.05)	

Notes : Total sample extends from 1964:I to 2011:IV for quarterly data; from 1973 to 2011 for annual data. Nonfarm business sector. PCE-deflated w ages. P-values are reported for a test of equality of variances across the tw o subsamples. Standard errors compute using GMM and the Delta method appear in parentheses below estimates.

Table 2.1 Changes in business cycle volatilties

2.2.4 Correlations

Table 2.2 reports the correlation coefficients of the three H-P filtered wage series, both with respect to non-farm business GDP and total non-farm business hours from the LPC. As before, the first panel shows results for quarterly data for the samples 1964:1-1983:4 and 1984:1-2011:4; and the second panel shows results for annual data for the samples 1973-1983 and 1984-2011. While there are noteworthy differences in the pre-84 period (e.g. the correlation of the CES wage with both output and hours is markedly higher than for the other two wage series), all three wage series experience a sizable drop in correlation into negative territory for the post-84 period.

	Correlations w/ GDPnfb			Correlations w/ Hours		
	Pre-84	*Post-84*	*Post - Pre 84*	*Pre-84*	*Post-84*	*Post - Pre 84*
Quarterly data						
LPC wage	0.35	-0.22	-0.57	0.21	-0.41	-0.62
	(0.18)	(0.10)		(0.14)	(0.12)	
CES wage	0.60	-0.34	-0.94	0.45	-0.35	-0.80
	(0.12)	(0.18)		(0.13)	(0.15)	
Annual data						
LPC wage	0.39	-0.25	-0.64	0.21	-0.43	-0.65
	(0.30)	(0.13)		(0.23)	(0.14)	
CES wage	0.66	-0.34	-1.01	0.52	-0.37	-0.89
	(0.22)	(0.23)		(0.19)	(0.22)	
CPS wage	0.17	-0.46	-0.63	0.06	-0.44	-0.51
	(0.27)	(0.23)		(0.33)	(0.17)	

Notes : Total sample extends from 1964:I to 2011:IV for quarterly data; from 1973 to 2011 for annual data. Nonfarm business sector. Cyclical indicator are: (1) real chained-$ nonfarm business GDP (NIPAs) per capita, and (2) hours per capita from LPC. Standard errors appear in parentheses below estimates.

Table 2.2 Changes in business cycle correlations

2.3 Potential explanations

Since each of the average hourly wage series is constructed by dividing an earnings measure with an hours worked measure, we start by decomposing the divergence in trend and business cycle volatility into differences coming from the earnings side and the hours side. Second, we consider three specific sources of divergence: (i) differences in earnings concepts; (ii) differences in population coverage; and (iii) measurement issues.

There are, of course, other differences between the wage series. However, as our analysis reveals, the three candidate sources we consider are likely to account for a large part of the divergence.

2.3.1 Earnings versus hours

Each of the average hourly wage series is constructed by dividing an earnings measure by an hours measure; i.e.

$$w_{it} = W_{it}/H_{it},$$

where w_{it} denotes the average hourly wage from data source i at time t; W_{it} the corresponding average (weekly) earnings measure; and H_{it} the corresponding average (weekly) hours measure. Hence, the divergence in the different average hourly wage series must come from different evolutions in either earnings, hours, or both.

Figures 2.2 and 2.3 plot the evolution of log average weekly earnings and log average weekly hours used in the computation of the three hourly wage series. Figure 2.2 shows that similarly to average hourly wages, there is already a level difference in 1973 between weekly earnings from the LPC and the two other weekly earnings measures. Thereafter, weekly earnings from both the LPC and the CPS grow consistently although the average growth rate of LPC weekly earnings is higher. By contrast, weekly earnings from the CES fall substantially between the mid-1970s and the early 1990s before recovering to their early 1970s level by 2010. Figure 2.3 shows that while the LPC and the CES measure of weekly hours both decrease in similar fashion over time, the CPS measure of weekly hours fluctuates around an approximately constant level.

To quantify the importance of these differences for the divergence in the three hourly wage series, we use growth accounting techniques. First, we decompose the log difference of the average hourly wage from data source i between 1973 and 2011 into the log differences of the corresponding weekly earnings and the

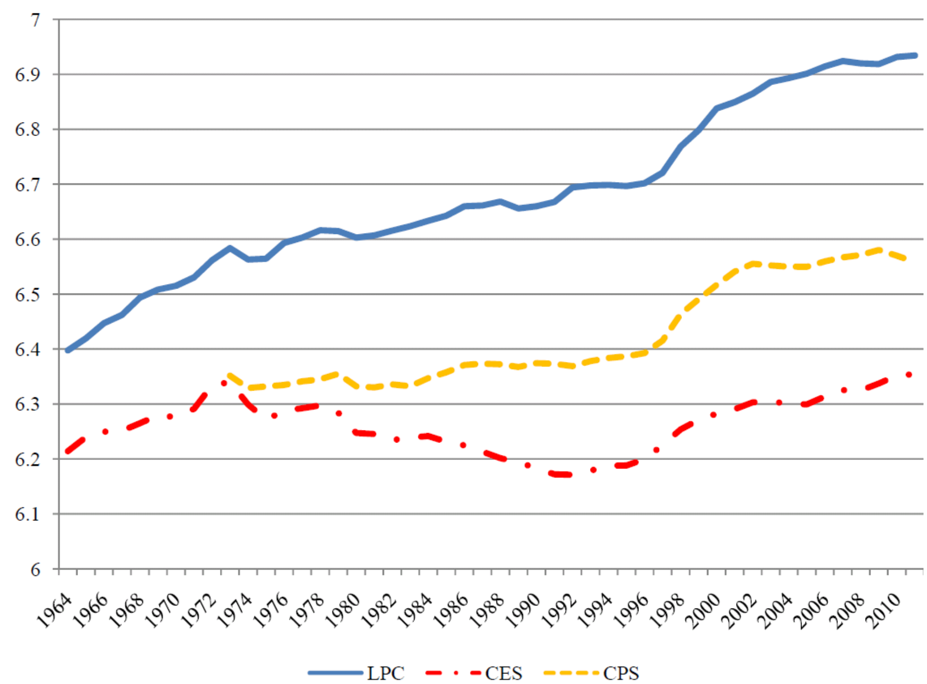


Figure 2.2 Log real weekly earnings (2005 dollars)

weekly hours measures. Then, we subtract the same decomposition for the log difference of the average hourly wage from data source j to obtain the percent contributions of differences in weekly earnings growth and weekly hours growth for the difference in average hourly wage growth; i.e.

$$\Delta \log w_i - \Delta \log w_j = (\Delta \log W_i - \Delta \log W_j) - (\Delta \log H_i - \Delta \log H_j)\,, \qquad (2.1)$$

where $\Delta \log w_i$ denotes the log difference in the average hourly wage from data source i between 1973 and 2011 and so forth. Figure 2.4 reports the results. Figure 2.4 shows that the divergence in average hourly wage growth between the LPC and CES is entirely due to the difference in earnings growth. By contrast, only about two thirds of the considerably smaller divergence in average hourly wage

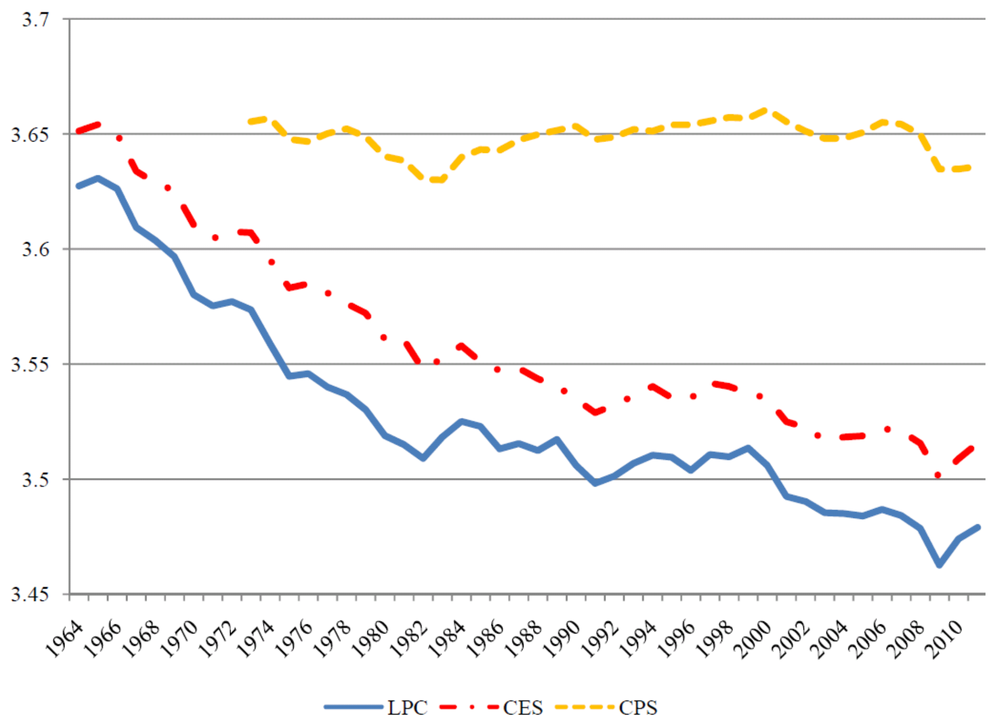
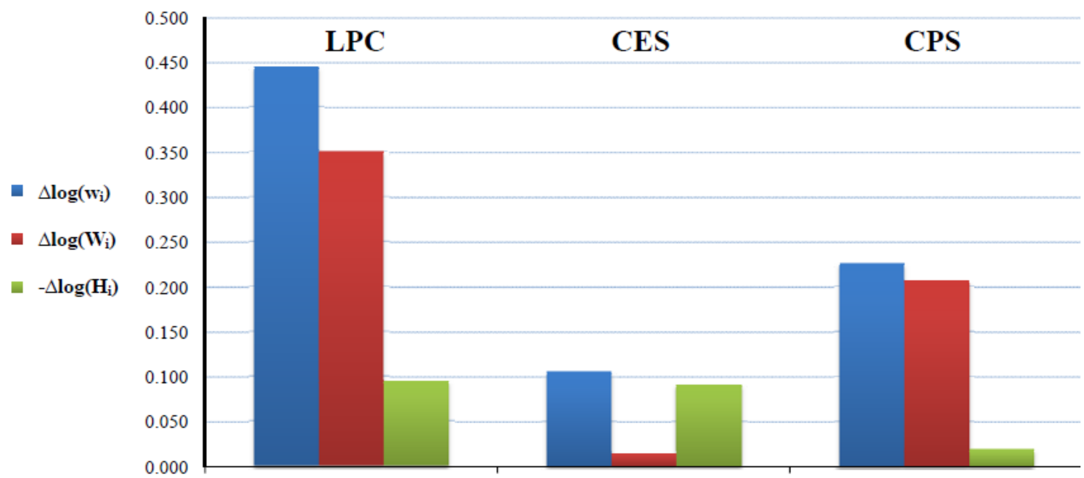


Figure 2.3 Log weekly hours

growth between the LPC and the CPS is due to smaller weekly earnings growth in the CPS. The remaining third of the divergence in average hourly wage growth is due to the fact that LPC weekly hours decreased consistently over time whereas CPS weekly hours remained approximately constant.

The results in Figure 2.4 confirm the previous findings by Abraham, Spletzer and Stewart (1998) for a substantially longer sample. The close association between LPC and CES hours should not come as a surprise since LPC hours are primarily constructed from CES hours. The divergence between CES (respectively LPC) hours and CPS hours is also relatively well-known and has been investigated in a recent paper by Frazis and Stewart (2010). We return to discussing their findings below.



	LPC-CES	%	LPC-CPS	%
$\Delta\log(w_{LPC}) - \Delta\log(w_i)$	0.339	100.00%	0.219	100.00%
$\Delta\log(W_{LPC}) - \Delta\log(W_i)$	0.336	99.12%	0.144	65.69%
$\Delta\log(H_{LPC}) - \Delta\log(H_i)$	0.003	0.88%	0.075	34.31%

Note: The figure decomposes total hourly wage growth (blue) between 1973 and 2011 into total earnings growth (red) and total hours growth (green), i.e:

$$\Delta\log(w) = \Delta\log(W) - \Delta\log(H)$$

where w denotes the average hourly wage, W denotes weekly earnings, and H denotes weekly hours worked for the LPC, CES, and CPS datasets. The accompanying table reports the differences in growth rates between the different components.

Figure 2.4 Accounting for the divergence in average hourly wage growth

The decomposition of average hourly wages into weekly earnings and weekly hours can also be used to analyze the divergence in business cycle volatility. Specifically, the variance of average hourly wage growth from data source i can be expressed as

$$\sigma^2_{w_i} = \sigma^2_{W_i} + \sigma^2_{H_i} - 2\rho_{W_i,H_i}\sigma_{W_i}\sigma_{H_i},$$

where $\sigma^2_{w_i} \equiv Var(\Delta\log w_{it})$; $\sigma^2_{H_i} \equiv Var(\Delta\log H_{it})$; and $\rho_{W_i,H_i} \equiv Corr(\Delta\log W_{it}, \Delta\log H_{it})$. By subtracting this decomposition for some subsample a from the decomposition of some other subsample b (i.e. between the pre-84 period and the post-84 period), we obtain

$$\begin{aligned}\sigma^2_{w_i}(b)-\sigma^2_{w_i}(a) &= \left[\sigma^2_{W_i}(b)-\sigma^2_{W_i}(a)\right]+\left[\sigma^2_{H_i}(b)-\sigma^2_{H_i}(a)\right] \\ &\quad -2\left[\rho_{W_i,H_i}(b)\sigma_{W_i}(b)\sigma_{H_i}(b)-\rho_{W_i,H_i}(a)\sigma_{W_i}(a)\sigma_{H_i}(a)\right].\end{aligned}$$

By manipulating this expression further to decompose the multiplicative parts, we end up with

$$\begin{aligned}\sigma^2_{w_i}(b)-\sigma^2_{w_i}(a) &= \left[\sigma^2_{W_i}(b)-\sigma^2_{W_i}(a)\right]+\left[\sigma^2_{H_i}(b)-\sigma^2_{H_i}(a)\right] \\ &\quad -\left\{\begin{array}{c} \frac{\rho_{W_i,H_i}(b)+\rho_{W_i,H_i}(a)}{2}\left[\begin{array}{c}\frac{\sigma_{H_i}(b)+\sigma_{H_i}(a)}{2}\left[\sigma_{W_i}(b)-\sigma_{W_i}(a)\right] \\ \frac{\sigma_{W_i}(b)+\sigma_{W_i}(a)}{2}\left[\sigma_{H_i}(b)-\sigma_{H_i}(a)\right]\end{array}\right] \\ +\frac{\sigma_{W_i}(b)\sigma_{H_i}(b)+\sigma_{W_i}(a)\sigma_{H_i}(a)}{2}\left[\rho_{W_i,H_i}(b)-\rho_{W_i,H_i}(a)\right]\end{array}\right\}.\end{aligned}$$

Hence, the change in variance of average hourly wage growth is accounted for by changes in either the volatility of earnings growth; the volatility of hours growth; or the correlation between earnings and hours growth. This allows us to quantify the sources of the divergence in business cycle volatility between the different average hourly wage series.

As a preliminary to this volatility accounting exercise, Table 2.3 shows the post-84 to pre-84 changes in volatilities and correlations of the three weekly earnings and weekly hours measures, together with the corresponding changes in the hourly wage volatilities reported in Table 2.1. Three observations stand out. First, the volatility of weekly earnings from both the LPC and the CPS experience a small decline although, interestingly, the volatility of weekly earnings from the CPS declines by a slightly smaller amount.[12] In comparison, the volatility of CES

[12] The small decline in volatility of weekly earnings from the LPC and the CPS is consistent with recent findings from micro-data that for most individuals, the volatility of labor income has remained approximately constant (e.g. Dynan et al., 2008; Jensen and Shore, 2008).

LPC	1973-1984	1984-2011	post 84 - pre 84
Std(hourly wage)	0.64	0.85	0.21
Std(weekly earnings)	*0.90*	*0.80*	*-0.10*
Std(weekly hours)	*0.41*	*0.45*	*0.04*
corr(weekly earnings, weekly hours)	*0.78*	*0.17*	*-0.61*

CES	1973-1984	1984-2011	post 84 - pre 84
Std(hourly wage)	1.01	0.50	-0.51
Std(weekly earnings)	*1.29*	*0.49*	*-0.79*
Std(weekly hours)	*0.38*	*0.36*	*-0.02*
corr(weekly earnings, weekly hours)	*0.79*	*0.35*	*-0.44*

CPS	1973-1984	1984-2011	post 84 - pre 84
Std(hourly wage)	0.64	0.76	0.12
Std(weekly earnings)	*0.76*	*0.69*	*-0.07*
Std(weekly hours)	*0.41*	*0.28*	*-0.13*
corr(weekly earnings, weekly hours)	*0.56*	*-0.04*	*-0.59*

*Note: Annual data, H-P filtered. Standard deviations are multiplied by 100.

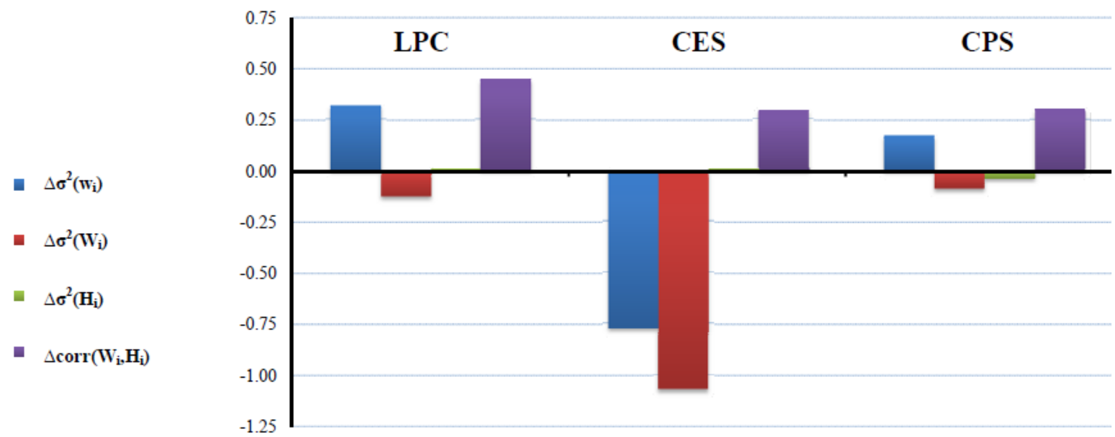
Table 2.3 Changes in standard deviations and correlations of weekly earnings and weekly hours

weekly earnings drops about 8 times as much. Second, the volatility of weekly hours remains approximately constant in the LPC and the CES but decreases slightly in the CPS. Third, the correlation of weekly earnings with weekly hours drops in all three data sets but the drop is larger for the LPC and the CPS.[13] These observations imply, maybe somewhat surprisingly, that the *increase* in volatility of the average hourly wage in the LPC and the CPS is entirely due to the drop in correlation between weekly earnings and weekly hours (since a drop in correlation affects hourly wage volatility positively). In turn, the large drop in volatility of the CES wage is driven by the large drop in volatility of weekly earnings.

Figure 2.5 displays the results of the volatility accounting exercise based on the

[13]Since LPC hours and CES hours are very highly correlated in both subsamples (0.99 and 0.98, respectively), the larger drop in correlation between earnings and hours in the LPC is entirely due to the different cyclical properties of earnings.

numbers in Table 2.3.[14] The figure provides quantitative confirmation for the



	LPC-CES	%	LPC-CPS	%
$\Delta\sigma^2(w_{LPC}) - \Delta\sigma^2(w_i)$	1.090	100.00%	0.1453	100.00%
$\Delta\sigma^2(W_{LPC}) - \Delta\sigma^2(W_i)$	0.941	86.34%	-0.0411	-28.31%
$\Delta\sigma^2(H_{LPC}) - \Delta\sigma^2(H_i)$	-0.002	-0.21%	0.0426	29.34%
$\Delta corr(W_{LPC},H_{LPC}) - \Delta corr(W_i,H_i)$	0.151	13.87%	0.1438	98.97%

Note: The figure decomposes the change in the variance of the hourly wage (blue) into changes in the variance of earnings (red), the variance of hours (green), and the correlation between earnings and hours (purple) between 1973-1983 and 1984-2011 for the LPC, CES, and CPS datasets. The accompanying table reports the differences in changes between the difference components.

Figure 2.5 Accounting for the divergence in business cycle volatility of average hourly wages

above observation that the large drop in correlation between earnings and hours is behind the increase in hourly wage volatility in the LPC and the CPS. The increase in the volatility of the LPC wage is larger than the increase in the volatility of the CPS wage because in the LPC, the drop in correlation between earnings and hours is attributed a larger weight in the above variance decomposition (due to larger *average* earnings and hours volatilities in the LPC). In turn, the large drop in the

[14] The volatility accounting formula is derived for first-differenced data whereas the results in Table 3 pertain to H-P filtered data. This introduces an approximation error that is, however, only of minor quantitative importance.

volatility of the CES wage is primarily due to the large fall in earnings volatility and the somewhat smaller drop in correlation between earnings and hours.

We take away two main lessons from the trend and volatility decomposition exercises:

1. The divergence in both trend and volatility between the LPC wage and the CES wage is entirely driven by the divergence in trend and volatility of weekly earnings. Weekly hours from the LPC and CES behave, by construction, very similarly.

2. The divergence in trend growth of the LPC wage relative to the CPS wage is due to the smaller growth of weekly earnings in the CPS and, to a lesser extent, the difference in the evolution of weekly hours. The larger increase in volatility of the LPC wage relative to the CPS wage is mainly due to a smaller contribution of the drop in correlation between earnings and hours in the CPS.

Based on these results, differences in earnings behavior become the main focus of our attempt to reconcile the divergence in average hourly wages.

2.3.2 Differences in earnings concepts

As described in Section 2, LPC earnings are based on a very broad concept that includes executive compensation, tips, bonuses and gains from executing non-qualified stock options; as well as supplements such as vacation pay and employer contributions to pension and health plans. By contrast, CPS and CES earnings only include compensation that is earned and paid each period; and completely exclude supplements.

Given the similarity in earnings concepts between the CPS and the CES, we focus on the comparison between LPC earnings and CPS earnings. First, we try to compare the wages and salaries component of the LPC to the one from the CPS. Second, we use information in the CPS on overtime, tips and commissions (OTC) to assess the importance of a particular type 'regular' bonus payments for hourly-paid workers. Third, we use wage share information on top income earners from Piketty and Saez (2003, updated to 2010) to quantify the role played by earnings of high-income individuals in the LPC.

Wages and salaries

To compare the wages and salaries component of LPC earnings to the one from the CPS, we need to strip out supplements components from LPC earnings. Unfortunately, this cannot be done directly in the LPC dataset because it does not contain separate information on these two components of compensation. Separate information on the two components is, however, provided by the income tables in the National Income and Product Accounts (NIPAs), from which the LPC program computes its earnings series. At the same time, the publicly available NIPA data do not contain all information to reconstruct the non-farm business coverage employed by the LPC.[15] We therefore consider a 'private non-agriculture' coverage of earnings that is straightforward to compute from the NIPAs.

Figure 2.6 plots the resulting NIPA series of average weekly earnings both for total compensation including supplements (labeled 'NIPA total compensation') and the wages and salaries component (labeled 'NIPA wages&salaries'). The figure also

[15] As explained in more detail in the appendix, the LPC non-farm business data excludes farms, households and non-profits and general government; but includes agricultural services, forestry and fishing, government services and imputed data for self-employed. Several of these added and subtracted components are unavailable publicly over the entire sample period.

contains, for comparison, the LPC (non-farm business) series of weekly earnings from above; and two weekly private non-agricultural earnings series computed from the CPS. The series labeled 'CPS private non-agricultural' is the equivalent of the CPS wage from above. The series labeled 'CPS non-agricultural with OTC' includes OTC payments and is discussed further below.As shown by the top two

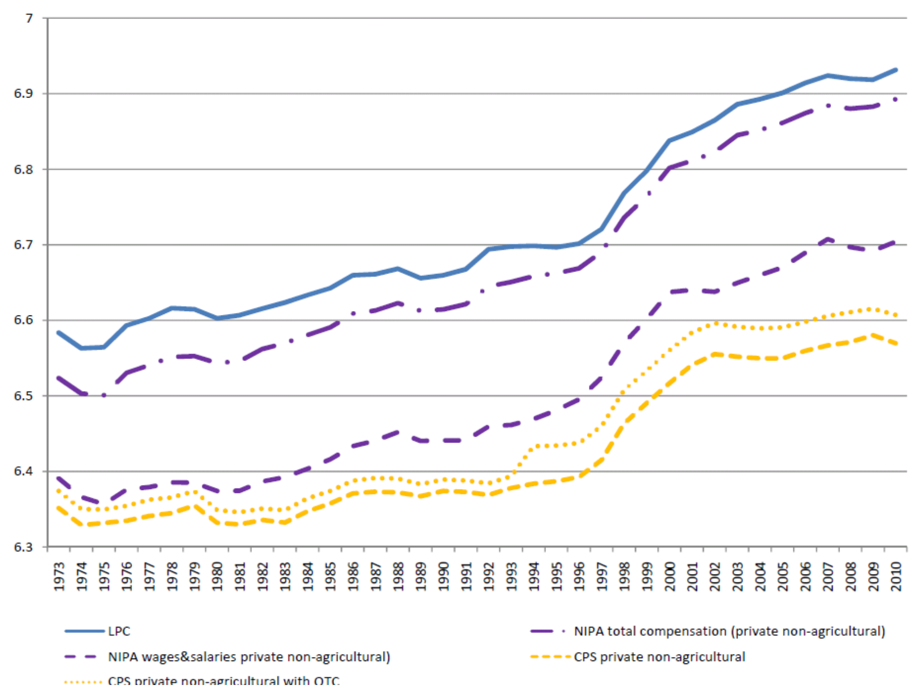


Figure 2.6 Comparison of aggregate weekly earnings measures

lines, there is some difference in total compensation (i.e. earnings including supplements) between non-farm business sector covered by the LPC and the private non-agricultural sector as computed from the NIPAs. However, this difference is small compared to the substantial and widening gap between NIPA private non-agricultural earnings based on total compensation and earnings based on the wages and salaries component. This gap, which started to appear in the 1960s illustrates that the inclusion of supplements are an important reason for the level difference and the divergence in trends between LPC earnings and CPS earnings (and therefore CES earnings).

Table 2.4 displays the business cycle volatility of the same earnings series for the pre-84 and post-84 subsamples. The decline in volatility of total compensation

Changes in Volatility : Average Weekly Earnings

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
HP-Filter						
Output (nfb)	2.91	1.42	0.49	1.00	1.00	1.00
	(0.19)	(0.22)				
LPC total compensation (nfb)	0.90	0.81	0.90	0.31	0.57	1.85
	(0.14)	(0.12)		(0.06)	(0.14)	
NIPA total compensation (private non-agri)	0.89	0.71	0.80	0.31	0.50	1.64
	(0.13)	(0.10)		(0.05)	(0.12)	
NIPA wages&salaries (private non-agri)	0.76	0.84	1.11	0.26	0.59	2.28
	(0.11)	(0.10)		(0.04)	(0.11)	
CPS (private non-agri)	0.76	0.69	0.90	0.26	0.48	1.84
	(0.13)	(0.12)		(0.04)	(0.13)	
CPS with OTC (private non-agri)	0.84	0.79	0.94	0.29	0.56	1.94
	(0.14)	(0.12)		(0.04)	(0.15)	

Notes : Total sample extends from 1973 to 2010. Annual data; PCE-deflated wages (2005 dollars). Standard errors computed using GMM and the Delta method appear in parentheses below estimates.

Table 2.4 Comparison of aggregate weekly earnings measures

in the post-84 period is slightly larger for the NIPAs private non-agricultural aggregate than for the LPC non-farm business aggregate. This difference is due to small differences in the evolution of volatility for segments of the population that are included in the LPC (such as self-employed) but excluded from the NIPAs aggregate and vice versa.

More interesting is the increase in volatility of the 'wages and salaries' component computed from the NIPAs. This result obtains because supplements, which are excluded in this 'wages and salaries' series but included in total compensation, fell in volatility in line with the business cycle. In other words, once supplements are stripped out from NIPA earnings (or, equivalently, LPC) earnings, there is thus also a divergence in earnings volatility between NIPA earnings and CPS earnings (which does not contain supplements).

Overtime, tips and commissions

As described in Section 2, salaried workers in the CPS report all earnings including OTC if earned and paid each period. Hourly-paid workers, by contrast, were historically asked to only report their regular hourly wage rate, thus excluding OTC. Since hourly-paid workers represent almost 60% of the workforce (and around 50% of the total wage bill), the CPS earnings measure is likely to understate the true level of regular earnings. Furthermore, since overtime work increased substantially during the 1980s and 1990s (see Kuhn and Lozano, 2008) and is likely to be more volatile than regular pay, the CPS earnings measure is also likely to understate the true trend and volatility of earnings over time.

To obtain a measure of earnings including OTC for hourly workers in the CPS, we proceed as follows. Prior to 1994, we use the greater of $weekly\_earnings$ and $wage\_rate * hours$ to obtain a measure of earnings that includes at least some of the OTC received by hourly-paid workers (see the appendix for details and a discussion on why this measure is incomplete). Starting in 1994, the CPS introduced a separate question about OTC earnings for hourly-paid workers, which we add to the usual $wage\_rate * hours$ series.

The last line in Figure 2.6 and Table 2.4 report the results, labeled 'CPS with OTC (private non-agricultural)'. Adding OTC for hourly-paid workers indeed leads to a systematic level increase with a discrete jump in 1994 when the OTC question was introduced. Including OTC thus covers at least part of the gap between CPS earnings and NIPA / LPC earnings. As Table 2.4 indicates, adding OTC also leads to a smaller drop in the volatility of CPS earnings for the post-1984 subsample.

Further analysis reveals, however, that this is mostly the result of a discontinuity resulting from the introduction of additional OTC earnings question in 1994. Once we control for this discontinuity, the smaller drop in volatility disappears.

Labor earnings of high-income individuals

While the CPS contains all information to construct a representative average weekly earnings series of private non-agricultural workforce, respectively the entire U.S. workforce, publicly available earnings data is topcoded for high-income individuals (see the description in Section 2), thus downweighing their contribution to average weekly earnings. But even if earnings for these high-income individuals was not topcoded, the CPS data would still miss a substantial portion of high-income individuals' compensation due to the restrictive earnings concept in the CPS. In contrast, the earnings concept in the LPC (and NIPAs) is much more comprehensive because the QCEW, its basis for earnings, includes irregular cash bonuses and gains from exercising non-qualified stock options. This may affect the evolution of earnings in non-trivial ways.[16]

This difference between CPS and LPC / NIPAs earnings are particularly interesting to investigate because recent evidence shows that the share of total labor income by high-earning individuals has increased importantly over the past decades. Most prominently, based on tabulations from the Internal Revenue Service (IRS), Piketty and Saez (2003, updated to 2010) document that the top 1% individuals of the income distribution saw their share of total economy-wide income increase from a stable 8% between the 1950s to the mid-1990s to 23.5% in 2007. This remarkable growth is due mostly to the growing inequality in labor income and

[16]Irregular bonuses, but not gains from exercises stock options, are included in the CPS March supplements. We plan to quantify the importance of these bonuses in a subsequent version of the paper.

implies earnings of high-income individuals play an increasingly important role for the trend of average weekly earnings as recorded in the LPC / NIPAs. Likewise, if earnings of high-income individuals have become more volatile, then this could explain why the volatility of the LPC hourly wage increased so much in the post-84 period.[17]

To assess the role played by earnings of high-income individuals, we use information on top wage income shares from Piketty and Saez to calculate a separate series of average weekly earnings for the top 5% earners and the remaining 95% in each year. We then compare the two series to average weekly earnings for the corresponding top 5% earners in the CPS (of which a fraction have topcoded earnings) and the remaining 95%.[18] Since the earnings concept of the IRS data used by Piketty and Saez is very similar to the one employed in the QCEW, the comparison allows us to consider the role played by high-income individuals and their irregular earnings that are not taken into account in the CPS. At the same time, since IRS data does not allow a distinction into different sectors, the Piketty-Saez data is only available for 'all economy'. We therefore recompute the CPS earnings series for an 'all economy' equivalent. Figure 2.7 shows the results. Unsurprisingly, there is a large and widening difference in average weekly earnings between the top 5% earners and the remaining 95%. What is striking, however, is that average weekly earnings for the 95% computed from Piketty and Saez (2003, 2011), labeled 'P-S 0-95', evolves almost identically to the one computed from

[17] This is particularly relevant for stock options because they are likely to be exercised in upturns when their value is higher than their fair-market value at the time they were granted (i.e. the time when they should have been recorded as compensation). See Mehran and Tracy (2001) who argue that the growth of stock options in the 1990s and their inclusion in compensation at the time of exercise has biased the evolution of compensation upwards. The authors also conjecture that increased use of stock options may render compensation more variable.

[18] We use a 5%-95% split simply because in the CPS data, the fraction of individuals with topcoded earnings never exceeds 5%.

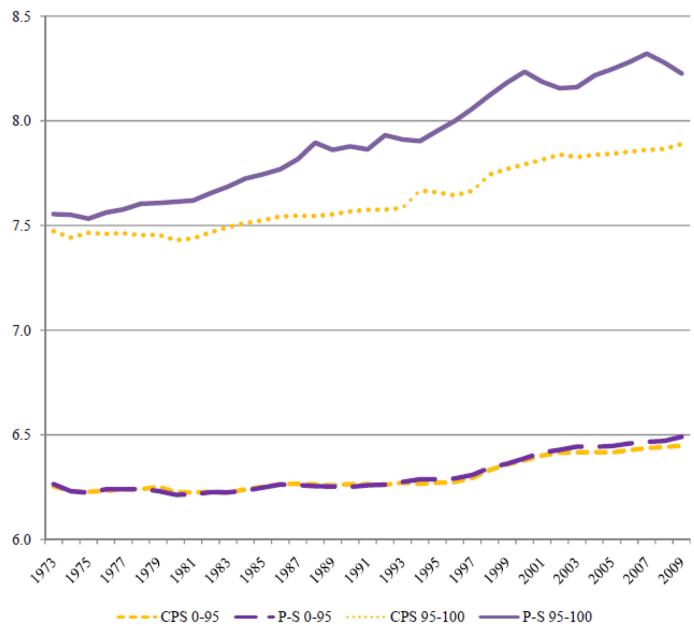


Figure 2.7 Log average real earnings for different income groups

the CPS, labeled 'CPS 0-95'. In contrast, for the top 5% earners, weekly earnings computed from Piketty-Saez grow at a substantially higher pace than weekly earnings for the 5% top earners in the CPS.

To further quantify the importance of this difference in weekly earnings for high-income individuals, we take Piketty and Saez' (2003, 2011) weekly earnings information for the top-income groups (i.e. top 0.01%, 0.1%-0.01%, 0.5%-0.1%,...to 1%-5%) and extrapolate new values for topcoded CPS earnings for each year from 1973 to 2009 (the last year for which the Piketty-Saez data is currently available). Based on this extrapolation, we then compute a new 'topcode corrected' weekly earnings measure for the CPS and analyze to what extent this measure tracks the evolution of weekly earnings from the NIPA wages and salaries portion. The specifics of the procedure are described in the appendix. Figure 2.8 shows the results. We notice that weekly earnings from the topcode corrected measure of

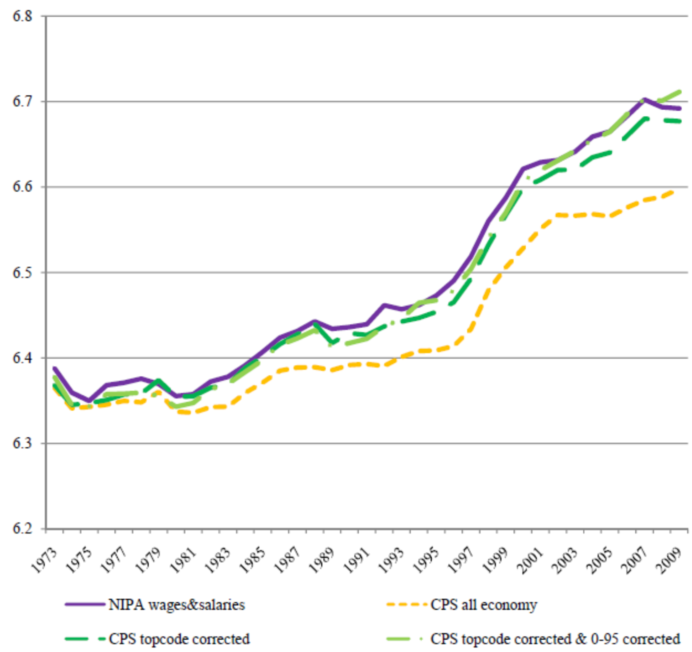


Figure 2.8 Log average real income corrected for high-income individuals

the CPS closes most of the gap with the NIPA wages and salaries series. If, in addition, we adjust for the small difference in weekly earnings for the remaining 95% earners between the CPS and the Piketty-Saez measure, labeled 'CPS topcode & 0-95 corrected', we basically close the gap.

Table 2.5 reports on the business cycle volatility of weekly earnings of the different series in Figures 2.7 and 2.8. For comparison, the table also shows the NIPA wages and salaries series for 'all economy'. The first panel confirms that weekly earnings for the top 5% earners are substantially more volatile than for the remaining 95% and have, according to the Piketty-Saez data, greatly increased in volatility for the post-84 period. The second panel shows that correcting the CPS earnings series with the Piketty-Saez data reduces the drop in volatility and, in one instance,

Changes in Volatility : Average Weekly Earnings

	Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*
Percentiles			
P-S P0-95	0.87	0.59	0.68
CPS P0-95	0.83	0.59	0.72
P-S P95-100	1.03	2.66	2.58
CPS P95-100	1.17	1.44	1.23
Aggregates			
NIPA wages&salaries all economy	0.85	0.68	0.80
CPS all economy	0.74	0.64	0.86
CPS with P-S topcode adjustment	0.73	0.76	1.04
CPS with P-S topcode adjustment and 0-95 lift	0.77	0.69	0.90

Notes: CPS May-MORG data and Piketty-Saez "Top income shares" database. Real Average Weekly Earnings (2005 dollars). Annual data. All economy. Sample: 1973 to 2009. All data are H-P filtered.

Table 2.5 Effect of high-income individuals on average earnings volatilities

slightly increases it.[19]

We conclude from this investigation that differences in earnings concept between the QCEW and the CPS explain the vast majority of the divergence in weekly earnings between the two data sets and therefore also account for at least part of the divergence in trend and volatility between the LPC wage and the CES wage.

2.3.3 Differences in population coverage

As described in Section 2, the LPC and the CES cover different segments of the U.S. workforce. Specifically weekly earnings in the LPC is based on the QCEW and includes labor income of the near totality of workers in the non-farm business sector. By contrast, the CES historical sample covers only earnings of production

[19] Also note from this panel that the volatility of the 'all economy' aggregate of NIPA wages and salaries falls substantially while it increased for the 'private non-agricultural' aggregate. By contrast, for the CPS, there is no corresponding fall in earnings volatility of the 'all economy' aggregate relative to the 'private non-agricultural' aggregate. We plan to analyze this issue further in subsequent versions of the paper.

and non-supervisory workers. In 2006, the CES started collecting earnings and hours information for all workers in the sampled establishments. Comparing earnings for this 'all worker' sample to earnings from the sample of production and non-supervisory workers should therefore provide information on the role played by the difference in population coverage. Figure 2.9 shows the result of this comparison, together with average earnings from the non-farm business population in the CPS (which, as discussed above, is based on a very similar earnings concept as the CES). The figure reveals that average weekly earnings for the 'all worker' sam-

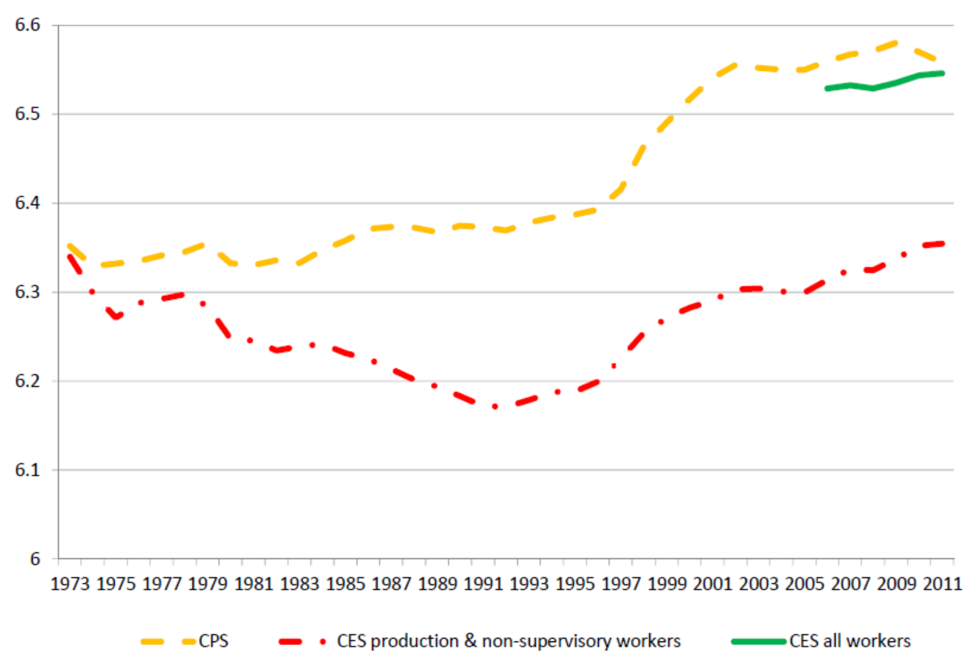


Figure 2.9 Log real average earnings for different population coverage in the CES

ple of the CES are about 20% higher than for the production and non-supervisory sample and almost match the level of average earnings in the CPS. The difference in population coverage therefore explains most of the gap between CES earnings and CPS earnings at the end of the sample (respectively LPC earnings once the difference in earnings concept is taken into account). What needs to be explored is whether the difference in population coverage also explains the divergence in trends and volatility over time between CES earnings and CPS earnings.

To assess this possibility, we employ the strategy used in Abraham, Spletzer and Stewart (1998) and create a weekly earnings measure from the CPS data intended to replicate the population coverage in the CES. In a first instance, we use the official definition of production and non-supervisory workers from the BLS. As can be seen from Figure 2.10, the resulting series, labeled 'CES replication 1', fails to generate the trend and business cycle dynamics of weekly earnings in the CES.[20] As opposed to CES earnings, from CES replication 1 are already substantially below CPS earnings in the early 1970s and grow at approximately the same pace as CPS earnings thereafter. This result confirms, for a substantially longer sample, the findings reported by Abraham, Spletzer and Stewart (1998).

Plewes (1982) and Abraham, Spletzer and Stewart (1998) argue, however, that establishments in the CES often mistakenly interpret production and non-supervisory workers as employees paid by the hour and other employees that are non-exempt under the Fair Labor Standards Act. Hence, by restricting the CPS sample to the definition of production and non-supervisory workers in the BLS, we may not necessarily capture what establishments in the CES sample report. In a second instance, we use an alternative definition of production and non-supervisory workers constructed by Abraham, Spletzer and Stewart (1998) based on their assessment of what CES establishments report.[21] As Figure 2.10 shows, the resulting series,

[20] The sample for this exercise stops in 2002 because occupations definitions in the CPS changed in 2003, making the construction of consistent occupation-specific series difficult.

[21] We thank Jay Stewart for kindly providing us with the Stata codes used in Abraham et al. (1998). Our second CES replication therefore uses exactly the same definitions they use in their paper.

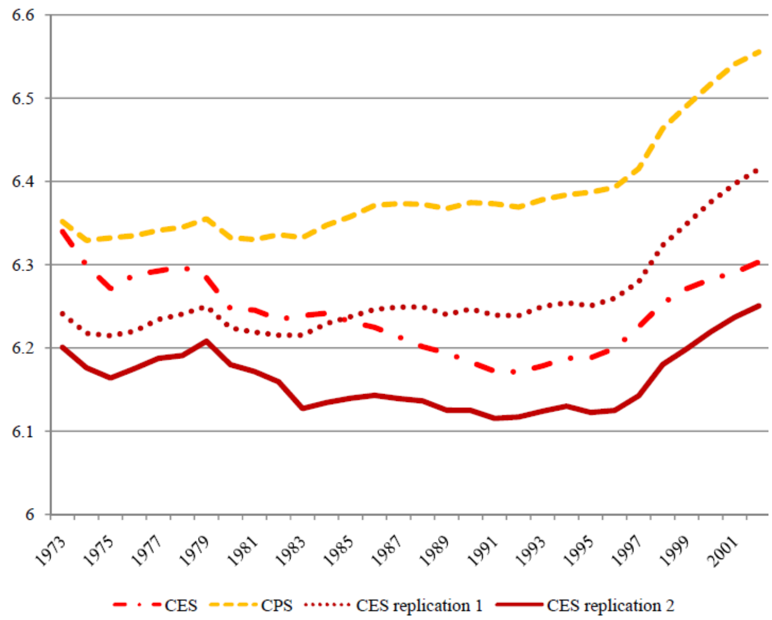


Figure 2.10 Replicating log average real earnings from the CES with CPS data

labeled 'CES replication 2', implies an even larger gap in earnings relative to the CES in the early 1970s. Thereafter, however, earnings from CES replication track earnings from the CES more closely, including a significant decline in earnings between the late 1970s and the early 1990s. Again, this result broadly confirms the findings reported in Abraham, Spletzer and Stewart (1998) for a longer sample.

It is also interesting to assess the extent to which the two CES replications are capable of generating the large fall in earnings volatility in the CES from the pre-84 to the post-84 subsample. Table 2.6 reports the results for both 1st-differenced and H-P filtered data. Earnings volatility from CES replication 1 drops somewhat more than earnings volatility from the CPS but not nearly enough to replicate the change in earnings volatility from the CES.[22] In contrast, CES replication 2 comes

[22] Notice that the CPS earnings volatility numbers for the post-1984 period are slightly different than in Table 3 because the sample here stops in 2002 instead of 2011.

Changes in average earnings volatility

	Standard Deviation		
	Pre-84	*Post-84*	*Relative*
1st-difference			
CPS	1.16	1.33	1.15
CES replication 1	1.32	1.32	1.00
CES replication 2	1.78	1.22	0.68
CES	1.95	1.27	0.65
HP-filter			
CPS	0.76	0.65	0.85
CES replication 1	0.96	0.62	0.65
CES replication 2	1.21	0.63	0.52
CES	1.29	0.51	0.39

Notes : CPS May-MORG data. Real Average Weekly Earnings (2005 dollars). Annual data. Sample: 1973 to 2002.

Table 2.6 Replicating average real earnings volatility from the CES with CPS data

close to matching the higher volatility of actual CES weekly earnings in the pre-84 period and, depending on the filtering method used, accounts for 79% to 91% of the decline in volatility of the CES weekly earnings in the post-84 period.[23] This further suggests that differences in population coverage can explain at least part of the divergence in trend and business cycle volatility of earnings in the CES.

Naturally, the same issues of representativeness may explain the different evolution of weekly hours from the CES and the CPS. In a recent paper, Frazis and Stewart (2010) investigate this possibility. They find that both CES replication 1 and 2 with the CPS sample decreases average hours by 1.3 to 1.7 hours, which basically closes the initial gap between CES and CPS hours. However, neither of the replications can account for the downward trend in CES hours. Nevertheless, it is interesting to assess the extent to which applying the two replication to both

[23] Because first-differencing cuts out a part of the fluctuations that are typically associated with the business cycle, we think that 79% is a more accurate and conservative estimate of how the CES replication 2 accounts for the decline in CES weekly earnings after 1984.

weekly earnings and weekly hours allows us to explain the divergence in trend and business cycle between the CES hourly wage and the CPS hourly wage (and therefore, the LPC hourly wage). Figure 2.11 and Table 2.7 display the results. In terms of trends, CES replication 2 comes surprisingly close to the CES hourly

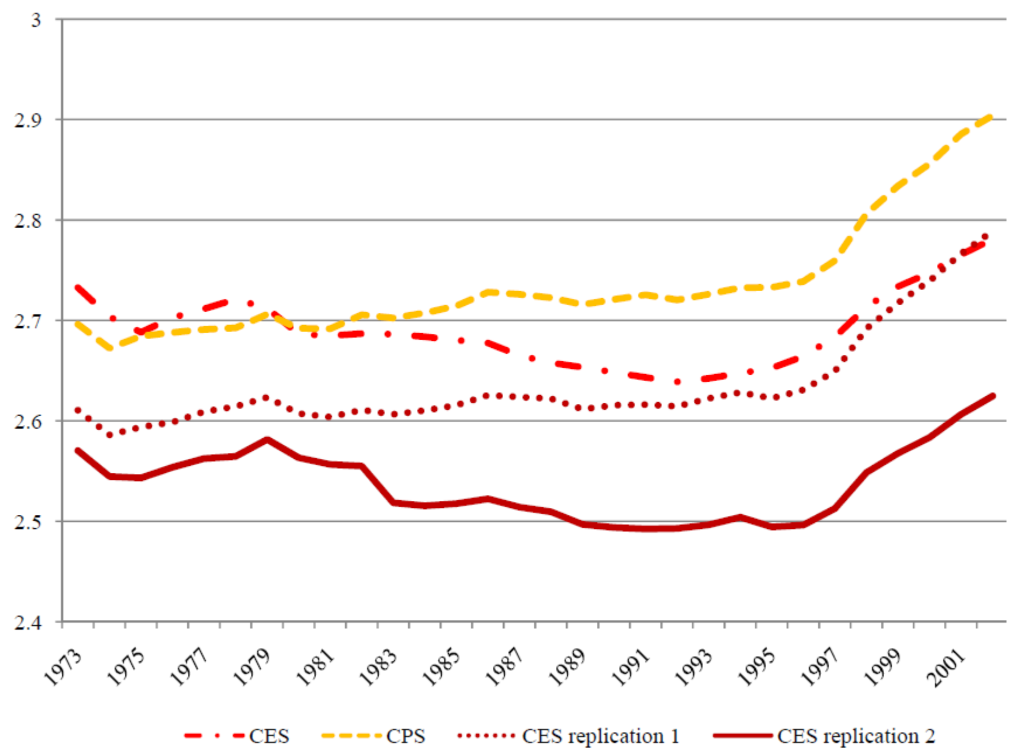


Figure 2.11 Replicating log average real hourly wages from the CES with CPS data

wage although there remains a large level difference between the two. In terms of business cycle volatility, results are broadly similar to the replication exercise for average earnings in Table 2.6. CES replication 1 generates hourly wage volatilities that remain close to the CPS hourly wage volatility. For first-differenced data, CES replication 2 accounts for the main share of the fall in volatility of CES hourly wages. For H-P filtered data, CES replication 2 accounts for about 55% of

Changes in average hourly wage volatility

	Standard Deviation		
	Pre-84	*Post-84*	*Relative*
1st-difference			
CPS	1.21	1.38	1.14
CES replication 1	1.18	1.34	1.14
CES replication 2	1.70	1.27	0.75
CES	1.49	1.17	0.79
HP-filter			
CPS	0.64	0.64	1.00
CES replication 1	0.69	0.59	0.87
CES replication 2	0.99	0.63	0.64
CES	1.01	0.35	0.34

Notes : CPS May-MORG data. Real average hourly earnings (2005 dollars). Annual data. Sample: 1973 to 2002.

Table 2.7 Replicating average real hourly wage volatility from the CES with CPS data

the fall in volatility of CES hourly wages relative to the fall in volatility of CPS hourly wages, which is somewhat less than was the case for weekly earnings but still substantial. Also, for H-P filtered data, CES replication 2 comes very close to generating the higher pre-84 hourly wage volatility in the CES.

Overall, the CES replication exercises with CPS data suggest that the segment of workers for which establishments in the CES sample have traditionally reported earnings is not representative of the non-farm business sector workforce and that this lack of representativeness plays a major role in the divergence of the CES wage from the other wage series. In addition, the difference between CES replication 1 and CES replication 2 suggest that the historical earnings and hours series from the CES do not even cover the subset of the workforce they are supposed to represent. This makes the use of historical CES earnings and hours series problematic.

2.3.4 Measurement issues

This last section describes a particular set of issues that affect the CES earnings and hours measures but not the LPC and CPS measures, and how these issues may explain the remaining part of the divergence in the CES earnings and hours measures.[24]

First, the CES sample underwent a substantial expansion from about 160,000 to 400,000 establishments between 1980 and 2006. This expansion is likely to have led to spurious changes in the CES average earnings measure. Specifically, based on UI microfiles, Plewes (1982) documents the following characteristics of the CES sample for the early 1980s:

- Whereas 72% of all private-sector employment came from services-providing industries, this proportion in the CES sample was only 30.4%.
- The service establishments that the CES captured were on average much larger and older than the ones in the UI records.[25] Since the proportion of small and young establishments in service-providing industries was higher than in goods-producing industries, this implied that the CES sample contained few small and young establishments.

The sample expansion of the CES that started in the early 1980s led to a better

[24] This is not to say that the CPS does not suffer from measurement issues. For example, as claimed by some researchers, hours in the CPS may be overreported (although Frazis and Stewart (2010) argue that once all the necessary adjustments for sample representation and reporting period are made, overreporting in the CPS is not significant). The point here is, however, that we are not aware of systematic changes in measurements issues for the CPS that could lead to a bias in the evolution of the CPS wage similar to, we argue, is the case for the CES earnings and hours.

[25] An important reason for this underrepresentation is, according to Plewes (1982), the inability / unwillingness of small establishments to provide information for the CES survey (BLS 790 questionnaire), which is voluntary.

representation of the service-providing industries and, more generally, of small and young establishments. Because small and young establishments in service industries hire on average less skilled workers for whom hourly wages are lower and have become less volatile (see Champagne and Kurmann, 2013), the observations by Plewes (1982) imply that the resulting shift in sample composition may have led to spurious changes in the CES average earnings measures – both in terms of trend and business cycle volatility.[26] It would be interesting to assess this conjecture using QCEW and CES earnings data that distinguishes establishments by industry and age. Such an exercise hinges on the availability of a micro-data that extends sufficiently far back in time.[27]

2.4 Conclusion

The evolution of average hourly wages is a key indicator for economic analysis. In the U.S., the Labor Productivity and Costs (LPC) program and the Current Employment Statistics (CES) provide the two most popular and most readily available measures of average hourly wages for the non-farm business sector. In

[26] Note that employment numbers in the CES are benchmarked once a year to UI records (the source of the QCEW). Earnings and hours are, however, not benchmarked and therefore do not undergo a regular bias correction.

[27] Furthermore, since average earnings in the CES are a weighted sum of earnings across industries, the sample expansion is likely have decreased the measurement error in some of the industries, thus reducing the volatility of average earnings. To see this, think of measured earnings across establishments in some industry i, $\widehat{W}_{i,t}$, as the sum of "true" earnings, $W_{i.t}$, plus an uncorrelated error term $\varepsilon_{i,t}$

$$\widehat{W}_{i,t} = W_{i.t} + \varepsilon_{i,t}.$$

The variance of measured earnings is therefore

$$Var(\widehat{W}_{i,t}) = Var(W_{i.t}) + Var(\varepsilon_{i,t}).$$

Under the hypothesis that the errors are i.i.d. across establishments of industry i, an increase in the number of establishments per industry leads to a decrease in the variance of errors and therefore a decrease in the variance of measured CES earnings.

this paper, we document that over the past four decades, the two measures diverged substantially both in terms of trend growth and business cycle volatility. Particularly, while the LPC wage is today about 70% higher in real terms than in 1970, the CES wage decreased by almost 10% between the mid-1970s and the mid-1990s and increased by only 20% total over the past four decades. Furthermore, while the volatility of the LPC wage increased by 35% to 45% since the early 1980s, the volatility of the CES wage dropped by about 50%.

We try to reconcile this divergence in trend and business cycle volatility of the LPC and the CES average hourly wages by first decomposing the total divergence into differences coming from the earnings side and the hours side. We find that the divergence between the LPC wage and the CES wage – both in terms of trend growth and business cycle volatility – is driven by the different evolution of average labor earnings. Average hours worked, by contrast, evolve very similarly. As a result, we turn the focus on earnings to explain the divergence between the two hourly wage series.

We use data from a third source, the Current Population Survey (CPS), to examine potential reasons for the different evolution of average earnings from the LPC and the CES. Earnings data in the CPS is based on a very similar earnings concept as the one used in the CES and at the same time allows us to cover the same worker population as in the LPC. We show that the evolution of average earnings from the CPS falls in between the evolution of LPC earnings and CES earnings, both in terms of trend growth and changes in business cycle volatility. Moreover, using additional information about the wage and salaries portion of earnings in the LPC as well as labor income share data for high-earning individuals computed by Piketty and Saez (2003), we show that differences in earnings concept account for almost all of the differences between CPS and LPC earnings. The CPS data therefore provides a representative measure of wages and salaries for large part of the U.S. workforce. Finally, we use occupational and industry information in the CPS to show that differences in worker population coverage can account for a substantial part of the divergence in trend growth and volatility between CPS earnings and CES earnings. However, the sources of the remaining differences remain an open question. We conjecture that compositional changes in the CES due to a major sample expansion occurring between the early 1980s and the late 1990s represent one of the most plausible candidates.

Even though our findings are suggestive of important structural changes in the U.S. labor market, it is not the focus of the paper. Instead, the primary contribution of the paper is to provide a detailed account of the divergence in different popular aggregate hourly wage series so as to obtain better guidance on which wage series to use when analysing different aspects of the U.S. labor market.

CHAPTER III

THE CARROT AND THE STICK: THE BUSINESS CYCLE IMPLICATIONS OF INCENTIVE PAY IN THE LABOR SEARCH MODEL

3.1 Introduction

It has largely been documented that the nature of business cycle fluctuations evolves over time. Many studies present evidence for changes in the dynamics of U.S. macroeconomic times series, such as McConnell and Pérez-Quirós (2000), Stock and Watson (2002), Galí and Gambetti (2009), Galí and van Rens (2010). A classic example of changing dynamics is the 25 years prior to the Great Recession, a period referred to as the Great Moderation where the business cycle volatility of output and other macro aggregates fell by more than 50%. However, this historically low macroeconomic volatility did not apply to one prominent labor market variable: real average wages. For instance, Champagne and Kurmann (2013a) document that, from 1953-1983 to 1984-2006, the business cycle volatility of average hourly wages relative to the volatility of aggregate output became 2.5 to 3.5 times larger over the two sample periods. As in Gali and van Rens (2010), they point towards changes in labor market dynamics as a common explanation for the decline in macro volatility and increase in real wage volatility.

Among the documented changes in labor market dynamics, the increase incidence of performance-pay compensation schemes has been advocated as an explanation for the increase in wage volatility. For example, Lemieux et al. (2009a) show, using PSID data, that the incidence of performance-pay schemes has increased significantly during the last 30 years in the U.S. Moreover, Lemieux et al. (2009b) find that wages of non-union workers with performance-pay contracts are most responsive to local labor market shocks and least responsive for union workers without performance-pay contracts, implying that performance-pay increase flexibility in wage setting. Finally, Champagne and Kurmann (2013a) suggest that structural changes in the labor market, in the form of more flexible wage setting, are promising candidates to account for the increase in relative wage volatility.

Motivated by these observations, this paper first introduces two types of incentive pay schemes in a business cycle model with matching frictions and wage bargaining. Second, it compares the business cycle implications of each compensation scheme, along with the basic labor search model where the intensive margin is constant (e.g. Shimer (2005)). Finally, it evaluates how a structural change in the way firms compensate their workers, from a state of the economy where efficiency-wages are pervasive to a state where performance-pay schemes are more present, in the light of Lemieux et al.'s (2009a) evidence, can account for the observed increase in the relative volatility of average real wages and the dynamics other labor market variables.

Specifically, I use a real business cycle DSGE model with labor search frictions (e.g. Andolfatto, 1996; Trigari, 2009) and variable effort that is costly for the worker to supply and unobservable to the firms. Then I use Lazaear's (1986) insights on 'input-based' and 'output-based' compensation schemes to formulate two different wage determination mechanisms.[1] Under each scenario, firms and workers negotiate over a joint surplus, but the wage outcome differs because the essence of incentive pay is different. Under the 'input-based' scenario, workers and firms negotiate pay in advance subject to an incentive compatibility constraint that guarantees a minimum effort level (i.e. an efficiency-wage / shirking type of model). On the other hand, under the 'ouput-based' wage contract (labelled 'performance-pay' wage throughout the paper) the object of the negotiation is a wage schedule that links pay to effort (i.e. performance), which the worker supplies such as to maximize his utility given the ex-ante negotiated wage schedule.[2] The first wage contract can be caricatured as 'the stick', while the second as 'the carrot'.

Simulations of the model yield interesting results. First, the performance-pay scheme implies greater wage volatility than under the efficiency-wage scenario (and vs. the benchmark labor search model), a finding robust even if we use different calibration strategies (e.g. Shimer, 2005; Hagedorn and Manovskii, 2008). This suggests that changes in the way firms compensated workers over the last decades, i.e. from an efficiency-wage type of compensation to pay schemes linked to output, are at least partially responsible for the observed increase in relative wage volatility. Second, while the model is not able to replicate fluctuations in unemployment and vacancies as observed in the data under the preferred calibration

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[1] Lazear (1986) offers two simple examples to illustrate the difference between 'input-based' and 'output-based' wage contracts: "*Two extreme examples are illustrative. Unskilled farm labor often is paid in the classic piece-rate fashion: an amount of payment per pound or piece harvested is specified in advance. Near the other extreme are middle managers of major corporations whose annual salaries are specified in advance, and who are then paid exactly that amount, independent of output. The qualifier is that, if effort falls below some specified level (e.g., he does not come to work regularly), the manager may be terminated.*"

[2] As put forward by the micro literature (e.g. Prendergast, 1999), this wage determination mechanism provides a natural alternative incentive device for subtle effort supplies that are very hard to monitor.

strategy,[3] it does fairly better under a more extreme calibration as in Hagedorn and Manovskii (2008). When the economy is calibrated to match the average incidence of performance-pay wage contracts in the U.S. economy before and then after 1984, simulations shows that an increase in the incidence of performance-pay leads to an increase in relative wage volatility of about 10%. But it also leads to counterfactual results like an increase in output volatility and an increase in the correlation between wages and output. The reason behind this is that effort is procyclical, amplifying the response of wages to technology shocks, but at the same time raising output volatility and the correlation between wages and output.

This paper tries to frame in a business cycle Dynamic Stochastic General Equilibrium (DSGE) model ideas from the microeconomic literature on incentive pay. A large body of studies have reached into many forms of compensation schemes and have pointed to different ways they can be used to incite effort from workers (e.g. Lazear, 1986; Prendergast, 1999). On the macroeconomic side, some papers introduced variable effort in different contexts and studied its impact on different key macroeconomic variables over the business cycle (e.g. Burnside, Eichembaum, and Rebelo (BER), 1993; in efficiency-wage frameworks: Alexopoulos, 2004; and Danthine and Kurmann, 2004; and in efficiency-wage and labor search frameworks: Costain and Jansen, 2010; Riggi, 2013). However, no studies have either tried to model the idea of performance pay into a DSGE framework, or looked at the consequences of having different incentive pay schemes into a single DSGE framework. And while Costain and Jansen (2010) and Riggi (2013) study the implications of efficiency-wages into a labor search framework, there is exogenous productivity in Costain and Jansen (2010), and no wage bargaining in Riggi (2013), two key elements to understand the effects of incentive pay on wages and

[3] This is consistent with Shimer (2005) as my preferred calibration strategy follow closely Shimer's.

the business cycle in general.[4]

The rest of the paper proceeds as follows. Section 2 summarizes recent empirical evidence on the increased incidence of performance-pay contracts and the increase in relative wage volatility in the U.S., which point towards more flexible wage setting happening over the last three decades. Section 3 presents the model with search frictions, variable effort and two different forms of incentive pay. Section 4 presents the calibration of the model, along with simulation results. Section 5 concludes.

3.2 Empirical evidence

This section summarizes the empirical evidence on the increased incidence of performance-pay wage contracts and relative wage volatility that serves as a motivation for the model and theoretical exercise developed in the next section.

The first piece of evidence comes from Lemieux, Macleod and Parent (2009a) who, using PSID data, document that the incidence of 'output-based' compensation schemes (i.e. 'performance-pay' contracts) has increased significantly during the 1980s and continued to rise (at a slower pace) in the 1990s, suggesting that it acted as an important driver behind the increase in wage inequality. At the same time, the U.S. experienced a sharp decline in unionization, which has been largely documented (e.g. Farber and Western, 2001; Hirsch and Macpherson (2010); Champagne and Kurmann, 2013a). Both phenomenons lead to more flexibility

[4] Lastly, note that the concept of incentive pay in this paper is very different from the 'performance-pay' wage in Champagne and Kurmann (2013). Apart from the fact that the wage schedule here is determined ahead of time-t information, the performance-pay wage in this paper differs from Champagne and Kurmann (2013) as in their model the performance-pay wage is equal to the marginal rate of substitution between consumption and leisure hours times an optimal markup the worker commands because of the imperfect substitutability of its labor service. This paper thus presents a more microfounded form of performance-pay.

in wage contracts between firms and workers. Figure 3.1 below plots Lemieux et al.'s (2009) measure of incidence of performance-pay between 1976 and 1998 (measured as the percentage of workers receiving part of their compensation as performance-pay) for the non-farm business sector.

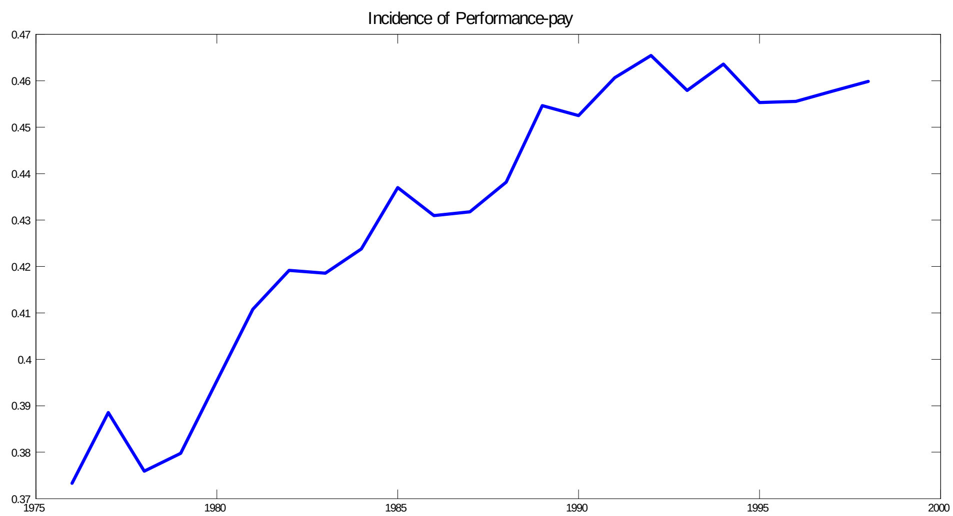

Figure 3.1 Evolution of incidence of performance-pay in the U.S. for the private nonfarm economy

Second, Champagne and Kurmann (2013a) document that, from 1953-1983 to 1984-2006, the business cycle volatility of average hourly wages increased by 15% to 60%, depending on the dataset and filtering method used. As a result, the business cycle volatility of average hourly wages relative to the volatility of aggregate output became 2.5 to 3.5 times larger over the two sample periods. Champagne and Kurmann (2013a) further document that this increase in relative wage volatility is pervasive across the labor market, albeit the magnitude of the increase varies for different groups of workers.[5] Table 3.1 presents a brief overview of these

[5] On the individual level, it has been documented that earnings has also become more

findings, updated to 2012, by showing volatilities and relative volatilities for real chained GDP, real average hourly compensation, and real average weekly compensation for the nonfarm business sector.[6,7] It shows that while the volatility of output decreased remarkably after 1984, the volatility of both average hourly and weekly earnings have increased, so that the relative volatility (to output) of hourly and weekly earnings increased by a factor of 2.36 and 1.69, respectively, between the 1953:2 to 1984:1 and 1984:2 to 2012:4 periods.

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
Output	2.57	1.58	0.61	1.00	1.00	1.00
	(0.24)	(0.20)				
Avg. hourly comp.	0.65	1.02	1.56	0.26	0.65	2.50
	(0.06)	(0.10)		(0.03)	(0.11)	
Avg. weekly comp.	0.87	0.96	1.10	0.34	0.61	1.80
	(0.10)	(0.10)		(0.04)	(0.10)	

Notes : Standard and relative standard deviations for output, average hourly compensation and average w eekly compensation computed using quarterly, HP-filtered data. Total sample extends from 1953:I to 2012:IV. Nonfarm business sector. PCE-deflated w ages. Standard errors computed using GMM and the Delta method appear in parentheses below estimates.

Table 3.1 Changes in business cycle volatilities

While the timing of the increases in performance-pay contracts and in relative wage volatility might not be causal but coincidental, Lemieux et al. (2009a)

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volatile in the last three decades. Starting with Gottschalk and Moffitt (1994), a number of papers using panel data show that labor income has on average become considerably more volatile across individual workers. Recent evidence based on PSID data by Dynan et al. (2008) and Jensen and Shore (2008) indicate that this increase in labor income volatility has remained approximately constant for most individuals but has increased greatly for individuals who already had volatile earnings in the past. Taken together, these panel studies imply that wages have become more volatile on average, and much more volatile relative to output.

[6] The reason I show volatilities for average weekly compensation is that it is the appropriate measure of wages in the model presented below (i.e. there are no 'hours' in the model).

[7] See the appendix for a detailed description of the data.

document that performance-pay is more frequent for skilled individuals that are employed in industries such as wholesale trade and FIRE, and also more concentrated into the upper end of the wage distribution, which is precisely where wage volatility is highest and increased the most in the last three decades.[8] Finally, based on the same PSID dataset as in Lemieux et al. (2009a), Lemieux et al. (2009b) find that wages of non-union workers with performance-pay contracts are most responsive to local labor market shocks and least responsive for union workers without performance-pay contracts. Together, these observations suggest that the increased incidence of performance-pay contracts result in greater wage flexibility, making wages more responsive to business cycle shocks.

3.3 A DSGE model with incentive pay and matching frictions

The model I present in this section is a real business cycle DSGE model with a representative household, a continuum of firms offering an homogenous good in a competitive market, and labor search frictions. The model has two notable features. First, effort is a production input that firms cannot observe and therefore cannot directly contract upon. Second, in the spirit of Lazear (1986), firms incite effort from their workers according to one of two compensation schemes. The first scheme is one where a firm and a worker negotiate ahead of time-t information over a wage and a minimum required amount of effort ($\bar{e}$).[9] With a given probability $0 < d < 1$, the firm can monitor if the worker actually supplies this required amount of effort. If the worker is found to supply less then this effort level, he is fired. I call this an 'efficiency-wage' type of compensation because it follows closely

[8] See Champagne and Kurmann (2013a) for a detailed account of the behavior of the relative volatility of wages across different segments of the workforce. Moreover, Champagne and Kurmann (2013b) document that the increase in relative wage volatility was most pronounced for workers in the upper end of the wage distribution.

[9] Consequently, the wage is predetermined in period-t.

the intuition of the shirking model by Shapiro and Stiglitz (1984).[10] The second compensation scheme is one where the negotiation occurs again ahead of time-t information, but where the object of the negotiation is a wage schedule that links the worker's wage to his output. The key feature here is that the worker can then adjust his effort level in any period given the state of the economy. Consequently, even though the wage schedule is predetermined, the resulting wage is not. I call this compensation scheme 'performance-pay'.

I assume a segmented labor market where a fraction $1-p$ of firms operate in in one segment and negotiate with workers over an efficiency-wage type of compensation, while the remaining firms (fraction p) operate in the other segment of the labor market and negotiate over a 'performance-pay' wage. Firms cannot switch from one segment to the other, i.e. they always use the same compensation scheme.

Timing. After random matching occurs, the firm negotiates with the worker over wages and effort, depending on its type. Then, shocks are observed, and firms take their optimal decisions over vacancies (for next period's hiring), while households choose their optimal consumption level and workers decide how much effort to supply.[11]

Below I lay out the details of the model, starting with a description of the labor market, the households and firms' optimization problems, and finally the bargaining process. At this last stage I will describe the efficiency-wage and performance-pay wage determination mechanisms separately, since this is where the differences

[10] Think of this efficiency-wage contract as one where the worker is offered a predetermined wage and, in return, has to show up to work and supply a fixed amount of effort. The firm can observe with probability d if he shows up to work, and fire him if he does not.

[11] In the efficiency-wage case, workers simply choose to either supply the (fixed) required amount of effort or shirk, while in the performance pay segment workers choose an optimal amount of effort to supply given the bargained wage schedule.

come from.

3.3.1 Labor market

The labor market is divided in two separate segments characterized by how the wage is negotiated. Within each segment, the labor market is standard and characterized by matching frictions (e.g. Shimer, 2005), and search is not directed: unemployed workers automatically search at no cost and firms pay to post vacancies.[12] In segment i, matching between unemployed individuals and vacancies occurs randomly according to an aggregate matching function

$$m(v_{i,t}, u_{i,t}) = (v_{i,t})^{\sigma} (u_{i,t})^{1-\sigma} \tag{3.1}$$

where $u_{i,t}$ is the measure of workers searching for a job and $v_{i,t}$ is the aggregate number of vacancies in segment i during period t. The parameter σ denote the elasticity of job matches with respect to the vacancy input. Finally, I define the labor market tightness in segment i, $\theta_{i,t}$, as the vacancy-unemployment ratio, i.e. $\frac{v_{i,t}}{u_{i,t}}$; the probability that an unemployed individual is matched to an open vacancy in segment i at date t is denoted $f_{i,t} = \frac{m(v_{i,t},u_{i,t})}{u_{i,t}}$; and, the probability that any open vacancy is matched with a searching worker in segment i at date t is $q_{i,t} = \frac{m(v_{i,t},u_{i,t})}{v_{i,t}}$. Households and firms take these probabilities as given.

Employment in segment i evolves according to the following dynamic equation:

$$n_{i,t+1} = (1-s)\, n_{i,t} + f_{i,t} u_{i,t} \tag{3.2}$$

At the beginning of period $t+1$, employment in segment i is equal to the number

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[12] A worker who loses his job automatically seaches for a job within the same segment of the labor market.

of surviving matches from period t, plus the new ones ($m(v_{i,t}, u_{i,t}) = f_{i,t}u_{i,t}$). Matches are separated each period with exogenous probability s ($0 < s < 1$). The number of unemployed individuals in the beginning of any period t (when production occurs) is $1 - n_{i,t}$.[13] However, this is different from the number of individuals searching for a job during period t, which is given by

$$u_{i,t} = 1 - (1 - s)n_{i,t} \tag{3.3}$$

The measures of unemployment ($1 - n_{i,t}$) and job seekers ($u_{i,t}$) differ, as some workers who produced in period t can then be exogenously separated and search for next period employment.[14]

3.3.2 Households

The households are thought of as very large "families" or "units" comprised of a continuum of members along the unit interval. A fraction $1 - p$ of household members are employed in the efficiency-wage segment of the labor market (labelled '*ew*' below), and a fraction p in the performance-pay segment (labelled '*pp*' below). As described above, workers cannot switch from one segment to the other, even

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[13]Because the labor force is normalized to one in each segment, $1 - n_{i,t}$ also corresponds to the unemployment rate.

[14]I based this sequencing of events following the insights of Ravenna and Walsh (2012) to allow some workers to work and search in the same period. As stated in their paper: "*In search models based on a monthly period of observation, it is more common to assume workers hired in period t do not produce until period $t + 1$. In this case, the number of job seekers in period t plus the number of employed workers adds to the total work force. Because we base our model on a quarterly frequency, we allow for some workers seeking jobs to find jobs and produce within the same period.*"

if they are separated. The household has period utility

$$u\left(c_t, e_t\right) = c_t - \left[(1-p)n_{ew,t}\frac{\left(e_{ew,t}\right)^{1+\eta}}{1+\eta} + pn_{pp,t}\frac{\left(e_{pp,t}\right)^{1+\eta}}{1+\eta}\right]$$

where c_t denotes consumption, e_t denotes average aggregate consumption, $e_{ew,t}$ denotes the effort level supplied by household members employed in efficiency-wage firms; $e_{ew,t} \in [0, \bar{e}]$, depending whether the employed member supplies the required amount of effort or if he shirks.[15] $e_{pp,t}$ denotes the effort level supplied by household members employed in performance-pay firms, and η is a parameter governing the effort supply elasticity. The household's period utility thus includes the gain in utility of consuming c_t, minus the disutility of supplying effort sending $n_t = (1-p)n_{ew,t} + pn_{pp,t}$ members in the labor market.[16]

Households in each period face the following budget constraint:

$$\begin{aligned} c_t &= (1-p)n_{ew,t}w_{ew,t} + pn_{pp,t}w_{pp,t} \\ &\quad + (1-(1-p)n_{ew,t} - pn_{pp,t})b + \Pi_t - T_t \end{aligned} \tag{3.4}$$

where b represents unemployment benefits (financed by lump-sum taxes on households, T_t); $w_{ew,t}$, $w_{pp,t}$ denote the efficiency-wage and the performance-pay wage, respectively; and $\Pi_t = p\Pi_{pp,t} + (1-p)\Pi_{ew,t}$ denotes the household's profits share from the firms. Note that $w_{ew,t}$, $w_{pp,t}$, $e_{ew,t}$ and $e_{pp,t}$ will be determined during the bargaining process.

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[15] See bargaining section below for more details.

[16] As it is standard in the unemployment literature, I assume that households provide perfect consumption insurance to its members. As a result, the consumption and investment decision rules are the same for every household member. See Andolfatto (1996) for a detailed structure that implements this full-insurance assumption in a search and matching framework, or Alexopoulos (2004) for a detailed structure in an efficiency-wage context.

The household's value function can therefore be written as

$$W(\Omega_t) = \max_{c_t} \left\{ \begin{array}{c} c_t - \left[(1-p)n_{ew,t}\frac{(e_{ew,t})^{1+\eta}}{1+\eta} + pn_{pp,t}\frac{(e_{pp,t})^{1+\eta}}{1+\eta}\right] \\ +\beta E_t \left[W\left(\Omega_{t+1}\right)\right] \end{array} \right\}$$

subject to the budget constraint (3.4) and employment evolution (3.2). $\Omega_t = (n_t; z_t)$ represents the state vector of the economy, while $\Omega_{i,t} = (n_{i,t}; z_t)$ represents the state of the economy in segment i of the labor market.

As in many papers from the labor search literature (e.g. Shimer, 2005; Hagedorn and Manovskii, 2008), I assume linear utility of consumption and thus the marginal utility of consumption of the household is constant. However, I provide an explicit form for the disutility of supplying effort instead of assuming that the outside option of the worker is constant and equal to b.[17]

3.3.3 Firms

There is a continuum of identical firms on the unit interval. As stated above, a fraction $1-p$ of firms bargain with workers over an 'efficiency-wage' type of compensation, while the remaining firms (fraction p) bargain with workers over a performance-pay wage schedule that links the worker's wage to output. Firms cannot switch type, i.e. they always offer the same type of compensation. Firms are owned by the households, and thus they discount expected future values according to

$$\Delta_{t,t+1} = \beta E_t \frac{u_1(c_{t+1})}{u_1(c_t)}$$

which is constant and equal to β because of linear utility. When a firm is matched with a suitable worker in segment i, it bargains over the wage (according to the

[17] I assume b represents unemployment benefits, the "constant" portion of the worker's outside option. See the bargaining section for more details on the workers' outside option.

incentive-pay scheme prevailing within the segment of the labor market) and then observes time-t information. Thereafter, it chooses the number of vacancies to post for next period's hiring at fixed cost per vacancy κ, and finally produces according to the following linear production function:

$$F(n_{i,t}e_{i,t}; z_t) = y_{i,t} = z_t n_{i,t} e_{i,t} \tag{3.5}$$

where z_t is an aggregate technology shock. As a result, in each period, the firm in segment i chooses the number of vacancies $v_{i,t}$ to post such as to maximize the present discounted value of their future profits stream. Since this decision problem is similar in each segment of the labor market, the firm's value function can be written as:

$$\begin{aligned} V(\Omega_{i,t}) &= \max_{v_t} \left\{ \begin{array}{c} F(n_{i,t}e_{i,t}; z_t) - n_{i,t}w_{i,t} - \kappa v_{i,t} \\ +\beta E_t \left\{ V\left(\Omega_{i,t+1}\right) \right\} \end{array} \right\} \\ \text{s.to} &: \quad n_{i,t+1} = (1-s)\, n_{i,t} + q_{i,t} v_{i,t} \end{aligned} \tag{3.6}$$

The first-order condition is:

$$\kappa = \beta E_t \left\{ \frac{\partial V(\Omega_{i,t+1})}{\partial n_{i,t+1}} \frac{\partial n_{i,t+1}}{\partial v_{i,t}} \right\} \tag{3.7}$$

where $\frac{\partial n_{i,t+1}}{\partial v_{i,t}} = q_{i,t}$. The value of an additional worker for the firm, i.e. $\frac{\partial V(\Omega_{i,t})}{\partial n_{i,t}}$, is:

$$\frac{\partial V(\Omega_{i,t})}{\partial n_{i,t}} = V_n(\Omega_{i,t}) = \frac{\partial F(n_{i,t}e_{i,t}; z_t)}{\partial n_{i,t}} - w_{i,t} + \beta E_t \left\{ \frac{\partial V(\Omega_{i,t+1})}{\partial n_{i,t+1}} \frac{\partial n_{i,t+1}}{\partial n_{i,t}} \right\}$$

Updating $V_n(\Omega_{i,t})$ by one period, using equations (3.5) and substituting back into (3.7) yields the vacancy-creation condition:

$$\frac{\kappa}{q_{i,t}} = \beta E_t \left\{ \left[\frac{y_{i,t+1}}{n_{i,t+1}} - w_{i,t+1} + (1-s)\frac{k}{q_{i,t+1}} \right] \right\} \tag{3.8}$$

The vacancy-creation condition states that in equilibrium the expected cost of hiring a worker is equal to the expected value of a match in each segment i. Equation (3.8) shows that an increase in expected future profits will decrease $q_{i,t}$, implying that the number of posted vacancies must rise. This increase in vacancies will then increase employment next period.

3.3.4 Bargaining

As mentioned above, I assume that bargaining occurs before time-t shocks are realized. Since the bargaining problems for each compensation scheme differ substantially, I describe them separately below.

Efficiency-wage bargaining

Under this scenario, firms ask workers to supply a minimum amount of effort in return for a predetermined wage. They incite effort using a punishment scheme: with a given detection probability d, they can catch shirkers (if caught shirking, workers are fired). The important thing to note here is that this required effort level is not an equilibrium outcome as in Alexopoulos (2004), but an implicit assumption that firms can only monitor basic effort such as showing up to work. The reason behind this is that I assume the constant detection probability d is an outcome of a contract enforcement device that can monitor only some basic type of effort, as showing up to work. However, it cannot help in enforcing more subtle effort supplies that are likely to be variable.[18]

The wage paid to workers is determined via bargaining over a surplus (a "surplus-sharing" rule), before time-t information is revealed. It can be formulated as

$$w_{ew,t} = \underset{w_{ew,t}}{\arg\max} E_{t-1} \left\{ \left[W_n^{ns}\left(\Omega_{ew,t}\right) - W_n^{s}\left(\Omega_{ew,t}\right) \right]^{\xi} V_n\left(\Omega_{ew,t}\right)^{1-\xi} \right\} \tag{3.9}$$

where $W_n^{ns}\left(\Omega_{ew,t}\right)$ and $W_n^{s}\left(\Omega_{ew,t}\right)$ are the values of being employed supplying effort level $\overline{e}$ and being employed shirking, respectively; $V_n\left(\Omega_{ew,t}\right)$ is the firm's value of hiring an additional worker, and ξ is the worker's bargaining power. As said earlier, expectations are in $t-1$ since bargaining occurs before time-t shocks are realized. Even though the problem is standard, the household's surplus in the match is not. Why such a formulation of the household's surplus? Because under this efficiency-wage scenario, the "threat point" of the worker is not the value of being unemployed, but the value of shirking at work. If the worker does not get the minimum wage at which the no-shirking condition binds, he will shirk instead of going into the unemployment pool because he is strictly better off shirking than being unemployed.

Before solving the wage bargaining problem, it is convenient to define the relevant surplus from employment for the firm and the worker. As laid out above, the firm's surplus from employment is

$$V_n(\Omega_{ew,t}) = \frac{y_{ew,t}}{n_{ew,t}} - w_{ew,t} + \frac{\kappa}{q_{ew,t}}(1-s) \tag{3.10}$$

[18] Riggi (2013) assumes that the effort level is not fixed and thus can vary with the state of the economy. For instance, after a negative shock to the level of capital, firms fire workers and those who keep their jobs increase their effort level due to the "unemployment threat", thereby increasing productivity and having prolonged (negative) effects on employment and job creation. Here, I assume that the firm's monitoring technology does not permit to verify more subtle effort supplies.

For the household, the value of having an additional member employed is different whether the employed member supplies effort or not. Since every worker will be considered shirking if he supplies $e_{ew,t} < \overline{e}$, the household maximizes utility by either choosing $e_{ew,t} = \overline{e}$ if the household wants its members to exert any effort, or $e_{ew,t} = 0$ otherwise.[19]

Consequently, write the values (in terms of current consumption) of being employed supplying effort level $\overline{e}$, $W_n^{ns}(\Omega_{ew,t})$, and of being employed shirking, $W_n^s(\Omega_{ew,t})$, as:[20]

$$\begin{aligned} W_n^{ns}(\Omega_{ew,t}) &= \begin{bmatrix} w_{ew,t} - b - \frac{\overline{e}^{1+\eta}}{(1+\eta)} \\ +\beta\left[(1-s)\left(1-f_{ew,t}\right)\right]E_t\left\{W_n(\Omega_{ew,t+1})\right\} \end{bmatrix} \\ W_n^s(\Omega_{ew,t}) &= \begin{bmatrix} (1-d)w_{ew,t} - b \\ +\beta\left[(1-s)\left(1-f_{ew,t}\right)(1-d)\right]E_t\left\{W_n(\Omega_{ew,t+1})\right\} \end{bmatrix} \end{aligned} \tag{3.11}$$

The first expression in (3.11) is standard: it states that the surplus from employment (in terms of current consumption) for a worker exerting the desired effort level $\overline{e}$, $W_n^{ns}(\Omega_{ew,t})$, is equal to his wage minus the forgone unemployment benefits and the cost of supplying effort, plus the discounted expected future value of being employed in the next period, i.e. $W_n\left(\Omega_{ew,t+1}\right)$. The second expression, $W_n^s(\Omega_{ew,t})$, states that the value of being employed shirking, in terms of current consumption, is the wage (discounted by the probability d of being caught shirking), less the forgone unemployment benefits, plus the discounted expected future value of being employed in the next period.

With the surpluses from the match defined, it is straightforward to solve the wage

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[19] Since all workers are similar, there will be only one equilibrium wage in each segment of the labor market.

[20] The detailed derivations of the surplus from employment are provided in the appendix.

bargaining problem. The first-order condition yields the optimality condition:[21]

$$(1-\xi)E_{t-1}\left\{W_n^{ns}(\Omega_{ew,t}) - W_n^{s}(\Omega_{ew,t})\right\} = d\xi E_{t-1}\left\{V_n(\Omega_{ew,t})\right\} \tag{3.12}$$

Expanding (3.12) using (3.10) and (3.11) and simplifying, we get the wage equation:

$$\begin{aligned} w_{ew,t} &= \xi\left[E_{t-1}\left\{\frac{y_{ewt}}{n_{ew,t}}\right\} + (1-s)E_{t-1}\left\{\frac{\kappa}{q_{ew,t}}\right\}\right] + (1-\xi)\frac{\overline{e}^{1+\eta}}{(1+\eta)}\frac{1}{d} && (3.13) \\ &\quad -(1-\xi)\beta(1-s)(1-E_{t-1}\left\{f_{ew,t}\right\})E_{t-1}\left\{[W_n(\Omega_{ew,t+1})]\right\} && (3.14) \end{aligned}$$

where

$$W_n(\Omega_{ew,t}) = w_{ew,t} - b - \frac{\overline{e}^{1+\eta}}{(1+\eta)} + \beta(1-s)(1-f_{ew,t})E_t\left\{W_n(\Omega_{ew,t+1})\right\}.$$

The resulting efficiency-wage is thus a predetermined variable; it is an expected sum (weighted by the worker's bargaining power) of the marginal product of a worker plus the expected cost of a vacancy and the discounted disutility of supplying effort, minus the (discounted) value of being employed next period.[22]

Performance-pay bargaining

Here, firms and workers negotiate prior to observing time-t shocks; after time-t information is revealed, workers can adjust their effort to any level. The outcome of this negotiation is a predetermined wage schedule that link the worker's wage

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[21] The expression $\{W_n^{ns} - W_n^{s}\}$ is actually equal to the incentive compatibility constraint. See the appendix for the derivation of the exact expression.

[22] If the value of being employed next period is expected to be high, then the Nash-bargained efficiency-wage will be lower today since the worker has an incentive to stay on the job for the next period.

to output. As a result, the wage schedule $w_{pp,t}$ will satisfy optimality condition:

$$w_{pp,t} = \underset{\{w_{pp,t}\}}{\arg\max} E_{t-1} \left\{ \left[W_t\left(\Omega_{pp,t}\right)\right]^{\xi} V_t\left(\Omega_{pp,t}\right)^{1-\xi} \right\} \tag{3.15}$$

where, as above, $V_{n,pp} = \frac{y_{pp,t}}{n_{pp,t}} - w_{pp,t} + (1-s)\frac{\kappa}{q_t}$ is the firm's value of an additional worker, and $W_n\left(\Omega_{pp,t}\right)$ denotes the worker' surplus from employment (in terms of current consumption), i.e.

$$W_n\left(\Omega_{pp,t}\right) = w_{pp,t} - b - \frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + \beta\left(1-s\right)\left(1-f_{pp,t}\right)E_t\left\{W_n\left(\Omega_{pp,t+1}\right)\right\} \tag{3.16}$$

The first-order condition yields the optimality condition:

$$(1-\xi)E_{t-1}\left\{W_2\left(\Omega_{pp,t}\right)\right\} = \xi E_{t-1}\left\{V_2\left(\Omega_{pp,t}\right)\right\} \tag{3.17}$$

Using the expression for $W_2\left(\Omega_{pp,t}\right)$ and $V_2\left(\Omega_{pp,t}\right)$, one gets the wage schedule:

$$w_{pp,t} = \xi\left[E_{t-1}\left\{\frac{y_t}{n_t}\right\} + (1-s)\kappa E_{t-1}\left\{\theta_{pp,t}\right\}\right] + (1-\xi)\left[\frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + b\right] \tag{3.18}$$

where $E_{t-1}\left\{\frac{y_t}{n_t}\right\} = z_t e_{pp,t}$ and $e_{pp,t}$ is the optimal level of effort determined after observing time-t shocks (see optimal condition below). This wage schedule is similar as in the basic labor search model with wage bargaining, as it depends on both the marginal product of the worker and his marginal rate of substitution. However, it also depends on $t-1$ expectations of labor market outcomes (i.e. $E_{t-1}\left\{\theta_{pp,t}\right\}; E_{t-1}\left\{\frac{y_t}{n_t}\right\}$). The key feature in the above wage equation is that while the wage schedule is predetermined, $w_{pp,t}$ is not, as $e_{pp,t}$ is determined after observing time-t shock. This performance-pay scheme resembles a right-to-manage assumption, where workers have the right-to-manage their effort as a function of the bargained wage. This right-to-manage analogy describes nicely the idea that performance-pay creates an incentive mechanism inciting workers to supply more effort.

Effort determination. After the wage schedule (3.18) is determined, workers observe shocks in t and choose the amount of effort to supply as to maximize the value of being employed:

$$\max_{e_{pp,t}} \{W_n(\Omega_{pp,t})\}$$
$$\text{s.to} \quad : \quad w_{pp,t} = \xi\left[z_t e_{pp,t} + (1-s)\kappa E_{t-1}\{\theta_{pp,t}\}\right] + (1-\xi)\left[\frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + b\right]$$

The optimal effort condition is thus

$$e_{pp,t}^{\eta} = z_t \tag{3.19}$$

the choice of effort equalizes the marginal product of effort and the marginal rate of substitution and is privately efficient.[23]

3.3.5 Aggregation and model dynamics

To close the model, I need to derive the aggregate identities for the variables that differ across the two firm types. First, the aggregate matching function is defined as

$$m(u_t, v_t) = v_t^{\sigma} u_t^{1-\sigma}$$

[23] Note that private efficiency occurs only because of linear utility.

where vacancies (v_t) and job searchers (u_t) can be expressed as

$$\begin{aligned} v_t &= (1-p)v_{ew,t} + pv_{pp,t} \\ u_t &= u_{ew,t} + u_{\,pp,t} \\ where &: \; p = \frac{u_{\,pp,t}}{u_t};\; and : 1-p = \frac{u_{\,ew,t}}{u_t} \end{aligned}$$

The aggregate market tension, average aggregate probabilities of finding a job and filling a vacancy are simply defined as

$$\begin{aligned} \theta_t &= \frac{v_t}{u_t} \\ f_t &= \frac{m(u_t, v_t)}{u_t} \\ q_t &= \frac{m(u_t, v_t)}{v_t} \end{aligned}$$

with $m(u_t, v_t)$, and aggregates u_t, and v_t defined above. Aggregate employment and output are defined as

$$\begin{aligned} n_t &= (1-p)n_{ew,t} + pn_{pp,t} \\ y_t &= (1-p)y_{ew,t} + py_{pp,t} \end{aligned}$$

and the aggregate unemployment rate is simply

$$urate_t = 1 - n_t$$

For variables where we use the "per worker value", such as the average the wage per worker or effort per worker, we aggregate these variables as

$$
\begin{aligned}
e_t &= (1-p)\frac{n_{ew,t}}{n_t}\overline{e} + p\frac{n_{pp,t}}{n_t}e_{pp,t} \\
w_t &= (1-p)\frac{n_{ew,t}}{n_t}w_{ew,t} + p\frac{n_{pp,t}}{n_t}w_{pp,t}
\end{aligned}
$$

Moreover, I get the aggregate resources constraint from the household's budget constraint (3.4), substituting in the definition of profits and using Euler's theorem. This yields

$$y_t = c_t + \kappa v_t \tag{3.20}$$

The model dynamics are obtained by taking a loglinear approximation around the steady state of the model. The appendix provides a complete set of the equations of the model.

3.4 Calibration and steady states

The model is calibrated to quarterly data for the U.S. economy. I lay out the calibration strategy in four steps. First, some parameters of the model are standard and thus are calibrated according to related literature. For example, the quarterly discount factor β is set to 0.99, the elasticity of effort supply $(1/\eta)$ to 1, the elasticity of matches to vacancies, σ, to 0.6, which is about the midpoint of what is typically used in the literature,[24] ξ is set to 0.4 such that the Hosios condition is satisfied, and s, the separation rate, is set to 0.10 as in den Haan, Ramey, and Watson (2000; DWR thereafter) and Shimer (2005). These standard parameters appear in the upper portion of Table 3.2.

The second step consists of finding steady state values for n, f, u, and the un-

[24] See for example Andolfatto (1996), Petrongolo and Pissarides (2001), or Trigari (2009).

Calibrated parameter values

Parameter	Definition	Value
β	Discount factor	0.99
1/η	Elasticity of effort supply	1
ξ	Worker's bargaining power	0.4
s	Separation rate	0.1
σ	Elasticity parameter, matching fct	0.6
n	Employed / (Employed + unemployed)	0.89
1-n	unemployment rate	0.11
f	Average job-finding rate	0.45
outsideOpt	Value of nonmarket activity	70%
b/w	Unemployment benefits as a fraction of the wage	0.15
κv/y	Vacancy-posting costs as a fraction of output	8%
d	Detection probability, Efficiency-wage	78%

Table 3.2 Calibrated parameter and steady state values

employment rate $(1-n)$ using the steady state equivalents of equations (3.2) and (3.3), i.e.

$$\begin{aligned} sn &= fu \\ u &= 1-(1-s)n \end{aligned}$$

To do this, I follow DRW's (2000) strategy as I abstract from labor force participation decisions and interpret unmatched workers as including "both unemployed individuals and those not in the labor force but stating that they want a job". According to DRW (2000), the steady state ratio of unmatched to matched workers (i.e. $(1-n)/n$), using the above definition of unmatched workers, is around 12%, which yields a value of $n = 0.89$. Consequently, the steady state unemployment rate $1-n$ is equal to 0.11, and the job-finding rate f is equal to 0.45.[25]

[25] I follow DRW (2000) to find target values for n, u,and f. It is hard to figure out what

The third step of the calibration strategy is less trivial because the wage equations differ substantially in each labor market segment while key labor market parameters, such as the unemployment benefits to wage ratio (b/w) or the vacancy-creation cost κ, need to be the same in each segment. I thus start with the remaining steady state equations defining the performance-pay segment of the model, find what are the implied values for b/w and κ/q, and then solve the rest of the steady state system.

The remaining equations defining the steady state of the performance-pay segment of the model are the steady state equivalents of the production function (3.5); the vacancy-creation condition (3.8); the performance-pay wage equation (3.18); the effort condition (3.19); and the aggregate resources constraint (3.20). Since there is one more variable (and free parameter) than there are equations left, I need one other assumption to solve the system. I thus assume that the worker's outside option is equal to 70% of the wage, a value consistent with Hall (2006) and in between Shimer (2005) and Hagedorn and Manovskii (2008).[26] With these assumptions in hand, solving the performance-pay segment is straightforward. Note that the steady state vacancy-creation condition in the performance-pay segment can be written as

$$\frac{\kappa v_{pp}}{y_{pp}} = \frac{\kappa}{q_{pp}} f_{pp} \frac{u_{pp}}{y_{pp}} = \frac{s}{(1/\beta - 1 + s)} \left[1 - \frac{w_{pp} n_{pp}}{y_{pp}} \right] \tag{3.21}$$

these values are in the steady state for each segment of the labor market. Consequently, I set $n_{ew} = n_{pp} = n$, and thus $u_{ew} = u_{pp} = u$, thus assuming only one steady state. The simulations below will therefore study the dynamics around this steady state.

[26] Calibrating the outside option as 70% of the steady state wage level implies that:

$$\left(\frac{e_{pp}^{1+\eta}}{(1+\eta)} + b \right) = 0.70w$$

while the performance-pay condition can be rewritten as

$$\frac{w_{pp}n_{pp}}{y_{pp}} = \frac{\xi}{[1-(1-\xi)OutOp]}\left[1+(1-s)\frac{\kappa}{q_{pp}}f_{pp}\frac{n_{pp}}{y_{pp}}\right] \tag{3.22}$$

where $OutOp$ is the worker's outside option, here equal to 70% of the wage. Substituting (3.22) into the vacancy-creation condition (3.21) defines the aggregate vacancy-posting costs as a fraction of output:

$$\frac{\kappa v_{pp}}{y_{pp}} = \frac{\kappa}{q_{pp}}f_{pp}\frac{u_{pp}}{y_{pp}} = \frac{s\left[1-(1-\xi)OutOp-\xi\right]}{\left[\left(\frac{1}{\beta}-1+s\right)(1-(1-\xi OutOp)+f_{pp}(1-s)\xi\right]} \tag{3.23}$$

at a value of about 8%. Using the national accounting equation, the effort condition, and the production function, I can find values for $\frac{c_{pp}}{y_{pp}}$, e_{pp}, and the steady state output level y_{pp}. I finally find the wage w_{pp} from (3.22). With these steady state values I can find (b/w) such that the outside option is equal to 70% of the steady state wage, and $\frac{\kappa}{q}$ such that $\frac{\kappa}{q}f\frac{u}{y_{pp}} = 0.08$. These values are reported in the bottom half of Table 2.

The fourth and final step is to close the steady state system by calibrating the remaining values in the efficiency-wage segment. The only additional parameter specific to this segment is d, the detection probability. For simplicity, I will assume that the labor share implied in the performance-pay segment 's calibration is the same in the efficiency-wage segment, and let d be determined by the steady state system of the model. This implies a detection probability of $d = 0.78$, similar to the preferred value of Riggi (2013).

One could argue that the steady state values found above, especially from the third step onwards, are debatable. For example, aggregate vacancy-posting costs, at 8% of output are arguably high; however, as seen in equation (3.23), vacancy-posting costs depend entirely on the value of the worker's outside option and some parameter values.[27] In the next section, I will show that a very high value for the worker's outside option à la Hagedorn and Manovskii (2008) yields a higher labor share and most importantly, lower vacancy-posting costs as a share of output. I will also show how simulation results differ under an alternative calibration strategy à la Hagedorn and Manovskii (2008).

Finally, for the technology shock, I assume that its logarithm follows an independent AR(1) process

$$z_t = \rho_a z_{t-1} + \varepsilon_{zt} \ \text{ with } \varepsilon_{at} \ iid \ (0, \sigma^2_{\varepsilon_z})$$

where $z_t = \log Z_t$. For the simulations below, I set $\rho_a = 0.978$ and $\sigma^2_{\varepsilon_z} = 0.80$, values found in Champagne and Kurmann (2013a) for the 1953-2006 period.

3.5 Simulations

In this section, I first simulate the model assuming that either all firms offer efficiency-wage compensation schemes (i.e. setting $p = 0$) or performance-pay schemes (i.e. setting $p = 1$), to get some intuition on how the model behaves within each segment of the labor market, and then compare the results to U.S. data and to a benchmark labor search model without effort. If wages turn out to be more volatile in the performance-pay segment of the model, then a shift towards performance-pay schemes in the last 30 years, as documented in Section 2, could be a potential explanation for the observed increase in relative wage volatility during the same period. Second, I discuss the results along with the problems the search and matching model has in amplifying fluctuations in the labor market, and I propose an alternative calibration in the spirit of Hagedorn

[27] Andolfatto (1996) sets vacancy-posting costs as a share of output at 1%, while Ravenna-Walsh (2013) set them at 5%.

and Manovskii (2008) and show how it affects the simulation results without changing the qualitative differences between the efficiency-wage and performance-pay segments. Finally, I perform a quantitative exercise where I vary exogenously the proportion of efficiency-wage and performance-pay firms in the economy (i.e. vary p), similar as in Champagne and Kurmann (2013a), to show how a reasonable shift towards performance-pay schemes can account for the increase in relative wage volatility.

3.5.1 Impulse response functions

To build intuition and to better understand the second moments below, it is useful to start by looking at impulse response functions following a 1% technology shock, first when all firms offer efficiency-wage contracts, and then when all firms offer performance-pay contracts, separately. Under the efficiency-wage scenario, firm and worker negotiate prior to time-t information, and agree on a wage to be paid for a fixed amount of effort. Therefore, the wage is predetermined and the worker cannot adjust his effort as it is constant. This is shown in Figure 3.2: when the technology shock hits the economy, the efficiency-wage (dashed blue line) does not react on impact. In the next period, it jumps to adjust to the positive shock, and then decrease back at sluggish pace to towards its steady state level. On the other hand, the performance-pay wage is not predetermined, although the wage schedule is. The reason is that workers adjust their effort supplies according to the state of the economy in period t. This is apparent from the red and green lines in Figure 3.2, which represent the impulse response functions of the wage and effort following the same technology shock. The performance-pay wage reacts contemporaneously following a technology shock because of contemporaneous adjustments along the effort margin by workers. Since the performance-pay wage reacts each time a technology shock hits the model economy whereas the efficiency-wage does not,

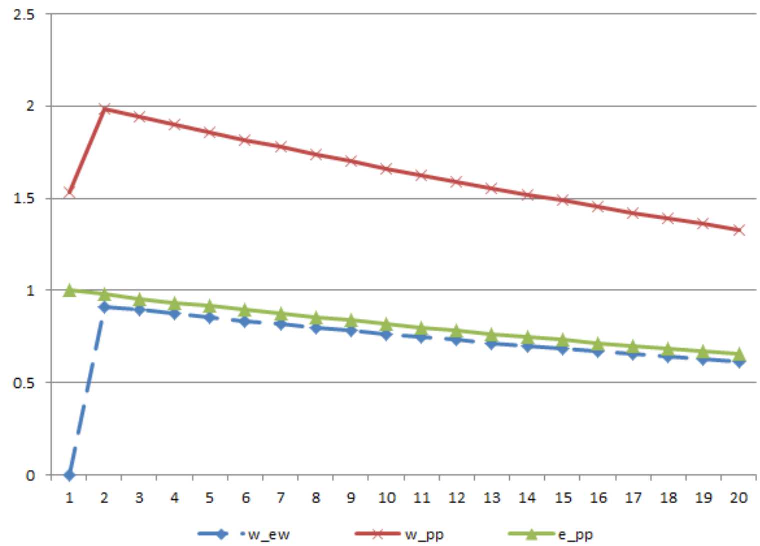

Figure 3.2 Impulse response functions (IRFs) following a technology shock

we can safely assume that it is also more volatile than the efficiency-wage. I show in the next subsection that it is indeed the case.

3.5.2 Second moments

Table 3.3 reports statistics summarizing the cyclical properties of the U.S. and model economies. The first three columns display second moments for the U.S. economy in three different sub-periods; the next three columns display moments from three model economies, i.e. a "benchmark model", the efficiency-wage segment, and the performance-pay segment of the model, respectively. The benchmark model is a standard labor search model without effort,[28] and wage bargaining

[28]Since there is no effort in the benchmark model, there is no disutility of providing effort in the worker's outside option (which equals b). Consequently, b in the benchmark model is calibrated to equal the same outside option value than in the efficiencywage/performance-pay model.

occurs as in the standard search and matching literature (e.g. Pissarides, 2000; Shimer, 2005).

	US Data			Benchmark	Efficiency-wage	Performance-pay
	All	*Pre-84*	*Post-84*	*no effort*	*e={0,constant}*	*(σ(e)/ σ(y)=0.45)*
σ(y)	2.14	2.57	1.58	1.30	1.39	2.32
σ(n)/ σ(y)	0.75	0.66	0.95	0.27	0.45	0.15
σ(w)/ σ(y)	0.42	0.34	0.61	0.75	0.68	0.86
σ(y/n)/ σ(y)	0.75	0.66	0.95	0.80	0.75	0.90
σ(urate)/ σ(y)	6.17	5.59	7.04	2.29	3.73	1.28
σ(v)/ σ(y)	6.68	6.28	7.50	2.27	2.52	1.27
ρ(y,w)	0.51	0.75	0.18	0.98	0.83	0.99
ρ(y,y/n)	0.79	0.80	0.79	0.98	0.91	0.99
ρ(v,y/n)	0.87	0.91	0.82	0.92	0.99	0.92
ρ(v,urate)	-0.92	-0.94	-0.90	-0.29	-0.23	-0.29

Note : The first five rows report respectively the standard deviation of output and relative standard deviations relative to standard deviation of output for respectively hours per capita, real average hourly wage, output per hour, and nominal average hourly wage. The next two rows report the correlation between output and respectively the real average hourly wage and output per hour. The last two rows report the correlation between hours and output per hour, and between the nominal average hourly wage and the price level. The 'Relative' column denotes the Post/Pre-84 ratios for standard deviations and the Post-Pre-84 differences for correlations. All series are HP-filtered and the real wage series is PCE-deflated. U.S. data: Total sample extends from 1953:1 to 20012:4 with split in 1984:1 using quarterly data for the non-farm business sector.

Table 3.3 Model simulations

Data

The data sample for the U.S. nonfarm business economy spans from 1953 to 2012, in quarterly terms; all series are logged and HP-filtered.[29] The first column displays second moments for the whole sample, whereas the second and third show second moments for two subsamples, before and after 1984:1. The sample split is motivated by the Great Moderation literature that estimates a break in output volatility in 1984 (e.g. McConnell and Perez-Quiros, 2000),[30] whereas many other papers document the changing business cycle behavior of other prominent macroeconomic variables (e.g. Barnichon, 2010; Champagne and Kurmann, 2013a; Gali

[29] See appendix for a detailed description of the data.

[30] Even though the Great Recession period (2007-2009) has been a turbulent period of economic activity, we see from Table 3 that output volatility has decreased by 40% after 1984, a period, up to the financial crisis, known as the Great Moderation.

and Van Rens, 2010; Nucci and Riggi, 2013). As documented in Champagne and Kurmann (2013b) and shown in Table 3.3, the relative volatility of real earnings per worker (measured as real average weekly earnings) to output has increased significantly after 1984, from a ratio of 0.34 between 1953:1 and 1984:1 to a ratio of 0.61 between 1984:2 and 2012:4. Employment and labor productivity (measured as real-chained GDP divided by employment) also experienced increases in relative volatility after 1984, but to a lesser degree than earnings per worker. In terms of correlations, we see that real average weekly earnings were strongly procyclical before 1984, and mildly procyclical since 1984.[31] Labor productivity, as measured by output per worker, remained strongly procyclical throughout the sample, which stands in stark contrast to the vanishing procyclicality of output per hour documented in Gali and Van Rens (2010) and Champagne and Kurmann (2013a).[32] Finally, as documented in many papers (e.g. Shimer, 2005; Hagedorn-Manovskii, 2008), there is a strong positive (negative) correlation between vacancies and labor productivity (unemployment).[33]

Model economies

The last three columns of Table 3.3 presents the results for a benchmark model with no effort à la Shimer (2005), along with the model simulated with all firms

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[31] Even though the drop in correlation of weekly earnings with output after 1984 is consistent with the drop in the correlation with output of real average hourly earnings after 1984 (as documented in Champagne and Kurmann (2013a,b)), the magnitude of the correlations are different. Champagne and Kurmann (2013a,b) report that hourly wages went from being midly procyclical before 1984 to mildly countercyclical after 1984.

[32] Champagne and Kurmann (2013a), Table 3, shows that the correlation between labor productivity (as measured by outout put hour) and real nonfarm GDP went from 0.65 (1964-1984) to 0.01 (1984-2006).

[33] Again, this is in stark contrast with the correlation between vacancies and output per hour; Barnichon (2010) reports (Table 1) that this correlation is 0.34 for the 1948-1984 period, and -0.31 for the 1984-2008 period.

bargaining over efficiency-wage contracts ($p = 0$) and over performance-pay contracts ($p = 1$). The first striking observation is that neither models come close to match the relative (to output) volatility of unemployment and vacancies, especially the performance-pay model. This result is a well-established one and known as the "Shimer puzzle" (Shimer, 2005). Moreover, when output is endogenous, and technology shocks are the only exogenous shocks in the model, it turns out that the labor search model is not only unable to generate a lot of amplification in unemployment and vacancies, but in output also. This second result is consistent with DRW (2000), who show that without endogenous separations (i.e. fluctuations in the job-destruction rate), the labor search model does not propagate well technology shocks. The second striking, and more interesting observation concerns the relative volatility of earnings per worker; in the performance-pay segment of the labor market, earnings are more volatile than in the efficiency-wage segment (by about 27%), and also vs. the benchmark model ($\sim$ 15%). Furthermore, as anticipated the efficiency-wage is less volatile than the standard wage bargained wage, implying that the shirking model along with the $t - 1$ bargaining assumption induce wage stickiness. Finally, it is interesting to note that while the performance-pay model worsens the Shimer (2005) puzzle (vs. the benchmark case), the efficiency-wage generates more amplification in unemployment and vacancies; because the wage predetermined and does not react contemporaneously to productivity shocks, firms have a greater incentive to post vacancies following a positive technology shock.[34] Also note that all three models are able to generate a negative Beveridge curve, even though the curve is not as steep as in the data.

Lastly and unsurprisingly, the performance-pay model generates a larger cor-

[34] This is the argument put forward by Shimer (2005) and Hall (2005), i.e. sticky wages are a potential solution to the unemployment and vacancies volatility puzzle.

relation between the wage and output than the efficiency-wage (and also than the benchmark model). It is not surprising in the sense that by definition a "performance-pay" wage should follow more closely production than a more sticky wage. At the same time, if performance-pay as become more pervasive in the economy, it is inconsistent with the observed decline of this correlation in the U.S. data.

3.5.3 The Shimer puzzle and an alternative calibration strategy

As discussed in the calibration section above, one could argue that some values implied by the steady state system of equations are more or less realistic, such as vacancy-posting costs at 8% of output. High vacancy-creation costs reduce the incentive to post vacancies, and thus worsen the unemployment / vacancies volatility puzzle. Essentially, Shimer (2005) states that the standard labor search model cannot reproduce the volatility observed in the unemployment rate and vacancy-posting because following a positive productivity shock, the increase in the job-finding rate pulls down unemployment and thus the $\frac{v}{u}$ ratio increases, raising the workers' threat point and consequently raising wages, which then take the bulk of the productivity increase and eliminate the incentive to post vacancies. Here I propose a new calibration strategy in the spirit of Hagedorn and Manovskii (2008), where I set the worker's outside option at a very high value (at 95% of the steady state wage value). As a result, $\frac{\kappa}{q}$ and b will be different than in the above strategy.

Table 3.4 presents the parameters and steady state values for this second calibration strategy.We can see that this new calibration strategy using an outside option value in the spirit of Hagedorn and Manovksii (2008) yields a very low value for vacancy-posting costs (as a share of output). This can be easily seen

Calibrated parameter values

Parameter	Definition	Value
β	Discount factor	0.99
$1/\eta$	Elasticity of effort supply	1
ξ	Worker's bargaining power	0.4
s	Separation rate	0.1
σ	Elasticity parameter, matching fct	0.6
n	Employed / (Employed + unemployed)	0.89
1-n	unemployment rate	0.11
f	Average job-finding rate	0.45
outsideOpt	Value of nonmarket activity	95%
b/w	Unemployment benefits as a fraction of the wage	0.44
$\kappa v/y$	Vacancy-posting costs as a fraction of output	1%
d	Implied detection probability, Efficiency-wage	54%

Table 3.4 Alternative calibration strategy

using equation (3.22); for a given labor share, the higher the outside option of the worker (as a fraction of the wage), the lower the vacancy-posting costs (as a share of output).

Table 3.5 presents the results for this alternative calibration strategy. As in Table 3.4, the first three columns present the same key data moments for three different sample periods, and the last three columns present moments for the model economies (i.e. the benchmark, efficiency-wage, and performance-pay models). First note that this calibration strategy yield much more fluctuations in output than the previous strategy in all three models. Second, as put forward by Hagedorn and Manovskii (2008), calibrating the outside option of workers at a very high proportion of the wage helps solving the Shimer (2005) puzzle. As we see in Table 3.5, the benchmark model comes close replicating the relative volatility of unemployment and vacancies to output. To understand this result, we simply need to

	US Data			Benchmark	Efficiency-wage	Performance-pay
	All	*Pre-84*	*Post-84*	*no effort*	*e={0,constant}*	($\sigma(e)/\sigma(y)=0.16$)
$\sigma(y)$	2.14	2.57	1.58	2.76	3.88	3.21
$\sigma(n)/\sigma(y)$	0.75	0.66	0.95	0.72	0.87	0.62
$\sigma(w)/\sigma(y)$	0.42	0.34	0.61	0.32	0.22	0.42
$\sigma(y/n)/\sigma(y)$	0.75	0.66	0.95	0.38	0.27	0.49
$\sigma(u)/\sigma(y)$	6.17	5.59	7.04	5.98	7.28	5.15
$\sigma(v)/\sigma(y)$	6.68	6.28	7.50	5.94	4.93	5.12
$\rho(y,w)$	0.51	0.75	0.18	0.83	0.75	0.95
$\rho(y,y/n)$	0.79	0.80	0.79	0.83	0.58	0.88
$\rho(v,y/n)$	0.87	0.91	0.82	0.92	0.99	0.92
$\rho(v,u)$	-0.92	-0.94	-0.90	-0.29	-0.23	-0.29

Note: The first five rows report respectively the standard deviation of output and relative standard deviations relative to standard deviation of output for respectively hours per capita, real average hourly wage, output per hour, and nominal average hourly wage. The next two rows report the correlation between output and respectively the real average hourly wage and output per hour. The last two rows report the correlation between hours and output per hour, and between the nominal average hourly wage and the price level. The 'Relative' column denotes the Post/Pre-84 ratios for standard deviations and the Post-Pre-84 differences for correlations. All series are HP-filtered and the real wage series is PCE-deflated. U.S. data: Total sample extends from 1953:1 to 20012:4 with split in 1984:1 using quarterly data for the non-farm business sector.

Table 3.5 Model simulations

look at the volatility of average wages: in all three models, the relative volatilities of wages are much lower than in the previous calibration. This implies more stickiness in the wage, increasing the firms' incentive to post vacancies. However, and most importantly, even if wages are less volatile in all three models under this calibration strategy, results are qualitatively consistent with the previous calibration on three aspects: (1) the performance-pay model generates higher relative volatilities of earnings per workers (about 117% higher than the efficiency-wage, and 56% higher than the benchmark model); (2) the performance-pay model worsen the Shimer (2005) puzzle, in the sense that it yields lower relative volatilities of vacancies and unemployment than the benchmark model; and (3) it increases the correlation between output (and productivity) with wages.

3.5.4 Quantitative exercise

To further assess how the increase incidence of performance-pay contracts can be behind the increase in average wage volatility, I use the first calibration of the previous section, set the proportion of performance-pay firms in the economy (i.e. p) as in Champagne and Kurmann (2013) such as to match the pre-1984 average incidence of performance-pay contracts in the U.S. economy, and simulate the model. Then I set p to match the post-1984 average incidence of performance-pay contracts and again simulate the model to see how the change in the pervasiveness of pay-for-performance can account for the increase in relative wage volatility in the model. Table 3.6 below presents the results of the quantitative exercise. Consistent with the results found in the previous subsection, more performance-

	US Data		Model	Model
	Pre-84	*Post-84*	**p=0.30**	**p=0.60**
$\sigma(y)$	2.57	1.58	1.68	1.97
$\sigma(n)/\sigma(y)$	0.66	0.95	0.37	0.31
$\sigma(w)/\sigma(y)$	0.34	0.61	0.71	0.78
$\sigma(y/n)/\sigma(y)$	0.66	0.95	0.81	0.84
$\sigma(urate)/\sigma(y)$	5.59	7.04	3.08	2.62
$\sigma(v)/\sigma(y)$	6.28	7.50	2.10	1.77
$\rho(y,w)$	0.75	0.18	0.93	0.96
$\rho(y,y/n)$	0.80	0.79	0.94	0.96
$\rho(v,y/n)$	0.91	0.82	0.99	0.99
$\rho(v,urate)$	-0.94	-0.90	-0.23	-0.23

Note: See tables 3.3 and 3.3 for data description. p is set at 0.30 to match pre-1984 average of performance-pay incidence, and at 0.6 to match post-1984 average of ppay incidence.

Table 3.6 Model simulations - Quantitative exercise

pay contracts in the economy increase average wage volatility, but only by about 10%. Labor productivity also becomes more volatile, but the increase is again very small. Counterfactually, the increase in performance-pay schemes increases the volatility of output, along with the correlation between average wages and output (and productivity). As mentioned earlier, this is due to the fact that effort is strongly procyclical under the performance-pay scenario, linking more closely the wage to output.

This quantitative exercise shows the challenges faced by advocates (e.g. Lemieux et al., 2009a; Champagne and Kurmann, 2013a) of the performance-pay story (i.e. changes in the structure of pay over the past three decades as a driver of the increase in relative wage volatility and by the same token of increased macroeconomic stability): when one takes a microfounded approach to model performance-pay into a general equilibrium framework with explicit effort determination, it is difficult to generate business cycle statistics as observed before and during the Great Moderation.

3.6 Conclusion

Some researchers have argued that changes in the dynamics of labor markets can be a potential explanation for the changing nature of business cycle fluctuations. For instance, during the Great Moderation period, a period of unprecedented macroeconomic stability, average real wages have become more volatile in the U.S. economy, putting the labor market on the front stage.

Among the documented changes in labor market dynamics, the increase incidence of performance-pay compensation schemes has been advocated as an explanation for the increase in wage volatility. For example, Lemieux et al. (2009a) show that the incidence of performance-pay schemes has increased significantly during the last 30 years in the U.S. Moreover, Lemieux et al. (2009b) find that wages of non-union workers with performance-pay contracts are most responsive to local labor market shocks and least responsive for union workers without performance-pay contracts, implying that performance-pay increase flexibility in wage setting. Finally, Champagne and Kurmann (2013a) suggest that structural changes in the labor market, in the form of more flexible wage setting, are promising candidates to account for the increase in relative wage volatility.

Motivated by these observations, this paper first introduces two types of incentive pay schemes in a business cycle model with matching frictions and wage bargaining. Second, it compares the business cycle implications of each compensation scheme, along with basic the labor search model where the intensive margin is constant (e.g. Shimer (2005)). Finally, it evaluates how a structural change towards more performance-pay contracts, in the light of Lemieux et al.'s (2009a) evidence, affects the relative volatility of average real wages and other labor market variables.

Specifically, I use a real business cycle DSGE model with labor search frictions, two types of incentive pay with explicit effort determination. To model incentive pay, I use Lazaear's (1986) insights on 'input-based' and 'output-based' compensation schemes to formulate two different wage determination mechanisms: one where bargaining occurs over an efficiency-wage (i.e. no-shirking) type of compensation scheme, while the other occurs over a wage schedule that links pay to effort (i.e. performance) that is costly for the workers to supply. The first wage contract can be caricatured as 'the stick', while the second as 'the carrot'.

Simulations of the model yield interesting and counterfactual results. First, the performance-pay scheme implies greater wage volatility than under the efficiency-wage scenario (and vs. the benchmark labor search model), a finding robust across different calibration strategies (e.g. Shimer, 2005; Hagedorn and Manovskii, 2008). Second, while the model is not able to replicate fluctuations in unemployment and vacancies as observed in the data (consistent Shimer, 2005) under the preferred calibration strategy, it does fairly better under a more extreme calibration as in Hagedorn and Manovskii (2008). Third, when the economy is calibrated to match the average incidence of performance-pay wage contracts in the U.S. economy before and then after 1984, simulations shows that an increase in the incidence of performance-pay leads to an increase in relative wage volatility of about

10%. But it also leads to counterfactual results like an increase in output volatility and an increase in the correlation between wages and output. The reason behind this is that effort is procyclical, amplifying the response of wages to technology shocks, but at the same time raising output volatility and the correlation between wages and output.

These results pose a challenge to the story that an increase in performance-pay wage contracts yields more flexibility in wage setting, increasing average wage volatility and lowering fluctuations in output. When one tries to model the idea of performance-pay seriously (i.e. more microfounded with an explicit effort determination), it is difficult to generate the observed business cycle fluctuations observed over the last three decades.

Nonetheless, the idea of changes in the pay structure as an explanation behind changes in labor market dynamics and business cycle fluctuations is intriguing. Having a good theory of incentive pay in a DSGE framework can give good insights not only on the business cycle, but also to assess the role of incentive pay on wage inequality, economic growth, etc. With a good DSGE framework with incentive pay, other research avenues could be explored: for example, heterogenous workers with different skill sets could sort themselves towards (or not) performance-pay jobs; endogenous separation rates, where matches between low skill workers and performance-pay jobs are terminated at a high frequency; or endogenizing the firm's decision to offer some type of incentive contract.

CONCLUSION

During the Great Moderation, a period of unprecedented macroeconomic stability in the U.S. and in many industrialized countries, the business cycle volatility of real hourly wages in the U.S. has increased significantly such that the relative volatility of real hourly wages to output became 2.5 to 3.5 times larger than before the Great Moderation period. The three chapters have all tried to tackle this observation in one way or another, seeking what we can understand on the labor market from wage dynamics and vice versa. The first chapter aims directly at this observation and documents that over the past 25 years, real average hourly wages in the United States have become substantially more volatile relative to output. Microdata from the Current Population Survey (CPS) is used to show that this increase in relative volatility is predominantly due to increases in the relative volatility of hourly wages across different groups of workers. Compositional changes of the workforce, by contrast, account for only a small fraction of the increase in relative wage volatility. Simulations with a Dynamic Stochastic General Equilibrium (DSGE) model illustrate that the observed increase in relative wage volatility is unlikely to come from changes outside of the labor market (e.g. smaller exogenous shocks or more aggressive monetary policy). By contrast, greater flexibility in wage setting due to deunionization and a shift towards performance-pay contracts as experienced by the U.S. labor market is capable of accounting for a substantial fraction of the observed increase in relative wage volatility. Greater wage flexibility also decreases the magnitude of business cycle fluctuations, suggesting an interesting new explanation for the Great Moderation. The second chapter builds on the first chapter as it documents the gradual divergence in trend growth and business cycle volatility of two popular aggregate hourly wage series for the U.S. economy: average hourly compensation from the Labor Productivity and Cost (LPC) program and average hourly earnings from the Current Employment Statistics (CES). While the LPC wage increased by about 70% over the past four decades and became markedly more volatile starting in the 1980s, the CES wage grew by only about 20% over the same period and experienced a large drop in volatility post-1980. We establish that the divergence between the two aggregate hourly wage series is due to the different evolution of average labor earnings. Average hours worked, by contrast, evolve very similarly. We then use labor earnings data from the Current Population Survey (CPS), the National Income and Product Accounts (NIPAs), and Piketty and Saez (2003) in an attempt to reconcile the divergence between LPC and CES labor earnings. Our analysis indicates that differences in earnings concept and population coverage can account for a large part of the divergence. Our analysis also shows that earnings differences between the CPS and the LPC can be attributed almost entirely to earnings of high-income individuals and supplements such as employer contributions to pension and health plans, which are included in the LPC but not in the CPS. This result is interesting in its own right given the widespread use of micro earnings data from the CPS in cross-sectional studies. Finally, the third chapter aims at first defining a more "serious" theory of performance-pay in general equilibrium and then takes this theory to the data. It considers a real business cycle model with labor search frictions where two types of incentive pay are explicitly introduced following the insights from the micro literature on performance-pay (e.g. Lazear, 1986). While in both schemes workers and firms negotiate ahead of time-t information, the object of the negotiation is different. The first scheme is called an 'efficiency-wage' as it follows closely the intuition of the shirking model by Shapiro and Stiglitz (1984), while the second is called a 'performance-pay' wage as the negotiation occurs over a wage schedule that links the worker's wage to his output. The key feature here is that the worker can then adjust his effort (i.e. performance) level in any period. I simulate a shift towards performance-pay contracts as experienced by the U.S. labor market to asses if it can account simultaneously for two documented business cycle phenomena: the increase in relative wage volatility and the Great Moderation. While the model yields higher wage volatility when performance-pay is more pervasive in the economy, it produces higher volatility of output and higher procyclicality of wages, two results counterfactual to what the U.S. economy has experienced during the Great Moderation. These results pose a challenge to the idea that higher wage flexibility through an increase in performance-pay schemes can account for business cycle statistics observed over the last thirty years.

APPENDIX A

SUPPLEMENTAL MATERIAL FOR "THE GREAT INCREASE IN RELATIVE WAGE VOLATILITY IN THE UNITED STATES"

A.1 Data Description

This section describes in details the different variables used throughout the first chapter, along with data sources and series' IDs.

A.1.1 Macro Variables

The different macro variables used throughout the paper and in the appendix are:

- **Output**: Gross Domestic Product, Non-farm business, Chained-$2000. From the NIPA tables of the Bureau of Economic Analysis (BEA). Series ID: A358RX1. We divide this series by the U.S. population (see below) to get an hours per capita measure.

- **Price deflator**: The main series we use is the Personal Consumption Expenditure (PCE) deflator, from the NIPA tables of the BEA; index, 2000=100. Series ID: A002RD3. The alternative deflator we use is the GDP deflator, again from the NIPA tables; index, 2000=100. Series ID: A191RD3.

- **Population**: Non-civilian population, 16 years old and over; from the Bureau of Labor Statistics' (BLS) Labor Productivity and Costs (LPC) program. Series ID: LNU00000000Q.

A.1.2 Labor Productivity and Costs (LPC)

The Major Productivity and Costs program of the BLS produces labor productivity and costs (LPC) measures for the private-sector of the U.S. economy. Here are the three main variables used in the paper from the LPC dataset. All of them are available quarterly and seasonally adjusted.

- **Average hourly wages**: *Total hourly compensation* for the non-farm business sector, ID: PRS85006103. Index (1992=100). This series is computed (in the LPC) as total compensation divided by total hours.

- **Total compensation**: Total compensation from the LPC dataset is comprised of a 'wages and salaries' component, and a 'supplements' component. The 'wages and salaries' component is based on earnings data from the Quarterly Census of Employment and Wages (QCEW), previously known as the BLS ES-202 program. The QCEW is "*...a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and the State Employment Security Agencies (SESAs)...[and] produces a complete tabulation of employment and wage information for workers covered by State unemployment insurance (UI) laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program*". This represents about 98 percent of all U.S. jobs. The definition of labor earnings in the QCEW are very comprehensive. Specifically: *"Wage and salary disbursements consist of the monetary remuneration of employees (including the salaries of corporate officers, commissions, tips, bonuses, and severance* *pay); employee gains from exercising nonqualified stock options; distributions from nonqualified deferred compensation plans; and an imputation for pay-in-kind (such as the meals furnished to the employees of restaurants)."* See http://www.bea.gov/regional/pdf/spi2005/Complete_Methodology.pdf for more information.

The 'supplements' components consists of employer contributions for employee pension and insurance funds and employer contributions for government social insurance.[1] To derive total compensation for the non-farm business sector, the LPC substracts compensation of employees working in public administration offices, in the farm sector, and in non-profit institutions and private households.[2] Moreover, the LPC imputes earnings of self-employed individuals using comparable data from workers in the CPS.

- **Total hours**: Total hours in the LPC database mainly comes from the Current Establishment Survey (CES) for production and nonsupervisory workers (see CES description below), supplemented by other sources to estimate hours of workers not covered by the CES. For example, LPC computes an estimate of average weekly hours for nonproduction and supervisory workers by applying a CPS-based ratio of [nonproduction & supervisory workers] / [production & non-supervisory workers] to CES production & nonsupervisory worker average weekly hours. When reporting statistics for total hours, we use the non-farm business portion of total hours, ID: PRS84006033 (index 1992 =100), and divide it by the U.S. population (i.e. hours per capita).

[1] The estimates for the 'supplements' portion of total compensation come from various sources, such as the IRS, the Medical Expenditure Panel Survey, or the American Counsil on Life Insurance. The estimates are compiled by the Bureau of Economic Analysis (BEA).

[2] Note that workers employed in 'general government' are not included in the non-farm business measure, while workers in 'governement enterprises' are.

A.1.3 The Current Population Survey (CPS)

Overview

The Current Population Survey (CPS) is a monthly survey of about 60,000 households. It collects a variety of information on households' demographics and employment.[3] To construct an average hourly wage series, we need data on earnings and hours from the CPS. However, earnings and hours questions are not asked to all CPS respondents each month. Specifically, an interviewed individual appears in the CPS for two periods of four consecutive months, separated by eight months during which the individual is left out of the survey. Between 1973 and 1978, the CPS asked all the respondents in the sample about weekly earnings and weekly hours once a year only. This data was collected in May in what is called the 'May supplements'. Starting in 1979, weekly earnings and hours questions are asked each month to the individuals who are at the end of a four-month rotation – the 'Outgoing Rotation Group' (ORG). Hence, from 1979 onward, one fourth of the CPS sample is asked about earnings and hours each month.[4]

Following Abraham et al. (1998) and Lemieux (2006), we use the earnings and hours information from the CPS May supplements and the ORG extracts to create an annual series of weighted average weekly earnings and weighted average weekly hours from 1973 onwards. The weights used in this calculation are provided by the CPS to make the resulting sample representative of the U.S. workforce. Finally,

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[3]For more documentation on the CPS and in particular the May / ORG extracts, see Schmitt (2003); and Roth and Feenberg (2007).

[4]In March of each year, the CPS also asks all inviduals in the sample about their annual labor earnings. While these 'March supplements' start in 1963, they do not provide information on annual hours worked prior to 1976, making it impossible to compute an hourly wage series. Furthermore, Lemieux (2006) argues that the earnings data from the March supplements is subject to measurement problems not present in the CPS May / ORGs. See his paper for details.

average hourly wages are computed by dividing average weekly earnings with average weekly hours.

To obtain a non-farm business equivalent comparable to the LPC data, all unemployed; self-employed; individuals under 16 years of age; government agricultural and private household workers; as well as armed force personnel are removed from CPS sample. For 1973-1978, the May supplements yield an average of 30,406 individual observations per year. For 1979-2006, the combination of 12 monthly ORG files yields an average of 139,230 individual observations per year.

Lastly, note that the actual CPS ORG extracts (1979-2006) used are from the Center for Economic Policy Research (CEPR).[5] These extracts are based on the 'Merged Outgoing Rotation Groups' files ('MORGs', i.e. the ORGs, merged in annual files) compiled by the National Bureau of Economic Research (NBER). We use the CEPR data because the CEPR modifies the NBER MORGs to make them more "user-friendly".[6] But the greatest advantage with the CEPR data is that they provide detailed documentation on the modifications they make to the NBER's MORG files. We carefully use this documentation to replicate the CEPR's adjustments for the NBER MORG extracts for the CPS May Supplement files so as to have a consistent sample from 1973 to 2006.

Creating a consistent average hourly wage series

Workers in the CPS May/ORG extracts report earnings in two different ways, depending on whether they are salaried or paid by the hour. Salaried workers re-

[5] See Center for Economic and Policy (CEPR) Research. 2006. CPS ORG Uniform Extracts, Version 1.2.2. Washington, DC (http://www.ceprdata.org/).

[6] For instance, the coding of some variables in the CPS survey changes through time, e.g. the variable 'education'. The CEPR MORGs are formatted such that there is consistency in each variable through time.

port usual weekly earnings, defined as compensation normally received, including bonuses, overtime, tips and commissions (OTC) if paid and earned each period but excluding payments in kind, stock options and any other form of irregular bonuses. Hourly-paid workers report their usual hourly rate, which is not supposed to take into account OTC or any form of irregular pay. Hence, CPS earnings contain some fraction of bonuses and OTC if paid and earned each period but no irregular form of compensation.

To create a consistent average hourly wage series from this data, two issues need to be addressed. The first issue concerns topcoding of high earnings; the second issue concerns the CPS redesign in 1994.

Topcoding concerns the fact that the CPS limits (i.e. topcodes) publicly available data of high earning individuals to a maximum value that varies over time and depends on whether a worker reports weekly earnings or the hourly wage rate. For the latter, the CPS topcodes the hourly rate at \$99.99, which is a threshold rarely crossed. For the former (i.e. salaried workers), the CPS topcodes weekly earnings at \$999 until 1989; \$1923 between 1989 and 1997; and \$2884 from 1998 onwards. For certain years, this puts a substantial share of workers above the topcode, which may lead to discontinuities around topcode changes, thus inducing spurious volatility in the post-1984 sample. To reduce this risk, we multiply topcoded weekly earnings by a factor of 1.3 before averaging across individuals. While this constant-factor adjustment is standard in the labor literature (e.g. Abraham et al., 1998; Lemieux, 2006), it does not completely eliminate the possibility of discontinuities from topcode changes. Alternatively, one can use more sophisticated adjustment methods that estimate mean earnings of individuals above the topcode from the cross-sectional distribution of earnings below the topcode. The most popular among these methods is based on the Pareto distribution, which has been shown to provide the best approximation of the actual earnings mean in confidential CPS samples.[7] We use a battery of different topcode adjustment methods, including the Pareto distribution, and find that our volatility results do not differ across methods. For simplicity and because it is relatively standard in the labor literature, the constant-factor adjustment of 1.3 is the only topcode adjustment used throughout the paper.

The second issue with creating a consistent average hourly wage series from CPS data concerns the redesign of the CPS survey in 1994. Specifically, as part of the redesign, the CPS introduced an additional question on weekly earnings from OTC that is asked to hourly-paid workers but not to salaried workers. Because OTC earnings are growing in importance (see Kuhn and Lozano, 2008) and are potentially more volatile than regular earnings, we include this additional information in the calculation of weekly earnings for hourly-paid workers.[8] At the same time, we need to avoid creating a discontinuity in the average wage of hourly-paid workers between 1993 and 1994 due to the introduction of the OTC question. We therefore adjust the average hourly wage for hourly-paid workers before 1994 with a linear trend. Specifically, we take the average hourly wage between 1994 and 2006 of skilled and unskilled hourly-paid workers and estimate a linear trend for each of the two series. For both skilled and unskilled hourly-paid workers, we then take the difference between the actual average wage in 1993 and the 1993 wage implied by the linear trend; apply this difference to the rest of the observations before 1993; and average the thus adjusted series for skilled and unskilled hourly-

[7]See Feenberg and Poterba (1992), Polivka (2000) and Schmitt (2003).

[8]Specifically, before 1994, weekly earnings of hourly-paid workers are computed as $\max(wage\_rate * weekly\_hours,\ weekly\_earnings)$; from 1994 onward, weekly earnings of hourly-paid workers are computed as $\max(wage\_rate * weekly\_hours + OTC,\ weekly\_earnings)$. This calculation takes into account that especially before the redesign in 1994, hourly-paid workers reported both their hourly wage rate and usual weekly earnings. The reasons for this double reporting are not entirely clear. One possibility is that some hourly-paid workers reported weekly earnings if they had compensation from OTC payments that they were not allowed to report as part of their hourly wage. Our calculation accounts for this possibility.

paid workers back into an average hourly wage series for all hourly-paid workers. While this adjustment procedure removes any potential discontinuity from the redesign, it also removes any change in hourly-paid workers' wages between 1993 and 1994 that is due to other, business cycle related reasons. The adjustment procedure may therefore lead to an overly conservative estimate of the post-1984 wage volatility.[9]

A.1.4 Current Employment Statistics

The CES is a monthly survey including about 140,000 U.S. firms representing about 400,000 establishments.[10] While it reports data for all employees as far back as 1939, it only reports earnings and hours from 1964 onwards and *only* for production workers in the goods-producing sector and nonsupervisory workers in the service-providing sector.[11] As a result, no public administration workers nor farm workers are included.

- **Average Hourly Earnings (AHE)**: the AHE measure discussed in the paper was downloaded directly from the BLS website, series ID: CES0500000008. It is computed (in the CES) as total earnings divided by total hours.

- **Total earnings**: Chapter 2 of the BLS Handbook of Methods states that: "*Aggregate payrolls include pay before deductions for Social Security, unemployment insurance, group insurance, withholding tax, salary reduction*

[9] We also implement the adjustment procedure with a polynomial trend and obtain similar results.

[10] As discussed in the text, the CES grew from about 166,000 to about 330,000 establishments between 1980 and 1993; and then to over 400,000 establishments in 2006.

[11] Note that since March 2006, the CES also publishes series of weekly earnings and hours that cover all employees in the non-farm business sector.

plans, bonds, and union dues. The payroll figures also include overtime pay, shift premiums, and payments for holidays, vacations, sick leave, and other leave made directly by the employer to employees for the pay period reported. Payrolls exclude bonuses, commissions, and other lump-sum payments (unless earned and paid regularly each pay period or month), or other pay not earned in the pay period (such as retroactive pay). Tips and the value of free rent, fuel, meals, or other payments in kind are not included."

- **Total Hours**: Chapter 2 of the BLS Handbook of Methods states that: "*Total hours during the pay period include all hours worked (including overtime hours), hours paid for standby or reporting time, and equivalent hours for which employees received pay directly from the employer for sick leave, holidays, vacations, and other leave. Overtime and other premium pay hours are not converted to straight-time equivalent hours.*"

A.2 Computation of Standard Errors

Standard errors and relative standard errors in the text are obtained using the delta method from GMM-based estimates. In the first stage, define

$$f(x_{it}, \mu) = \begin{bmatrix} x_{1t} - \mu_1 \\ \dots \\ x_{Nt} - \mu_N \\ x_{1t}x_{1t} - \mu_{11} \\ \dots \\ x_{Nt}x_{Nt} - \mu_{NN} \end{bmatrix},$$

where x_{it} are the time series of interest for $t = 1, ..., T$; $\mu_i = E(x_{it})$ for $i = 1, ..., N$; and $\mu_{ij} = E(x_{it}x_{jt})$ for $i, j = 1, ..., N$. The GMM estimator sets $\widehat{\mu}$ such that

$\frac{1}{T}\sum_{t=1}^{T} f(x_{it},\mu) = 0$. The asymptotic distribution of the GMM estimator is given by

$$\sqrt{T}(\widehat{\mu} - \mu) \longrightarrow N\left(0, \left\{D'S^{-1}D\right\}^{-1}\right),$$

where

$$D = E\left[\left(\frac{\partial f(x_{it},\mu)}{\partial \mu'}\right)\right]'$$

is the Jacobian matrix (N x N since our GMM procedure is just-identified), and where

$$S = \sum_{j=-\infty}^{\infty} E\left[f(x_t,\mu)f(x_t,\mu)'\right].$$

Next, compute the covariance matrix for the standard errors

$$COV(\mu) = \frac{\left\{D'S^{-1}D\right\}^{-1}}{T}.$$

To construct a sample analog of S, we use the Newey-West estimate of S:

$$\widehat{S}_T = \sum_{j=-k}^{k}\left\{\left(\frac{k-|j|}{k}\right)\frac{1}{T}\sum_{t=1}^{T} f(x_t,\widehat{\mu})f(x_{t-j},\widehat{\mu})'\right\}.$$

Now, the moments of interest are standard deviations and relative standard deviations (non-linear functions of the moments found above), so we use the delta Method to estimate the standard errors of these standard deviations and relative standard deviations. For example, consider the standard deviation of a random variable x_{it}:

$$\sigma_x = \left[E(x_t^2) - E(x_t)^2\right]^{1/2}.$$

Here we interpret σ_x as a function of the population moments $E(x_t)$ and $E(x_t^2)$. Moreover, define

$$\mu = \left[\begin{array}{cc} E(x_t) & E(x_t^2) \end{array}\right] \equiv \left[\begin{array}{cc} \mu_x & \mu_x \end{array}\right],$$

and thus

$$\sigma_x(\mu) = (\mu_{xx} - \mu_x^2)^{1/2} = X(\mu_x, \mu_{xx}).$$

The delta method states that

$$\sqrt{T}(\widehat{X} - X) \longrightarrow N\left(0, \frac{\partial X}{\partial \mu}\left\{D'S^{-1}D\right\}^{-1}\frac{\partial X'}{\partial \mu}\right).$$

Since $D = \frac{\partial f}{\partial \mu} = -I$, where I denotes the identity matrix of appropriate dimension, $\left\{D'S^{-1}D\right\}^{-1}$ reduces to S. Furthermore, we can compute the derivative of X with respect to μ

$$\frac{\partial X}{\partial \mu} = \frac{\partial \sigma_x}{\partial \mu} = \begin{bmatrix} \frac{\partial \sigma_x}{\partial \mu_x} \\ \frac{\partial \sigma_x}{\partial \mu_{xx}} \end{bmatrix} = \begin{bmatrix} -\mu_x/\sigma_x \\ 1/(2\sigma_x) \end{bmatrix}.$$

With these in hand, along with the estimate of S, $\widehat{S}_T$, we can compute the standard error of σ_x. Note that we use the same procedure to find the standard errors for relative standard deviations (e.g. the ratio of the standard deviations of wages and output), where the derivative of X with respect to μ is:

$$\frac{\partial X}{\partial \mu} = \frac{\partial\left\{\sigma_x/\sigma_y\right\}}{\partial \mu} = \begin{bmatrix} \frac{\partial \sigma_x}{\partial \mu_x} \\ \frac{\partial \sigma_y}{\partial \mu_y} \\ \frac{\partial \sigma_x}{\partial \mu_{xx}} \\ \frac{\partial \sigma_y}{\partial \mu_{yy}} \end{bmatrix} = \begin{bmatrix} \frac{-\mu_x}{\sigma_x \sigma_y} \\ \frac{\mu_y X}{\sigma^2} \\ \frac{1}{2\sigma_x \sigma_y} \\ -\frac{1}{2}\frac{X}{\sigma^2} \end{bmatrix}.$$

A.3 Aggregate Moments – Robustness checks

A.3.1 Alternative price deflator

Tables A.1 and A.2 present the same statistics as in Tables 1.1 and 1.2 of the paper, but use an alternative deflator, the GDP deflator, in the computation of real average hourly wages.

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*p-value*	*Pre-84*	*Post-84*	*Post/Pre-84*
First-Difference							
Output	1.52	0.68	0.45	0.00	1.00	1.00	1.00
	(0.10)	(0.07)					
Wage	0.45	0.63	1.42	0.01	0.29	0.93	3.17
	(0.03)	(0.06)			(0.02)	(0.10)	
HP-Filter							
Output	2.57	1.28	0.50	0.00	1.00	1.00	1.00
	(0.24)	(0.14)					
Wage	0.51	1.05	2.07	0.00	0.20	0.82	4.16
	(0.04)	(0.11)			(0.02)	(0.12)	
BP-Filter							
Output	2.50	1.16	0.46	0.00	1.00	1.00	1.00
	(0.26)	(0.11)					
Wage	0.43	0.95	2.21	0.00	0.17	0.82	4.79
	(0.04)	(0.11)			(0.02)	(0.13)	

Note: Total sample extends from 1953:2 to 2006:4 with split in 1984:1. HP-filtered, quarterly data. GDP-deflated wages. Non-farm business sector. P-values are reported for a test of equality of variances across the two subsamples. Standard errors computed using GMM and the Delta method appear in parentheses below estimates.

Table A.1 Changes in volatility

The tables indicate that the results reported in the paper are robust to using the GDP deflator instead of the PCE deflator. In fact, with the GDP deflator, the volatility of hourly wages increases even *more* after 1984. This is also true for the CES wage; however, the CES wage still does not increase in volatility relative to output.

A.3.2 Alternative hourly wage series

Here we present further evidence of the increase in aggregate wage volatility with other wage series constructed from dataset that are less commonly used in the macro literature: Dale Jorgenson's Private Economy labor Quality (PELQ) dataset; and the NBER Productivity database.

PELQ: The PELQ dataset was used by Jorgenson and coauthors to construct labor input indices for various productivity analyses. For example, see Jorgenson, Ho and Stiroh (2008). The primary source of compensation and hours' data

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
Annual						
Ouput	2.90	1.15	0.40	1.00	1.00	1.00
	(0.19)	(0.13)				
LPC wage	0.44	0.97	2.20	0.15	0.84	5.53
	(0.06)	(0.10)		(0.03)	(0.12)	
CPS wage	0.33	0.70	2.11	0.12	0.61	5.29
	(0.03)	(0.12)		(0.01)	(0.14)	
Quarterly						
Output	2.73	1.28	0.47	1.00	1.00	1.00
	(0.31)	(0.14)				
LPC wage	0.54	1.05	1.94	0.20	0.82	4.14
	(0.05)	(0.11)		(0.03)	(0.12)	
CES wage (AHE)	0.92	0.44	0.48	0.34	0.34	1.02
	(0.17)	(0.05)		(0.06)	(0.06)	

Note : Total sample extends from 1964 to 2006 for quarterly data; 1973 to 2006 for annual data. HP-filtered data. GDP deflated wages. Nonfarm business sector. Standard errors computed using GMM and the Delta method appear in parentheses below estimates.

Table A.2 Changes in volatility

across industries are the NIPA tables. Moreover, the CPS and the Censuses of Population are used to obtain detailed cross-classifications by characteristics of individual workers. After aggregating compensation and hours worked across all groups of workers in each year, we compute the average hourly wage by dividing total compensation with total hours worked.

NBER Productivity database: This database is a collaboration between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies, containing annual industry-level data on output, employment, payroll and other input costs, investment, capital stocks, TFP, and various industry-specific price indexes. It contains information on 450 (4-digit) manufacturing industries from 1958 to 2003.[12] After aggregating earnings and hours across industries, we compute an average hourly wage measure from this database

[12] We use a new version of the NBER manufacturing database kindly sent to us by Wayne Gray. This version of the database covers the years 1958 to 2003.

by dividing total earnings by total hours.

Table A.3 presents the evidence for hourly wages constructed from the PELQ and the NBER Productivity data. For comparison, the table also includes results for real private nonfarm GDP, the LPC wage and the CPS wage. The table indicates

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
First-Difference						
Output	3.89	1.76	0.45	1.00	1.00	1.00
	(0.30)	(0.27)		(0.00)	(0.00)	
LPC wage	0.99	1.49	1.51	0.25	0.85	3.40
	(0.15)	(0.23)		(0.03)	(0.18)	
PELQ wage	0.86	1.33	1.55	0.23	0.75	3.26
	(0.05)	(0.16)		(0.03)	(0.20)	
NBER manufacturing wage	1.57	2.20	1.40	0.41	1.15	2.80
	(0.09)	(0.34)		(0.05)	(0.25)	
CPS wage	1.11	1.29	1.17	0.28	0.73	2.58
	(0.23)	(0.24)		(0.05)	(0.19)	
HP-Filter						
Output	2.90	1.15	0.40	1.00	1.00	1.00
	(0.19)	(0.13)		(0.00)	(0.00)	
LPC wage	0.60	0.93	1.55	0.21	0.80	3.81
	(0.08)	(0.09)		(0.04)	(0.13)	
PELQ wage	0.59	0.80	1.36	0.21	0.78	3.71
	(0.05)	(0.05)		(0.03)	(0.16)	
NBER manufacturing wage	1.15	1.22	1.06	0.40	1.09	2.73
	(0.14)	(0.17)		(0.05)	(0.27)	
CPS wage	0.63	0.72	1.14	0.22	0.62	2.86
	(0.06)	(0.12)		(0.03)	(0.15)	

Note: Total sample extends from 1973 to 2006 with split in 1984, except for PELQ wage sample (1976-2000), and the NBER's manufacturing database sample (1973 to 2002). Annual data. PCE-deflated wages. Standard errors appear in parentheses below estimates.

Table A.3 Replicating average real hourly wage volatility from the CES with CPS data

that for both the PELQ and the NBER productivity data, the volatility of hourly wages increases post-1984; and the relative wage volatility increases by a factor of 2.7 to 3.8, depending on the filtering used.

A.3.3 Total Compensation vs. Wage and Salaries

Total compensation from LPC includes supplements such as vacation pay and employer contributions to pension and health plans. To assess the role of these supplements for the increase in wage volatility in the LPC, we strip out supplements and compute the wage volatility for the wages and salaries part only.

Unfortunately, this exercise cannot be done directly with the LPC dataset since it does not contain separate information on the wage and salary and supplements portions of LPC's total compensation. This information is, however, available in the NIPAs. We therefore switch to the NIPAs and compare non-farm business sector measures of hourly wages based on the wages and salary part (from the QCEW); and the 'total compensation' part (i.e. 'wages and salaries' plus 'supplements').[13]

The left panel of Figure A.1 plots the resulting hourly wage series. The widening gap between the two series indicates that supplements have become an increasingly important part of total compensation over the past 40 years. However, as can be seen in the right panel of Figure A.1, the H-P filtered components of the two series behave very similarly throughout the sample. Table A.4 takes a closer look at the volatilities of the two NIPA wage series for different business cycle filtering methods, along with the LPC hourly compensation series.[14] Comparing the results for the hourly wage series based on total compensation with the results for the LPC wage used in the paper, notice that the increase in volatility in the post-84 period is similar (differences in wage volatility increases across filtering methods

[13]To compute NIPA hourly wages, we divide the relevant earnings series by NIPA hours; the NIPA hours series is constructed from the product of LPC average weekly hours (without self-employed) and employment from QCEW.

[14]Data in Table A.4 is in annual terms, since NIPA hours are only available on an annual basis.

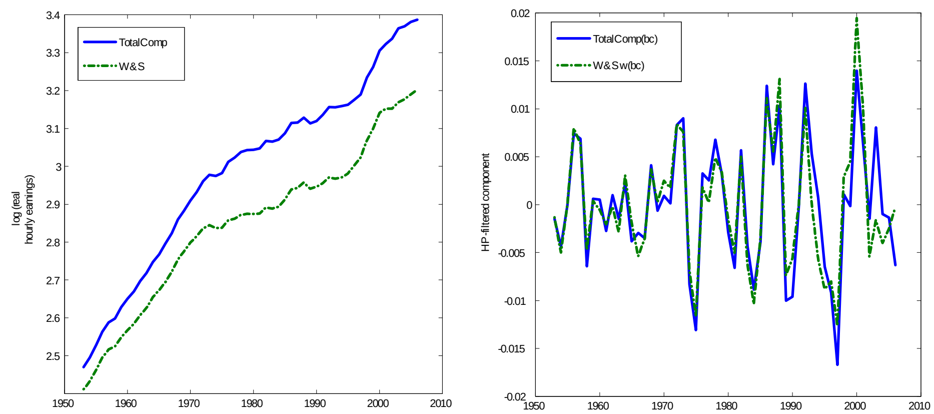

Figure A.1 Real average hourly compensation and wages and salaries, in logs levels (left) and respective HP-filtered components (right)

- i.e. LPC's hourly compensation volatility increase is higher than NIPA's hourly compensation - are very small). The likely reason for these small differences is the inclusion of self-employed individuals in the LPC series (whereas NIPA earnings and hours do not include self-employed individuals).

Next, notice that the hourly wage series based on the wages and salaries part experiences a somewhat larger increase in volatility than the hourly wage series based on total compensation; this is because supplements evolve relatively smoothly over the business cycle. Consequently, Figure A.2 and Table A.4 show that the increase in average hourly wage volatility presented in Table 1.1 of the paper is not an artifact of the inclusion of supplements in total compensation.

	Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
1st-Difference						
Output	3.43	1.76	0.51	1.00	1.00	1.00
	(0.25)	(0.27)				
Total compensation (LPC)	1.06	1.49	1.40	0.31	0.84	2.73
	(0.12)	(0.23)		(0.03)	(0.19)	
Total compensation (NIPA)	1.10	1.37	1.24	0.32	0.78	2.42
	(0.12)	(0.20)		(0.03)	(0.16)	
Wages & Salaries (NIPA)	1.09	1.37	1.26	0.32	0.78	2.44
	(0.11)	(0.22)		(0.03)	(0.03)	
Hodrick-Prescott filter						
Output	2.29	1.15	0.50	1.00	1.00	1.00
	(0.25)	(0.13)				
Total compensation (LPC)	0.54	0.93	1.71	0.24	0.80	3.40
	(0.07)	(0.09)		(0.03)	(0.13)	
Total compensation (NIPA)	0.53	0.83	1.59	0.23	0.72	3.16
	(0.08)	(0.07)		(0.03)	(0.10)	
Wages & Salaries (NIPA)	0.49	0.85	1.76	0.21	0.74	3.50
	(0.07)	(0.09)		(0.02)	(0.11)	
Bandpass filter						
Output	2.33	1.11	0.48	1.00	1.00	1.00
	(0.31)	(0.12)				
Total compensation (LPC)	0.61	0.90	1.48	0.25	0.81	3.24
	(0.07)	(0.12)		(0.02)	(0.14)	
Total compensation (NIPA)	0.60	0.84	1.41	0.26	0.76	2.96
	(0.09)	(0.10)		(0.02)	(0.11)	
Wages & Salaries (NIPA)	0.52	0.83	1.60	0.22	0.75	3.36
	(0.06)	(0.06)		(0.02)	(0.11)	

Note: Total sample extends from 1953 to 2006. Annual data. PCE-deflated wages. Non-farm business sector. NIPA tc and w&s hourly wages computed by dividing the relevant measure of compensation with total hours from NIPA. LPC series corresponds to Table 1 in the paper, but in annual terms. Standard errors computed using GMM and the Delta method appear in parentheses below estimates.

Table A.4 Changes in volatility : Total Compensation vs. Wages and Salaries

A.3.4 Hours: LPC vs. CES

In the paper, we discuss that the divergence in wage volatility between the LPC wage and the AHE come from divergent earnings' volatility and not from divergent hours' volatility. Here, we back up this claim.

Since the publicly available data from the CES does not contain separate information on total hours, we construct an index of CES hours index from the available information on employment and average weekly hours as

$$CES\ hours = avg\ weekly\ hours * employment \tag{A.1}$$

In the LPC database, total hours is also and index, normalized to 100 in 1992. We thus normalize the above CES hours index to the same base. Figure A.2 compares both series in indexes (logs) and HP-filtered. As Figure A.2 shows, the business

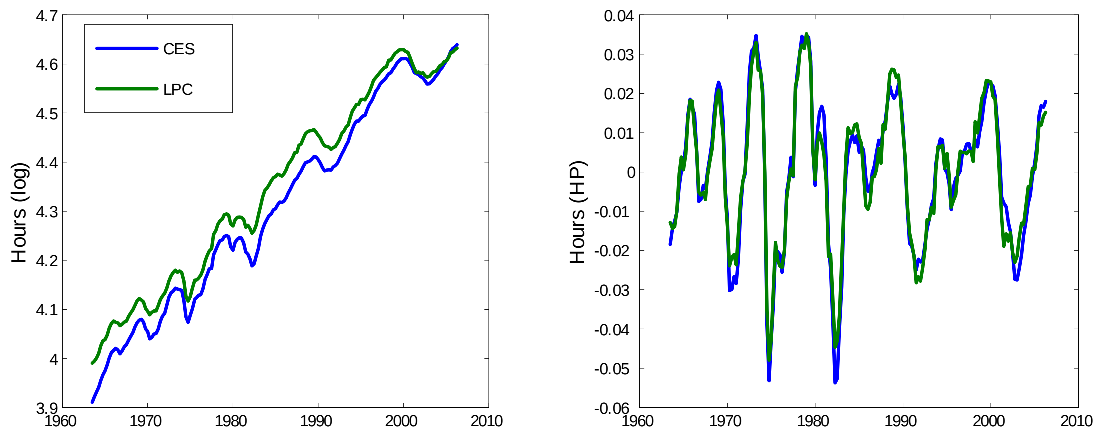

Figure A.2 LPC and CES total nonfarm business hours in logs (left) and HP-filtered (right)

cycle components of both hours series move very closely together.

A.4 Wage volatility across decompositions

A.4.1 Detailed results

This section presents more details about the disaggregated CPS data from Tables 1.4 and 1.5. Specifically, changes in average wage shares and changes in the volatility of hours' shares for each of the decompositions are shown. Tables A.5 to A.8 below provide the detailed results. For the industry / education decomposition in Table A.8 (Table 1.5 in the paper), the 10 'major industry groups' are defined by the following 3-digit 1980 SIC codes (in brackets):[15]

[15] As stated in the paper, agriculture, forestry and fishing industries, armed forces occupations, and public administration workers are removed from the sample to cover only the non

1. Mining, Oil, and Gas Extraction (40-50)
2. Construction (60)
3. Manufacturing - Durables (230-391)
4. Manufacturing - Non-Durables (100-222)
5. Transportation & Utilities (400-432, 450-472)
6. Communications (440-442)
7. Wholesale Trade (500-571)
8. Retail Trade (580-691)
9. Finance, Insurance, and Real Estate (700-712)
10. Other Services (761-893)

	Average Wage Share		**Standard Deviation**			**Relative Standard Deviation**		
	Pre-84	*Post-84*	*Pre-84*	*Post-84*	*Post/Pre-84*	*Pre-84*	*Post-84*	*Post/Pre-84*
Male unskilled	0.55	0.41						
Wage			0.71	0.83	1.16	0.25	0.72	2.92
Hours share			0.70	0.35	0.50	0.24	0.30	1.26
Male skilled	0.18	0.24						
Wage			0.41	1.11	2.71	0.14	0.96	6.80
Hours share			2.62	0.77	0.29	0.90	0.67	0.74
Female unskilled	0.24	0.24						
Wage			0.78	0.73	0.94	0.27	0.63	2.35
Hours share			0.52	0.39	0.76	0.18	0.34	1.90
Female skilled	0.04	0.11						
Wage			1.47	0.84	0.57	0.51	0.73	1.43
Hours share			2.48	0.78	0.32	0.85	0.68	0.79

Note: Total sample extends from 1973 to 2006 with split in 1984. HP-filtered, annual data. Non-farm business sector.

Table A.5 Evolution of Education/Gender Wage Components

farm business sector.

	Average Wage Share		Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*
16-29 Unskilled	0.26	0.17						
Wage			0.98	1.00	1.02	0.34	0.87	2.56
Hours share			1.68	0.90	0.53	0.58	0.78	1.34
16-29 Skilled	0.06	0.06						
Wage			1.13	1.45	1.28	0.39	1.26	3.23
Hours share			2.83	1.41	0.50	0.98	1.22	1.25
30-59 Unskilled	0.48	0.46						
Wage			0.80	0.76	0.95	0.28	0.66	2.37
Hours share			0.53	0.42	0.79	0.18	0.36	1.98
30-59 Skilled	0.15	0.27						
Wage			0.75	0.94	1.25	0.26	0.82	3.15
Hours share			2.03	0.68	0.33	0.70	0.59	0.84
60-70 Unskilled	0.04	0.03						
Wage			1.35	0.97	0.72	0.47	0.85	1.81
Hours share			3.37	1.73	0.52	1.16	1.50	1.29
60-70 Skilled	0.01	0.014						
Wage			2.65	1.63	0.62	0.92	1.42	1.55
Hours share			8.72	3.13	0.36	3.01	2.72	0.90

Note : Total sample extends from 1973 to 2006 with split in 1984. HP-filtered, annual data. Non-farm business sector.

Table A.6 Evolution of Education/Age Wage Components

A.4.2 Occupation / Gender decomposition

Another interesting decomposition of the labor force (not shown in the paper) is on the occupation and gender level (instead of education and gender). Following Eckstein and Nagypal (2004), we create three occupation groups (Blue-collar and white-collar workers, and Professional and Managerial occupations). Note that the sample stops in 2002 because reclassification of occupations in 2003 makes it hard to compute consistent occupation groups before and after 2002.[16]

Table A.9 provides the same insights as Table 1.4 in the paper, except that here the skill groups are based on occupations instead of education. We can notice an interesting shift in the composition of the work force: women moved into white-collar and professional occupations. This is certainly in line with the move towards

[16] Eckstein and Nagypal (2004) make the same statement and cut their sample in 2002.

	Average Wage Share		Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*
Hourly, unskilled	0.48	0.42						
Wage			0.96	0.89	0.92	0.33	0.77	2.32
Hours share			1.38	0.42	0.31	0.48	0.37	0.77
Hourly, skilled	0.03	0.06						
Wage			1.48	1.48	1.00	0.51	1.28	2.51
Hours share			3.95	2.03	0.51	1.36	1.76	1.29
Salaried, unskilled	0.31	0.24						
Wage			1.21	0.85	0.70	0.42	0.74	1.76
Hours share			1.70	0.84	0.50	0.59	0.73	1.24
Salaried, skilled	0.19	0.28						
Wage			0.44	0.91	2.09	0.15	0.79	5.24
Hours share			2.47	0.68	0.27	0.85	0.59	0.69

Note : Total sample extends from 1973 to 2006 with split in 1984. HP-filtered, annual data. Non-farm business sector.

Table A.7 Evolution of Education/Compensation Status Wage Components

more skilled jobs, and also with the increased participation of women in the labor force. We also observe that relative wage volatilities increase across the board for all occupations, except female professionals. The major increase comes from male professionals, which represent the second largest share in the total wage bill, and had the second biggest increase in relative wage volatility (3.10). These results are in line with our argument in the paper that performance-pay is a contributor behind the increase in wage volatility. According to Lemieux et al. (2009a), male professionals are a group of individuals where the incidence of performance-pay is high compare to other occupations. All in all, these results reaffirm the ones found in Table 1.4 of the paper.

A.5 Volatility accounting: Details

This section lays out the details of the variance decomposition of Section 3 in the paper. Let us start with equation (2) in the paper:

$$\frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)} \approx \sum_i \sum_j \bar{s}_i(b)\bar{s}_j(b)\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \sum_i \sum_j \bar{s}_i(a)\bar{s}_j(a)\frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}. \quad \text{(A.2)}$$

	Average Wage Share		Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*
MinOilGas unskilled	0.015	0.008						
Wage			2.40	1.71	0.71	0.83	1.53	1.85
Hours share			9.11	4.17	0.46	3.14	3.73	1.19
Construct unskilled	0.071	0.060						
Wage			1.33	0.96	0.72	0.46	0.86	1.87
Hours share			3.99	1.97	0.49	1.38	1.76	1.28
Manuf-D unskilled	0.181	0.118						
Wage			0.81	1.04	1.27	0.28	0.93	3.30
Hours share			3.16	1.05	0.33	1.09	0.94	0.86
Manuf-ND unskilled	0.105	0.071						
Wage			0.78	1.23	1.57	0.27	1.10	4.07
Hours share			1.75	1.06	0.61	0.60	0.95	1.57
T&U unskilled	0.064	0.053						
Wage			1.13	0.87	0.77	0.39	0.78	2.00
Hours share			2.27	1.22	0.54	0.78	1.09	1.39
Comm unskilled	0.021	0.017						
Wage			2.22	1.29	0.58	0.77	1.15	1.51
Hours share			5.73	3.24	0.57	1.98	2.90	1.46
Whole T unskilled	0.045	0.037						
Wage			1.18	0.89	0.75	0.41	0.79	1.95
Hours share			3.25	2.08	0.64	1.12	1.86	1.66
Retail T unskilled	0.116	0.108						
Wage			1.11	1.01	0.91	0.38	0.90	2.35
Hours share			1.62	0.69	0.42	0.56	0.61	1.10
FIRE unskilled	0.049	0.050						
Wage			1.26	1.01	0.80	0.43	0.90	2.08
Hours share			3.22	1.84	0.57	1.11	1.65	1.48
Services unskilled	0.116	0.146						
Wage			0.56	0.68	1.21	0.19	0.61	3.15
Hours share			1.80	0.73	0.40	0.62	0.65	1.04
MinOilGas skilled	0.004	0.004						
Wage			5.31	3.86	0.73	1.83	3.45	1.88
Hours share			11.28	8.35	0.74	3.89	7.47	1.92
Construct skilled	0.006	0.008						
Wage			2.38	1.88	0.79	0.82	1.68	2.05
Hours share			4.11	3.45	0.84	1.42	3.08	2.17
Manuf-D skilled	0.041	0.050						
Wage			1.26	1.24	0.98	0.44	1.11	2.53
Hours share			2.92	2.21	0.75	1.01	1.97	1.96
Manuf-ND skilled	0.024	0.029						
Wage			1.53	1.18	0.77	0.53	1.05	1.99
Hours share			5.98	2.44	0.41	2.06	2.18	1.06
T&U skilled	0.010	0.015						
Wage			2.74	2.26	0.83	0.94	2.02	2.14
Hours share			5.70	2.41	0.42	1.97	2.15	1.10
Comm skilled	0.005	0.010						
Wage			4.76	2.17	0.46	1.64	1.94	1.18
Hours share			8.43	3.53	0.42	2.91	3.16	1.08
Whole T skilled	0.015	0.018						
Wage			1.02	1.47	1.44	0.35	1.31	3.73
Hours share			7.72	2.68	0.35	2.66	2.40	0.90
Retail T skilled	0.016	0.024						
Wage			3.04	1.90	0.63	1.05	1.70	1.62
Hours share			4.26	1.84	0.43	1.47	1.65	1.12
FIRE skilled	0.026	0.044						
Wage			0.89	1.25	1.40	0.31	1.11	3.63
Hours share			4.16	1.81	0.44	1.44	1.62	1.13
Services skilled	0.068	0.131						

Table A.8 Evolution of Education / Industry(10) Wage Components

By adding and subtracting elements, expand this equation in two different ways

$$\begin{aligned}
\frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)} &\approx \sum_i \sum_j \left[\bar{s}_i(b)\bar{s}_j(b) - \bar{s}_i(a)\bar{s}_j(a)\right] \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)} \\
&\quad + \sum_i \sum_j \bar{s}_i(b)\bar{s}_j(b) \left[\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}\right] \\
&\approx \sum_i \sum_j \left[\bar{s}_i(b)\bar{s}_j(b) - \bar{s}_i(a)\bar{s}_j(a)\right] \frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} \\
&\quad + \sum_i \sum_j \bar{s}_i(a)\bar{s}_j(a) \left[\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}\right].
\end{aligned} \tag{A.3}$$

	Average Wage Share		Standard Deviation			Relative Standard Deviation		
	Pre-84	*Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*	*Pre-84*	*Post-84*	*Pre/Post-84*
Male blue-collar	0.35	0.27						
Wage			1.02	0.96	0.94	0.35	0.86	2.44
Hours share			1.13	0.47	0.42	0.39	0.42	1.09
Male white-collar	0.12	0.12						
Wage			0.95	0.90	0.95	0.33	0.81	2.46
Hours share			1.49	1.06	0.71	0.51	0.95	1.85
Male professional	0.22	0.23						
Wage			0.82	0.98	1.20	0.28	0.88	3.10
Hours share			1.88	0.74	0.40	0.65	0.67	1.02
Female blue-collar	0.09	0.07						
Wage			0.98	1.25	1.28	0.34	1.12	3.31
Hours share			1.83	0.72	0.39	0.63	0.64	1.01
Female white-collar	0.17	0.20						
Wage			0.82	0.68	0.82	0.28	0.61	2.13
Hours share			1.35	0.84	0.62	0.47	0.75	1.60
Female professional	0.04	0.10						
Wage			2.09	0.64	0.32	0.70	0.57	0.82
Hours share			1.63	0.96	0.59	0.56	0.86	1.53

Note: Total sample extends from 1973 to 2002 with split in 1984. HP-filtered, annual data. Non-farm business sector.

Table A.9 Evolution of Occupation/Gender Wage Components

The first expansion decomposes the change in the relative variance of average hourly wage growth into changes in wage shares *weighted by the covariances of the wage components for the first subsample* and changes in covariances of the wage components *weighted by the wage shares for the second subsample.* The second expansion decomposes the relative variance of the average hourly wage growth into changes in wage shares *weighted by the covariances of the wage components for the second subsample* and changes in covariances of the wage components *weighted by the wage shares for the first subsample.* Since there is no economic justification to prefer one 'base period' over the other, we take the average over the two expansion and obtain[17]

$$\frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)} \approx \sum_i \sum_j [\bar{s}_i(b)\bar{s}_j(b) - \bar{s}_i(a)\bar{s}_j(a)] \left[\frac{\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} + \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}}{2} \right] \quad \text{(A.4)}$$

$$+ \sum_i \sum_j \left[\frac{\bar{s}_i(b)\bar{s}_j(b) + \bar{s}_i(a)\bar{s}_j(a)}{2} \right] \left[\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)} \right].$$

The first line on the right-hand side of (A.4) captures the effect of changes in workforce composition on the relative variance of average hourly wages. The second line captures the effect of changes in the relative variances and correlations of the different $x_{i,t}$ terms. Using the fact that $\Delta \log x_{i,t} = \Delta \log w_{i,t} + \Delta \log h_{i,t}$ and applying the same averaging of 'base periods', we can expand this second part further into a weighted sum of changes in the relative variances of hourly wage growth of the different groups, changes in the relative variances of hours share growth of the different groups and changes in the various correlation terms.

For example, take the case where $i = j$, thus $\sigma_{x_i,x_j} = \sigma_{x_i}^2$. It is possible to decompose the change in the relative variance of each wage component (between subsamples b and a) as

$$\frac{\sigma_{x_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i}^2(a)}{\sigma_y^2(a)} = \left(\frac{\sigma_{w_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{w_i}^2(a)}{\sigma_y^2(a)} \right) + \left(\frac{\sigma_{h_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{h_i}^2(a)}{\sigma_y^2(a)} \right) + \quad \text{(A.5)}$$

$$2 \left[\rho(w_i(b), h_i(b)) \frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)} - \rho(w_i(a), h_i(a)) \frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)} \right].$$

By adding and subtracting elements as we did above, we can expand the second line as:

[17] This problem of choosing a 'base period' is conceptually similar to the problem faced in national accounting when computing *real* macro aggregates (e.g. real GDP). Our approach to use an average as the 'base period' for the weights resembles the chain-type method used in the NIPAs.

$$2\left[\begin{array}{c}\rho(w_i(b),h_i(b))\left(\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)}-\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}\right)\\ +\left[\rho(w_i(b),h_i(b))-\rho(w_i(a),h_i(a))\right]\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}\end{array}\right],$$

or alternatively,

$$2\left[\begin{array}{c}\left[\rho(w_i(b),h_i(b))-\rho(w_i(a),h_i(a))\right]\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)}\\ +\rho(w_i(a),h_i(a))\left(\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)}-\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}\right)\end{array}\right].$$

Take the average over the two methods and write (A.5) as:

$$\begin{aligned}\frac{\sigma_{x_i}^2(b)}{\sigma_y^2(b)}-\frac{\sigma_{x_i}^2(a)}{\sigma_y^2(a)} &= \left(\frac{\sigma_{w_i}^2(b)}{\sigma_y^2(b)}-\frac{\sigma_{w_i}^2(a)}{\sigma_y^2(a)}\right)+\left(\frac{\sigma_{h_i}^2(b)}{\sigma_y^2(b)}-\frac{\sigma_{h_i}^2(a)}{\sigma_y^2(a)}\right)+\\ &\quad 2\left\{\begin{array}{c}avg_{ab}\rho_{wh}\left(\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)}-\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}\right)+\\ avg_{ab}\sigma_{wh}\left[\rho(w_i(b),h_i(b))-\rho(w_i(a),h_i(a))\right]\end{array}\right\}.\end{aligned}$$

where

$$\begin{aligned}avg_{ab}\rho_{wh} &= \frac{\rho(w_i(b),h_i(b))+\rho(w_i(a),h_i(a))}{2}\\ avg_{ab}\sigma_{wh} &= \frac{\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)}+\frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}}{2}\end{aligned}$$

are averages over subsamples a and b of correlations between wages and hours, and product of variances of wages and hours, respectively. Moreover, we can also expand $\left(\frac{\sigma_{w_i}(b)\sigma_{h_i}(b)}{\sigma_y^2(b)} - \frac{\sigma_{w_i}(a)\sigma_{h_i}(a)}{\sigma_y^2(a)}\right)$ in the same fashion as above, and finally get:

$$\frac{\sigma_{x_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{x_i}^2(a)}{\sigma_y^2(a)} = \left(\frac{\sigma_{w_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{w_i}^2(a)}{\sigma_y^2(a)}\right) + \left(\frac{\sigma_{h_i}^2(b)}{\sigma_y^2(b)} - \frac{\sigma_{h_i}^2(a)}{\sigma_y^2(a)}\right) + 2\left\{\begin{array}{c} avg_{ab}\rho_{wh}\left[\begin{array}{c} \frac{\frac{\sigma_{h_i}(b)}{\sigma_y(b)}+\frac{\sigma_{h_i}(a)}{\sigma_y(a)}}{2}\left(\frac{\sigma_{w_i}(b)}{\sigma_y(b)} - \frac{\sigma_{w_i}(a)}{\sigma_y(a)}\right) \\ +\frac{\frac{\sigma_{w_i}(a)}{\sigma_y(a)}+\frac{\sigma_{w_i}(b)}{\sigma_y(b)}}{2}\left(\frac{\sigma_{h_i}(b)}{\sigma_y(b)} - \frac{\sigma_{h_i}(a)}{\sigma_y(a)}\right) \end{array}\right] \\ avg_{ab}\sigma_{wh}\left[\rho(w_i(b), h_i(b)) - \rho(w_i(a), h_i(a))\right] \end{array}\right\}.$$

The last equation shows that changes in the relative variance of each wage component can be expressed as changes in the relative volatility of hourly wages and hours' shares, and as changes in the correlations between the two. Finally, decompose the change in the relative covariance between two wage components (i.e. when $i \neq j$) as the same fashion as above. Putting everything together and rearranging, we get,

$$\frac{\sigma_w^2(b)}{\sigma_y^2(b)} - \frac{\sigma_w^2(a)}{\sigma_y^2(a)}$$

$$= \sum_i \sum_j \left[\bar{s}_i(b)\bar{s}_j(b) - \bar{s}_i(a)\bar{s}_j(a)\right]\left[\frac{\frac{\sigma_{x_i,x_j}(b)}{\sigma_y^2(b)} + \frac{\sigma_{x_i,x_j}(a)}{\sigma_y^2(a)}}{2}\right]^{(i)} +$$

$$\sum_i \sum_j \bar{s}_{ij}(a,b)\left\{\begin{array}{c} \left[\begin{array}{l} avg_{ab}\rho_{w_iw_j}\left(\frac{\sigma_{w_i}(b)\sigma_{w_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{w_i}(a)\sigma_{w_j}(a)}{\sigma_y^2(a)}\right) + \\ avg_{ab}\rho_{w_ih_j}\frac{\frac{\sigma_{h_j}(b)}{\sigma_y(b)}+\frac{\sigma_{h_j}(a)}{\sigma_y(a)}}{2}\left(\frac{\sigma_{w_i}(b)}{\sigma_y(b)} - \frac{\sigma_{w_i}(a)}{\sigma_y(a)}\right) \end{array}\right]^{(ii)} + \\ \left[\begin{array}{l} avg_{ab}\rho_{h_ih_j}\left(\frac{\sigma_{h_i}(b)\sigma_{h_j}(b)}{\sigma_y^2(b)} - \frac{\sigma_{h_i}(a)\sigma_{h_j}(a)}{\sigma_y^2(a)}\right) + \\ avg_{ab}\rho_{w_ih_j}\frac{\frac{\sigma_{w_i}(b)}{\sigma_y(b)}+\frac{\sigma_{w_i}(a)}{\sigma_y(a)}}{2}\left(\frac{\sigma_{h_j}(b)}{\sigma_y(b)} - \frac{\sigma_{h_j}(a)}{\sigma_y(a)}\right) \end{array}\right]^{(iii)} + \\ \left[2\frac{\frac{\sigma_{w_i}(b)\sigma_{h_j}(b)}{\sigma_y^2(b)}+\frac{\sigma_{w_i}(a)\sigma_{h_j}(a)}{\sigma_y^2(a)}}{2}\left[\begin{array}{c} \rho(w_i(b), h_j(b)) \\ -\rho(w_i(a), h_j(a)) \end{array}\right]\right]^{(iv)} \end{array}\right\}$$

where $\bar{s}_{ij}(a,b) = \frac{[\bar{s}_i(b)\bar{s}_j(b)+\bar{s}_i(a)\bar{s}_j(a)]}{2}$, and, using the same logic as above as above,

$avg_{ab}\rho_{w_i w_j}$ is defined as $\frac{\rho(w_i(b),w_j(b))+\rho(w_i(a),w_j(a))}{2}$, and so forth. Expression (i) is unchanged from the first term on the right-end side of equation (A.4) and measures the portion of the change in the relative variance of aggregate wages accounted for by compositional changes in the workforce as measured by the difference in wage shares. Expression (ii) is the portion of the change in the relative variance of aggregate wages accounted for by changes in relative wage volatility of different worker groups; expression (iii) is the portion accounted for by changes in the relative volatility of hours shares; and expression (iv) is the portion accounted for by changes in correlations coefficients across hourly wages and hours shares.

A.6 DSGE Model: Details

A.6.1 Model

The economy is populated by three types of agents: a continuum of infinitely-lived workers; a continuum of infinitely-lived firms; and a government that determines monetary and fiscal policy. Workers discount time at rate β and have preferences over consumption and leisure. Total expected lifetime utility of worker i is

$$\mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t Z_{t-1} \left[\log C_t - \frac{N_t(i)^{1+\phi}}{1+\phi} \right], \tag{A.6}$$

and the per period budget constraint is

$$C_t + K_{t+1} - (1-\delta)K_t + \frac{B_{t+1}}{R_t^n P_t} + T_t \leq \frac{W_t(i)N_t(i)}{P_t} + R_t^K K_t + \frac{B_t}{P_t} + D_t + \digamma_t(i). \tag{A.7}$$

$\mathbf{E}_0$ denotes the expectations operator; Z_{t-1} an exogenous preference shock common to all workers; C_t a composite consumption good; $N_t(i)$ hours worked; $K_{t+1} - (1-\delta)K_t$ investment in physical capital; B_t nominal bond holdings; T_t lump-sum taxes; D_t dividends from a perfectly diversified portfolio of claims to firms; $\digamma_t(h)$ the net return from a state-contingent insurance mechanism; $W_t(i)$ the nominal wage rate; R_t^K the real net rental rate of capital; R_t^n the gross nominal bond return; and P_t the aggregate price level. Labor income $W_t(i)N_t(i)$ is worker-specific due to the labor market frictions described below. As in Erceg et al. (2000), the net return $\digamma_t(i)$ is such that workers remain identical with respect to their consumption and savings decisions.

Workers' first-order conditions with respect to consumption, nominal bond holdings and capital are

$$\begin{aligned} \frac{Z_{t-1}}{C_t} &= \lambda_t, \\ \frac{\gamma\lambda_t}{R_t^n P_t} &= \beta E_t\left[\lambda_{t+1}\left(\frac{1}{P_{t+1}}\right)\right], \\ \gamma\lambda_t &= \beta E_t\left[\lambda_{t+1}(R_t^K + 1 - \delta)\right], \end{aligned} \tag{A.8}$$

where γ is deterministic growth (variables are normalized).

Each worker supplies a differentiated labor service and either belongs to a union or not. Firms produce with a labor composite N_t that is made up of union labor N_t^u and non-union labor N_t^{nu} according to the aggregator

$$N_t = \left[s^u(N_t^u)^{\frac{\mu-1}{\mu}} + s^{nu}(N_t^{nu})^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}}, \tag{A.9}$$

where s^u and $s^{nu} \equiv 1 - s^u$ are fixed weights that pin down the average wage shares of the union sector and the non-union sector; and $\mu > 1$ is the elasticity of substitution determining the extent to which firms can switch between union and non-union labor over the business cycle. Union and non-union labor are themselves a Dixit-Stiglitz aggregate of the differentiated labor services of union and non-union workers, respectively

$$N_t^l = \left[\int_0^1 N_t^l(i)^{\frac{\mu^l-1}{\mu^l}} dh\right]^{\frac{\mu^l}{\mu^l-1}} \quad \text{for } l \in \{u, nu\}. \tag{A.10}$$

The elasticities $\mu^u > 1$ and $\mu^{nu} > 1$ determine the extent to which union workers and non-union workers, respectively, are substitutable among each other. Given (A.9) and (A.10), we can find the firms' optimal labor demand for a union worker charging $W_t^u(h)$ and for a non-union worker charging $W_t^{nu}(h)$ by solving the following cost-minimization problem

$$\begin{aligned}
&\min_{N_t^u, N_t^{nu}} \; W_t^u N_t^u + W_t^{nu} N_t^{nu} \\
&s.t. \quad \left(\left[s^u (N_t^u)^{\frac{\mu-1}{\mu}} + (1-s^u)(N_t^{nu})^{\frac{\mu-1}{\mu}}\right]^{\frac{\mu}{\mu-1}} \leq N_t\right)
\end{aligned}$$

The first-order conditions are

$$\begin{aligned}
\frac{W_t^u}{W_t} &= N_t^{1/\mu} s^u (N_t^u)^{-1/\mu} \qquad \text{(A.11)} \\
\Rightarrow \; N_t^u &= \left[\frac{1}{s^u}\left(\frac{W_t^u}{W_t}\right)\right]^{-\mu} N_t.
\end{aligned}$$

Thus, the demand for each individual worker i in the union sector is

$$N_t^u(i) = \left(\frac{W_t^u(i)}{W_t^u}\right)^{-\mu^u} N_t^u.$$

Substituting (A.11) into the above equation yields

$$N_t^u(i) = \left(\frac{W_t^u(i)}{W_t^u}\right)^{-\mu^u} \times \left(\frac{1}{s^u}\frac{W_t^u}{W_t}\right)^{-\mu} N_t \tag{A.12}$$

Thus we can generalize this labor demand for both union and non-union workers as

$$N_t^l(i) = \left(\frac{W_t^l(i)}{W_t^l}\right)^{-\mu^l} \times \left(\frac{1}{s^l}\frac{W_t^l}{W_t}\right)^{-\mu} N_t \quad \text{for } l \in \{u, nu\}, \tag{A.13}$$

where W_t^u and W_t^{nu} denote the aggregate union and non-union wage; and W_t is the aggregate index of the labor composite N_t that firms use to produce, and can be written as

$$W_t^{1-\mu} = \left[\left(\frac{1}{s^u}\right)^{-\mu} (W_t^u)^{1-\mu} + \left(\frac{1}{1-s^u}\right)^{-\mu} (W_t^{nu})^{1-\mu}\right] \tag{A.14}$$

$$W_t^{1-\mu} = \left[(s^u)^{\mu} (W_t^u)^{1-\mu} + (1-s^u)^{\mu} (W_t^{nu})^{1-\mu}\right] \tag{A.15}$$

Performance-pay workers in either the union or the non-union sector can adjust their wages with time t information. In each period, these workers therefore solve the following problem

$$\max_{W_t^{l,p}(i)} \left[\frac{1}{C_t}\frac{W_t^{l,p}(i)}{P_t} N_{t+j}^{l,p}(i) - \frac{N_{t+j}^{l,p}(i)^{1+\phi}}{1+\phi}\right]$$

for $l \in \{u, nu\}$, where $N_{t+j}^{l,p}(i)$ is given by (A.13). The resulting first-order condition is

$$\frac{W_t^{l,p}(i)}{P_t} = \frac{\mu^l}{\mu^l - 1} N_t^{l,p}(i)^{\phi} C_t \quad \text{for } l \in \{u, nu\}, \tag{A.16}$$

where $N_t^{l,p}(i)^{\phi} C_t$ is the marginal rate of substitution; and $\frac{\mu^l}{\mu^l-1}$ is the optimal markup that performance-pay workers command because they provide a differentiated labor service to the firm. The higher μ^l, the more substitutable labor services are and thus, the lower the markup.

Workers without performance-pay set nominal wages in advance of time t information according to a variant of Erceg et al. (2000). In the union sector, the fraction of non-performance-pay workers (or equivalently, the fraction of unions) that get to reoptimize their nominal wage for next period is $1 - \xi^u$. In the non-union sector, the equivalent fraction is $1-\xi^{nu}$. For all other non-performance pay workers (a fraction ξ^u in the union sector and a fraction ξ^{nu} in the non-union sector), wages are indexed to the steady state growth rate of consumption γ and partially to realized gross inflation Π_{t-1}; i.e. their nominal wage adjusts according to $W_t^{l,np}(i) = \gamma \Pi_{t-1}^{\omega} W_{t-1}^{l,np}(i)$ with ω denoting the inflation indexing factor. The optimal wage contract of a non-performance-pay worker who gets to reoptimize for time t therefore solves

$$\max_{W_t^{l,np}(i)} E_{t-1} \sum_{j=0}^{\infty} (\beta\xi^l)^j \left[\frac{1}{C_{t+j}} \frac{W_t^{l,np}(i) X_{t,t+j}}{P_{t+j}} N_{t+j}^{l,np}(i) - \frac{N_{t+j}^{l,np}(i)^{1+\phi}}{1+\phi} \right] \quad for\ l \in \{u, nu\} \tag{A.17}$$

subject to labor demand (A.13) and

$$X_{t,t+j} \equiv \prod_{s=1}^{j} \gamma \Pi_{t+s-1}^{\omega} \text{ for } j \geq 1 \text{ and } X_{t,t+j} = 1 \text{ for } j = 0$$

Alternatively, we can write this problem as

$$\max_{W_t^{l,np}(i)} E_{t-1} \sum_{j=0}^{\infty} (\beta\xi^l)^j \left[\frac{W_t^{l,np}(i) X_{t,t+j}}{P_{t+j}} - mrs_{t+j}^{l,np}(i) \right] N_{t+j}^{l,np}(i) \quad for\ l \in \{u, nu\}$$

subject to same conditions as above, and where $mrs_{t+j}^{l,np}(i) = C_{t+j} N_{t+j}^{l,np}(i)^{\phi}$ denotes the marginal rate of substitution of worker i in sector l who is not performance-paid. Now, use constraints in (A.17) and rewrite the problem as

$$\max_{W_t^{l,np}(i)} E_{t-1} \sum_{j=0}^{\infty} (\beta\xi^l)^j \left[\begin{array}{c} \lambda_{t+j} \frac{\left(W_t^{l,np}(i) X_{t,t+j}\right)^{1-\mu^l}}{P_{t+j}\left(W_{t+j}^{l,np}\right)^{-\mu^l}} N_{t+j}^{l,np} \\ -\frac{1}{1+\phi} \left(\frac{W_t^{l,np}(i) X_{t,t+j}}{W_{t+j}^{l,np}} \right)^{-\mu^l(1+\phi)} \left(N_{t+j}^{l,np} \right)^{1+\phi} \end{array} \right] \quad for\ l \in \{u, nu\}$$

The first-order condition is

$$
\begin{aligned}
0 &= E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left[\begin{array}{c}(1-\mu^l)\frac{\lambda_{t+j}W_t^{l,np}(i)^{-\mu^l}X_{t,t+j}^{1-\mu^l}}{P_{t+j}\left(W_{t+j}^{l,np}\right)^{-\mu^l}}N_{t+j}^{l,np} \\ +\mu^l W_t^{l,np}(i)^{-\mu^l(1+\phi)-1}\left(\frac{X_{t+j}}{W_{t+j}^{l,np}}\right)^{-\mu^l(1+\phi)}\left(N_{t+j}^{l,np}\right)^{1+\phi}\end{array}\right] \\
&= E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left[(1-\mu^l)\frac{\lambda_{t+j}X_{t,t+j}}{P_{t+j}}N_{t+j}^{l,np}(i)+\mu^l\frac{N_{t+j}^{l,np}(i)^{1+\phi}}{W_t^{l,np}(i)}\right] \\
&= E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left[(1-\mu^l)\frac{\lambda_{t+j}X_{t,t+j}}{P_{t+j}}N_{t+j}^{l,np}(i)+\mu^l\frac{mrs_{t+j}^{l,np}(i)\lambda_{t+j}N_{t+j}^{l,np}(i)}{W_{t+j}^{l,np}(i)}\right]
\end{aligned}
$$

The optimal wage that solves the above problem is thus

$$
W_t^{l,np^*}(i)=\frac{\mu^l}{\mu^l-1}\frac{E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left\{\lambda_{t+j}mrs_{t+j}^{l,np}(i)N_{t+j}^{l,np}(i)\right\}}{E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left\{\lambda_{t+j}\frac{X_{t,t+j}}{P_{t+j}}N_{t+j}^{l,np}(i)\right\}} \tag{A.18}
$$

Notice that expectations are taken w.r.t. to $t-1$ by assumption of the timing described above. Since (by assumption) the reoptimization problem does not depend on a household's prior situation but only on aggregate states, each reoptimizing household will set the same optimal wage; i.e. $W_t^*(i)=W_t^*$. Furthermore, since the reoptimizing wage setters are chosen at random, the non-reoptimizing households have on average a period t wage equal to $\gamma W_{t-1}\Pi_{t-1}^{\omega}$. The aggregate nominal wage for non-performance paid workers is therefore

$$
\left(W_t^{l,np}\right)^{1-\mu}=(1-\xi^l)\left(W_t^{*l,np}\right)^{1-\mu}+\xi^l\left(\gamma W_{t-1}^{l,np}\Pi_{t-1}^{\omega}\right)^{1-\mu}. \tag{A.19}
$$

The rest of the model is standard. Firms produce output Y_t with Cobb-Douglas technology

$$Y_t = A_t N_t^{1-\alpha} K_t^{\alpha}, \tag{A.20}$$

where A_t is an exogenous technology shock. Each firm's good represents a differentiated intermediate that is sold to a wholesaler who turns the different intermediate goods into a final composite using the Kimball (1995) aggregator.[18] Firm sets prices according to Calvo (1983) partial adjustment mechanism, with each firm facing a constant probability in any given period of being able to reoptimize its price. Finally, the government conducts monetary policy according to the following interest rate rule

$$R_t^n = \left(R_{t-1}^n\right)^{\rho} \left(\Pi_t\right)^{(1-\rho)\theta_{\pi}} \left(Y_t / Y_{t-1}\right)^{(1-\rho)\theta_y}. \tag{A.21}$$

and limits fiscal policy to a constant spending rule that is fully financed by lump-sum taxes.

A.6.2 Some linearizations

Before linearizing, we need to normalize the variables to take care of the deterministic growth (γ) in our model; i.e. from now on we define $\lambda_{t+j} = \lambda_{t+j}\gamma^{t+j}$, $mrs_{t+j}^{l,np} = mrs_{t+j}^{l,np}/\gamma^{t+j}$, etc. for the other macro aggregates.

Next, we linearize the normalized variables of the optimal wage equation around

[18] Kimball's (1995) aggregator is a generalization of the Dixit-Stiglitz aggregator and provides flexibility in mapping micro data on price adjustment to aggregate inflation dynamics. See, for example, Eichenbaum and Fisher (2007).

the respective steady state values; i.e.

$$
\begin{aligned}
\ln\left(W_t^{l,np^*}(i)\right) &= \ln\left(\frac{\mu^l}{\mu^l-1}\right) + \ln\left(E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left\{\lambda_{t+j}mrs_{t+j}^{l,np}(i)N_{t+j}^{l,np}(i)\right\}\right) \\
&\quad - \ln\left(E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left\{\lambda_{t+j}\frac{X_{t,t+j}}{P_{t+j}}N_{t+j}^{l,np}(i)\right\}\right) \\
\widehat{W_t^{l,np^*}}(i) &= \frac{1}{\sum_{j=0}^{\infty}(\beta\xi^l)^j}\left[\begin{array}{c} E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left(\begin{array}{c}\widehat{\lambda}_{t+j}+\widehat{mrs}_{t+j}^{l,np}(i) \\ +\widehat{N_{t+j}^{l,np}}(i)\end{array}\right) \\ -E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left(\begin{array}{c}\widehat{\lambda}_{t+j}+\widehat{X}_{t,t+j} \\ -\widehat{P}_{t+j}+\widehat{N_{t+j}^{l,np}}(i)\end{array}\right)\end{array}\right] \\
\widehat{W_t^{l,np^*}}(i) &= (1-\beta\xi^l)E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left[\widehat{mrs}_{t+j}^{l,np}(i)-\widehat{X}_{t,t+j}+\widehat{P}_{t+j}\right],
\end{aligned}
$$

where hatted variables represent percent deviations from the respective steady states. Likewise, linearize $X_{t,t+j}$ as

$$
\begin{aligned}
\ln(X_{t,t+j}) &= \sum_{s=1}^{\infty}\ln\left(\gamma\Pi_{t+s-1}^{\omega}\right) \\
\widehat{X}_{t,t+j} &= \omega\sum_{s=1}^{\infty}\widehat{\Pi}_{t+s-1} = \omega\left(\widehat{\Pi}_t+\widehat{\Pi}_{t+1}+...+\widehat{\Pi}_{t+j-1}\right)
\end{aligned}
$$

noticing that

$$
\begin{aligned}
\widehat{P}_{t+j}-\widehat{P}_{t-1} &= \widehat{P}_{t+j}-\widehat{P}_{t+j-1}+\widehat{P}_{t+j-1}-\widehat{P}_{t+j-2}+...+\widehat{P}_t-\widehat{P}_{t-1} \\
&= \widehat{\Pi}_{t+j}+\widehat{\Pi}_{t+j-1}+...+\widehat{\Pi}_t;
\end{aligned}
$$

and linearize $mrs_{t+j}^{l,np}(i)$ as

$$\begin{aligned}
mrs_{t+j}^{l,np}(i) &= C_{t+j}N_{t+j}^{l,np}(i)^{\phi} \qquad \text{(A.22)}\\
\widehat{mrs}_{t+j}^{l,np}(i) &= \phi\widehat{N}_{t+j}^{l,np}(i)+\widehat{C}_{t+j}\\
\text{and }\ \widehat{N}_{t+j}^{l,np}(i) &= -\mu^{l}\left(\widehat{W}_{t}^{l,np*}(i)+\widehat{X}_{t,t+j}-\widehat{W}_{t+j}^{l,np}\right)+\widehat{N}_{t+j}^{l,np}\\
&\Rightarrow\ \widehat{mrs}_{t+j}^{l,np}(i) = -\mu^{l}\phi\left(\widehat{W}_{t}^{l,np*}(i)+\widehat{X}_{t,t+j}-\widehat{W}_{t+j}^{l,np}\right)+\widehat{mrs}_{t+j}^{l,np}
\end{aligned}$$

We can thus rewrite the linearized optimal wage as

$$\begin{aligned}
\widehat{W}_{t}^{l,np*}(i) &= (1-\beta\xi^{l})E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^{l})^{j}\left[\begin{array}{c}\widehat{mrs}_{t+j}^{l,np}+\widehat{P}_{t+j}-\widehat{X}_{t,t+j}\\ -\mu^{l}\phi\left(\begin{array}{c}\widehat{W}_{t}^{l,np*}(i)+\\ \widehat{X}_{t,t+j}-\widehat{W}_{t+j}^{l,np}\end{array}\right)\end{array}\right] \qquad \text{(A.23)}\\
(1+\mu\phi)\widehat{W}_{t}^{l,np*} &= (1-\beta\xi^{l})E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^{l})^{j}\left[\begin{array}{c}\mu^{l}\phi\widehat{W}_{t+j}^{l,np}-(1+\mu^{l}\phi)\widehat{X}_{t,t+j}\\ +\widehat{P}_{t+j}+\widehat{mrs}_{t+j}^{l,np}\end{array}\right],
\end{aligned}$$

where we replaced $\widehat{W_{t}^{l,np*}}(i)=\widehat{W_{t}^{l,np*}}$ because the wage setting history of reoptimizing individuals does not matter for the optimal new wage. Finally, the average wage for group l,np is

$$(W_{t}^{l,np})^{1-\mu^{l}}=(1-\xi^{l})(W_{t}^{l,np*})^{1-\mu^{l}}+\xi^{l}\left(\gamma W_{t-1}^{l,np}\Pi_{t-1}^{\omega}\right)^{1-\mu^{l}}$$

Linearizing, we get

$$\widehat{W}_{t}^{l,np}=(1-\xi^{l})\widehat{W}_{t}^{l,np*}+\xi^{l}\left(\widehat{W}_{t-1}^{l,np}+\omega\widehat{\Pi}_{t-1}\right) \qquad \text{(A.24)}$$

Notice that $\hat{W}_{t}^{l,np}$ is a predetermined variable (i.e. $E_{t-1}\hat{W}_{t}^{l,np}=\hat{W}_{t}^{l,np}$) because $\hat{W}_{t}^{l,np*}$, $\hat{W}_{t-1}^{l,np}$ and $\widehat{\Pi}_{t-1}$ are predetermined. Hence, we'll use the two expressions interchangeably below.

Now, rewrite (A.23) as

$$\begin{aligned}(1+\mu^l\phi)\widehat{W}_t^{l,np*} &= (1-\beta\xi^l)E_{t-1}\left[\mu^l\phi\widehat{W}_t^{l,np}+\widehat{mrs}_t^{l,np}+\widehat{P}_t\right] \\ &\quad +\beta\xi^l E_{t-1}\sum_{j=0}^{\infty}(\beta\xi^l)^j\left[\begin{array}{c}\mu^l\phi\widehat{W}_{t+1+j}^{l,np}-(1+\mu^l\phi)\widehat{X}_{t+1,t+1+j} \\ +\widehat{mrs}_{t+1+j}^{l,np}+\widehat{P}_{t+1+j}\end{array}\right] \\ &= (1-\beta\xi^l)E_{t-1}\left[\mu^l\phi\widehat{W}_t^{l,np}+\widehat{mrs}_t^{l,np}+\widehat{P}_t\right] \\ &\quad +(1+\mu^l\phi)\beta\xi^l E_{t-1}\widehat{W}_{t+1}^{l,np*}.\end{aligned}$$

where we made use of the fact that $\hat{X}_{t,t}=0$. Next, we use (A.24) to sub out the the optimal wage

$$(1+\mu^l\phi)\left[\begin{array}{c}\frac{1}{1-\xi^l}\widehat{W}_t^{l,np} \\ -\frac{\xi^l}{1-\xi^l}\left(\widehat{W}_{t-1}^{l,np}+\omega\widehat{\Pi}_{t-1}\right)\end{array}\right]=$$

$$\begin{aligned}&(1-\beta\xi^l)E_{t-1}\left[\mu^l\phi\widehat{W}_t^{l,np}+\widehat{mrs}_t^{l,np}+\widehat{P}_t\right] \\ &+(1+\mu^l\phi)\beta\xi^l E_{t-1}\left[\begin{array}{c}\frac{1}{1-\xi^l}\widehat{W}_{t+1}^{l,np} \\ -\frac{\xi^l}{1-\xi}\left(\widehat{W}_t^{l,np}+\omega\widehat{\Pi}_t\right)\end{array}\right].\end{aligned}$$

On the left-hand side, expand by $(1-\mu^l\phi)\frac{\xi^l}{1-\xi^l}\widehat{W}_t^{l,np}$; on the right-hand side, expand by $(1-\mu^l\phi)\beta\xi^l E_{t-1}\frac{1}{1-\xi^l}\widehat{W}_t^{l,np}$to obtain

$$\begin{aligned}(1+\mu^l\phi)\frac{\xi^l}{1-\xi^l}\left[\begin{array}{c}\Delta\widehat{W}_t^{l,np} \\ -\omega\widehat{\Pi}_{t-1}\end{array}\right] &= (1-\beta\xi^l)E_{t-1}\left[\mu^l\phi\widehat{W}_t^{l,np}+\widehat{mrs}_t^{l,np}+\widehat{P}_t\right] \\ &\quad -(1+\mu^l\phi)\widehat{W}_t^{l,np}+(1+\mu^l\phi)\beta\xi^l\widehat{W}_t^{l,np} \\ &\quad +(1+\mu^l\phi)\beta\frac{\xi^l}{1-\xi^l}E_{t-1}\left[\Delta\widehat{W}_{t+1}^{l,np}-\omega\widehat{\Pi}_t\right]\end{aligned}$$

or, after rearranging,

$$\Delta\widehat{W}_t^{l,np} - \omega\widehat{\Pi}_{t-1} = \Omega^l E_{t-1}\left[\widehat{mrs}_t^{l,np} - \widehat{W}_t^{l,np} + \widehat{P}_t\right] + \beta E_{t-1}\left[\Delta\widehat{W}_{t+1}^{l,np} - \omega\widehat{\Pi}_t\right]. \tag{A.25}$$

with

$$\Omega^l \equiv \frac{\left(1-\xi^l\right)\left(1-\beta\xi^l\right)}{\xi^l(1+\mu^l\phi)}. \tag{A.26}$$

Ω^l is a measure of wage flexibility; i.e. to what extent wages respond to expected changes in the expected markup of the real wage over the marginal rate of substitution.

Equation (A.25) is the linearized average nominal wage equation for group l, np. It can be rewritten in different ways. Most useful for us is to write it in terms of the real wage that firms use to determine their aggregate labor demand; i.e. $\widehat{w}_t^{l.np} \equiv \widehat{W}_t^{l,np} - \widehat{P}_t$. As opposed to the nominal wage $\widehat{W}_t^{l,np}$, this real wage is not predetermined because it depends on the realized time t price level $\widehat{P}_t$. To obtain an expression for the real wage, take (A.25) and rewrite it as

$$\begin{aligned}(\widehat{w}_t^{l.np} - \widehat{w}_{t-1}^{l.np}) + \widehat{\Pi}_t - \omega\widehat{\Pi}_{t-1} &= \Omega^l E_{t-1}\left[\widehat{mrs}_t^{l,np} - \widehat{w}_t^{l.np}\right] \\ &\quad + \beta E_{t-1}\left[(\widehat{w}_{t+1}^{l.np} - \widehat{w}_t^{l.np}) + \widehat{\Pi}_{t+1} - \omega\widehat{\Pi}_t\right]\end{aligned}$$

$$\begin{aligned}\widehat{w}_t^{l.np} + (\beta+\Omega^l)E_{t-1}\widehat{w}_t^{l.np} &= \widehat{w}_{t-1}^{l.np} - \widehat{\Pi}_t + \omega\widehat{\Pi}_{t-1} + \Omega^l E_{t-1}\widehat{mrs}_t^{l,np} \\ &\quad + \beta E_{t-1}\left[\widehat{w}_{t+1}^{l.np} + \widehat{\Pi}_{t+1} - \omega\widehat{\Pi}_t\right]\end{aligned}$$

or equivalently

$$\begin{aligned}\widehat{w}_t^{l.np} + \beta E_{t-1}\widehat{w}_t^{l.np} &= \widehat{w}_{t-1}^{l.np} + \beta E_{t-1}[\widehat{w}_{t+1}^{l.np} + \widehat{\Pi}_{t+1}] \\ &\quad -(\widehat{\Pi}_t + \beta\omega E_{t-1}\widehat{\Pi}_t) + \omega\widehat{\Pi}_{t-1} + \Omega^l E_{t-1}\left[\widehat{mrs}_t^{l,np} - \widehat{w}_t^{l.np}\right]\end{aligned}$$

After separating expectations from realized terms, we obtain

$$(1+\beta+\Omega^l)\widehat{w}_t^{l,np} = \widehat{w}_{t-1}^{l,np} + \beta E_{t-1}[\widehat{w}_{t+1}^{l,np} + \widehat{\Pi}_{t+1}] \tag{A.27}$$

$$-(1+\beta\omega)\widehat{\Pi}_t + \omega\widehat{\Pi}_{t-1} + \Omega^l E_{t-1}\widehat{mrs}_t^{l,np} \tag{A.28}$$

$$+(\beta+\Omega^l)(\widehat{w}_t^{l,np} - E_{t-1}\widehat{w}_t^{l,np})$$

$$+\beta\omega(\widehat{\Pi}_t - E_{t-1}\widehat{\Pi}_t) \tag{A.29}$$

The last two terms take into account that workers in group l, np set wages based on $t-1$ information. Specifically, if $\widehat{w}_t^{l.np} - E_{t-1}\widehat{w}_t^{l.np} < 0$ (ceteris paribus), then nominal wages (and thus real wages) are set lower because workers expect their markup to be higher and future nominal wage growth to be lower. Likewise if $\widehat{\Pi}_t - E_{t-1}\widehat{\Pi}_t < 0$ (ceteris paribus), then nominal wages (and thus real wages) are set lower because workers expect future optimal wages to be lower.

Next, we list the various linearized wage setting equations that together drive the aggregate real wage of the economy. First, note that the aggregate wage can then be described by linearizing (**??**) and using the steady state demands for unionized and non-unionized labor

$$\begin{aligned}\widehat{W}_t &= s^{\mu}\left(\frac{W^u}{W}\right)_t^{1-\mu}\widehat{W}_t^u + (1-s)^{\mu}\left(\frac{W^{nu}}{W}\right)^{1-\mu}\widehat{W}_t^{nu} \\ &= \frac{W^uN^u}{WN}\widehat{W}_t^u + \frac{W^{nu}N^{nu}}{WN}\widehat{W}_t^{nu}\end{aligned} \tag{A.30}$$

Since $\frac{W^uN^u}{WN} + \frac{W^{nu}N^{nu}}{WN} = 1$ by definition, this equation also holds in real terms

$$\begin{aligned}\widehat{w}_t &= \frac{W^uN^u}{WN}\widehat{w}_t^u + \frac{W^{nu}N^{nu}}{WN}\widehat{w}_t^{nu} \\ &= s^u\widehat{w}_t^u + (1-s^u)\widehat{w}_t^{nu}\end{aligned} \tag{A.31}$$

Next, the average union and non-union wage evolve according to

$$\left(W_t^l\right)^{1-\mu^l} = p^l \left(W_t^{l,p}\right)^{1-\mu^l} + (1-p^l) \left(W_t^{l,np}\right)^{1-\mu^l}, \quad for\ l \in \{u, nu\}$$

or in linearized terms

$$\widehat{W}_t^l = p^l \left(\frac{W^{l,p}}{W^l}\right)^{1-\mu^l} \widehat{W}_t^{l,p} + (1-p^l) \left(\frac{W^{l,np}}{W^l}\right)^{1-\mu^l} \widehat{W}_t^{l,np}, \quad for\ l \in \{u, nu\}$$

But in steady state, $W^{l,p} = W^l = W^{l,np}$. Hence,

$$\widehat{w}_t^l = p^l \widehat{w}_t^{l,p} + \left(1-p^l\right) \widehat{w}_t^{l,np} \quad for\ l \in \{u, nu\}. \tag{A.32}$$

Combining (A.31) with (A.32), we obtain

$$\begin{aligned} \widehat{w}_t &= s^u \widehat{w}_t^u + (1-s^u)\widehat{w}_t^{nu} \qquad \text{(A.33)} \\ &= s^u \left(p^u \hat{w}_t^{u,p} + (1-p^u)\, \hat{w}_t^{u,np}\right) + \left(p^{nu} \hat{w}_t^{nu,p} + (1-p^{nu})\, \hat{w}_t^{nu,np}\right). \end{aligned}$$

From here, (A.16) implies that the linearized real wage for performance-pay worker equals

$$\widehat{w}_t^{l,p} = \widehat{mrs}_t^{l,p} \quad for\ l \in \{u, nu\} \tag{A.34}$$

In turn, the linearized real wage for non-performance-pay workers is determined by equation (A.27). Now, we can link these equations for unionized non-performance and performance wages to aggregate mrs by using the above loglinearized equations

$$\begin{aligned} \widehat{mrs}_t^{u,np} &= -\mu^u \phi(\widehat{w}_t^{u,np} - \widehat{w}_t^u) + \widehat{mrs}_t^u \qquad \text{(A.35)} \\ &= -\mu^u \phi(\widehat{w}_t^{u,np} - \widehat{w}_t^u) - \mu\phi(\widehat{w}_t^u - \widehat{w}_t) + \widehat{mrs}_t \end{aligned}$$

and

$$\widehat{mrs}_t^{u,p} = -\mu^u \phi(\widehat{w}_t^{u,p} - \widehat{w}_t^u) - \mu\phi(\widehat{w}_t^u - \widehat{w}_t) + \widehat{mrs}_t. \tag{A.36}$$

The analogue system of linearized equations can be derived for the non-unionized sector. Equations (A.27) and (A.33)-(A.36) provide a system of equations that implicitly defines the link between aggregate mrs and the aggregate wage. The sensitivity of this link depends on the weights s^u, p^u, p^{nu} and the slope coefficients Ω^u and Ω^{nu}.

For the rest of the economy, the log-linearized equations are standard. Specifically, the (normalized) first-order conditions for investment in nominal bonds and physical capital imply

$$\widehat{C}_t = E_t\widehat{C}_{t+1} - (\widehat{R}_t^n - E_t\widehat{\Pi}_{t+1}) - \Delta\widehat{Z}_t, \tag{A.37}$$

$$\widehat{C}_t = E_t\widehat{C}_{t+1} - \beta r^k E_t\widehat{R}_{t+1}^k - \Delta\widehat{Z}_t. \tag{A.38}$$

The production function, in linearized form is

$$\widehat{Y}_t = \widehat{A}_t + \alpha\widehat{K_t} + (1-\alpha)\widehat{N}_t, \tag{A.39}$$

From the firms' optimization problem above, the relevant, log-linearized first-order conditions are for labor and capital inputs are

$$\widehat{w}_t = \widehat{W}_t - \widehat{P}_t = \widehat{mc}_t + \widehat{Y}_t - \widehat{N}_t \tag{A.40}$$

$$\widehat{R_t^k} = \widehat{mc}_t + \widehat{Y}_t - \widehat{K}_t, \tag{A.41}$$

where mc_t denotes real marginal cost. Finally, the log-linearized optimal pricing equation by firms together with the loglinearized equation for the aggregate price level yield, together, the familiar New Keynesian Phillips curve (NKPC)

$$\widehat{\Pi}_t = \beta E_t \widehat{\Pi}_{t+1} + \kappa \widehat{mc}_t, \tag{A.42}$$

where κ is a non-linear combination of Calvo pricing and Kimball aggregator parameters (see for example Eichenbaum and Fisher, 2007). In turn, the loglinearized interest rate rule to which monetary policy adheres is

$$\widehat{R^n_t} = \rho \widehat{R^n_{t-1}} + (1-\rho)[\theta_\pi \widehat{\Pi}_t + \theta_y (\widehat{Y}_t - \widehat{Y}_{t-1})]. \tag{A.43}$$

A.7 Model analysis

The simulation exercise in the paper proceeds in four steps. First, we simulate the model with all parameters set to their pre-84 values. Second, we change the shock process calibration to the post-84 estimates and assess to what extent the 'good luck hypothesis' can generate an increase in relative wage volatility. Third, we change $\frac{W^u N^u}{WN}$, p^u and p^{nu} to their post-84 values while keeping the shock processes at their pre-1984 estimates to evaluate the effects of deunionization and higher incidence of performance-pay. Fourth, we simulate the model with both the shock processes and $\frac{W^u N^u}{WN}$, p^u and p^{nu} set to their post-84 values to obtain the joint effect of all changes.

To understand the results obtained in the steps above, it is useful to consider a graphical illustration of the labor market, with the wage setting curve W^S approximating the aggregation of the different optimal wage conditions in (A.33)-(A.36) and the curve L^D representing aggregate labor demand in (A.40). Figure 3a depicts the response to a positive technology shock. Starting from point A, the technology shock moves labor demand to the right and shifts up the wage setting curve due to the positive income effect on the marginal rate of substitution. The new equilibrium establishes at point B. Smaller technology shocks change the size of these shifts and thus affect the *absolute magnitude* of the reaction in the real wage and labor. However, since the structure behind the two curves remains the same, the *relative magnitude* of adjustments in the real wage and labor remain more or less unchanged.[19] Figure 3b illustrates the effect of a preference shock. The preference shock reduces current consumption, implying a negative income effect that shifts the wage setting curve down. Aside from negligible equilibrium effects on the average markup, the labor demand schedule remains unaffected and thus, the economy adjusts from point A to point B. Similar to the technology shock, smaller preference shocks result in smaller shifts of the wage setting curve. But as long as the slope of this curve remains unchanged, the relative magnitude of adjustments in w and n remains approximately the same. This explains why changes in technology and preference shocks have hardly any effect on the *relative* volatility of wages. By contrast, changes in the relative importance of technology and preference shocks can have important effects on the cyclicality of wages and labor productivity. Technology shocks imply that both wages and labor productivity co-move with hours whereas preference shocks imply exactly the opposite. Hence, when preference shocks become relatively more important, the correlation of wages and labor productivity with hours (and thus output) falls and may even become negative. The graphical illustration suggests that similar conclusions apply for other exogenous shocks that shift either the wage setting curve (e.g. labor supply shocks, government spending shocks) or labor demand (e.g. monetary policy shocks). We confirm this conjecture in the next section of this appendix.

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[19] Our explanation ignores dynamic general equilbrium effects coming through movements in inflation that affect the two curves.

In the next step, we reset the shocks to their pre-1984 calibrations and change the labor parameters (what we call "deunionization" and "increased incidence of performance-pay"). It is again useful to consider a graphical illustration to understand the mechanisms behind the results obtained in this step. Figure 4a depicts the impact of a positive technology shock in a labor market with a relatively steep and a relatively flat wage setting curve. The relatively flat wage setting curve corresponds to a labor market with widespread unionization and little performance-pay where movements in the marginal rate of substitution have little contemporaneous effect on wage setting. A positive technology shock in such a situation leads to a relatively small change in equilibrium wages but a large change in labor and output (point B). As unionization declines and performance-pay becomes more widespread, wage setting increasingly depends on the marginal rate of substitution. The wage setting curve steepens and shifts more with general equilibrium income effects. As a result, the same positive technology shock now implies a much larger equilibrium response of wages relative to the equilibrium response of hours (point C). Furthermore, the correlation of wages with output conditional on technology shocks increases with wage flexibility because the reaction of wages becomes more contemporaneous. Likewise, the conditional correlation of labor productivity with output and hours increases with wage flexibility because productivity shocks affect output proportionally more than hours (due to decreasing returns to scale of hours in production). Figure 4b depicts the impact of a positive preference shock for the same two labor market situations. When unionization is widespread and there is little performance-pay, the income effect of the preference shock is small. Hence, the economy moves to new equilibrium point B, where wages adjust relatively little. Instead, when there is little unionization and performance-pay is widespread, the income effect of the preference shock is larger and the economy ends up at point C where the response of both wages and hours is larger. The larger shifts in the wage setting curve make wages more countercyclical conditional on preference shocks and labor productivity less procyclical (due to decreasing returns to scale of hours in production).

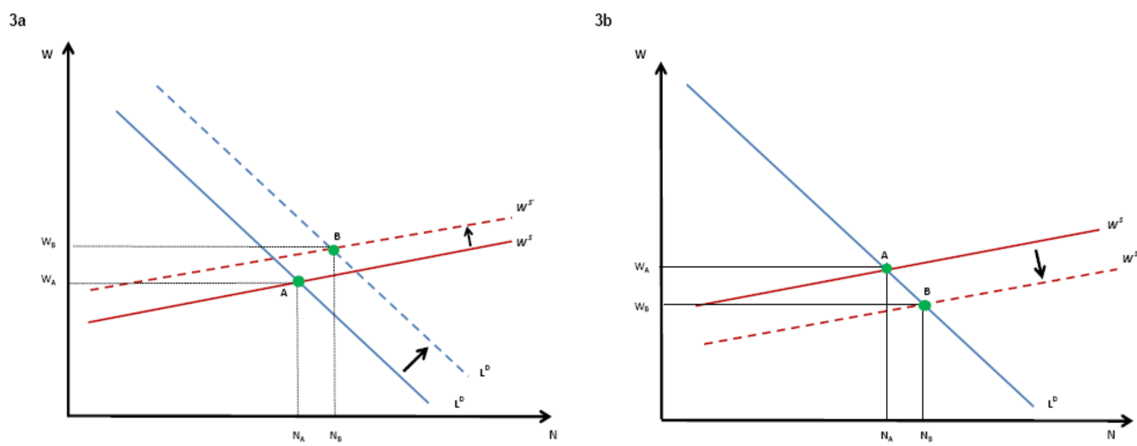

Figure A.3 Labor market responses to a positive technology shock (left) and a preference shock (right)

A.8 Robustness to other shocks

Here we present results for the model of Section 4 with three alternative shocks. We keep the technology shock as it is in the paper, but replace the preference shock with first a labor supply shock, then a monetary policy shock, and finally a government spending shock. The labor supply shock acts on the household's utility function, influencing the marginal rate of substitution between consumption and leisure; the monetary policy shock is a stochastic disturbance term to the interest rate rule; and finally, the government spending shock renders the government transfers (collected from lump-sum taxes) stochastic.

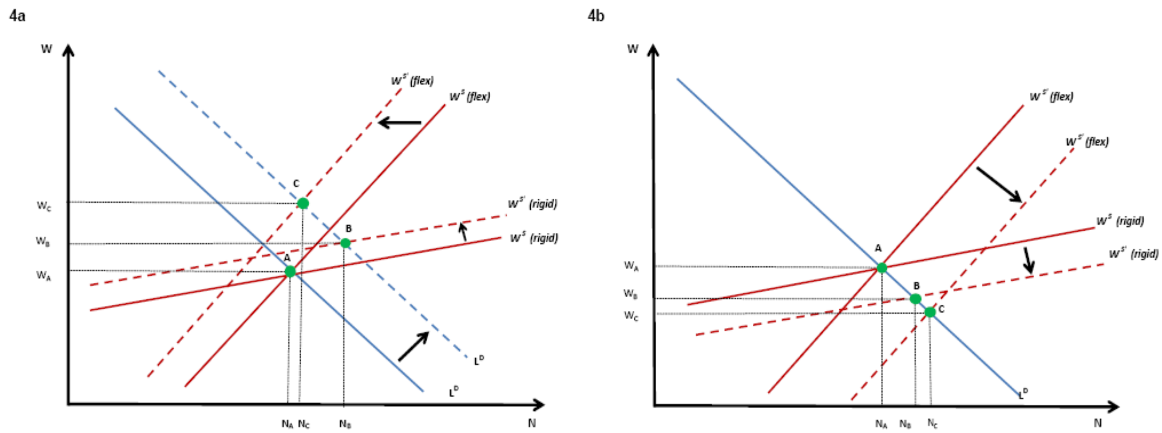

Figure A.4 Labor market responses to a technology shock (left) and a preference shock (right) under rigid and flexible wage setting

For each of the three shocks, we specify an AR(1) process. As described in the paper, none of these processes can be estimated easily from the data since we are missing observable measures of the shocks (or observable measures cannot be easily inferred from model equations). Our calibration strategy therefore consists of specifying the respective non-technology shock process such that the model generates the pre-84 volatility of output conditional on the pre-84 calibration of all model parameters and the technology shock, as described in Table 1.7 of the paper. Then, we change the calibration of the technology shock process to its post-1984 estimate while keeping all other parameters including the parameters for the respective non-technology shock process at their pre-1984 calibration values. As a result, the relative importance of the technology shock process becomes substantially smaller. The main goal of this strategy is to assess whether large changes in the relative importance of exogenous shocks can generate an increase in the relative volatility of wages.

As Table A.10 shows, none of the three alternative shock processes change any of the results even though there is a large decrease in the relative importance of the technology shock in each case. In particular, the relative volatility of the real wage remains more or less unchanged. Therefore, we conclude that the results reported in the paper are robust to a variety of alternative popular non-technology shocks. Table A.10 also shows that the large reduction in the relative importance of the

	US Data			Labor Supply Shock		Monetary Policy Shock		Govt Spending Shock	
				Pre-84 calibration,		*Pre-84 calibration,*		*Pre-84 calibration,*	
	Pre-84	*Post-84*	*Relative*	*Post-84 tech shock*	*Relative*	*Post-84 tech shock*	*Relative*	*Post-84 tech shock*	*Relative*
$\sigma(y)$	2.56	1.28	0.50	1.60	0.62	1.59	0.62	1.61	0.63
$\sigma(n)/\sigma(y)$	0.78	1.15	1.47	0.94	1.07	0.94	1.07	0.94	1.07
$\sigma(w)/\sigma(y)$	0.24	0.80	3.33	0.31	1.10	0.24	0.95	0.25	0.98
$\sigma(y/n)/\sigma(y)$	0.49	0.59	1.20	0.35	1.06	0.35	1.06	0.34	1.04
$\sigma(nomW)/\sigma(y)$	0.37	0.82	2.22	0.33	0.69	0.27	0.95	0.27	0.94
$\rho(y,w)$	0.36	-0.14	-0.50	0.30	-0.19	0.61	-0.01	0.54	-0.05
$\rho(y,y/n)$	0.65	0.01	-0.64	0.34	-0.16	0.34	-0.16	0.35	-0.16
$\rho(n,y/n)$	0.21	-0.50	-0.71	-0.01	-0.21	-0.01	-0.21	0.01	-0.20
ρ(nomW,P)	0.81	0.28	-0.53	0.61	-0.09	0.66	-0.05	0.34	-0.16

Note : U.S. data: Total sample extends from 1953:2 to 2006:4 with split in 1984:1. HP-filtered, quarterly data. PCE-deflated wages. Non-farm business sector. The 'Relative' column denotes the Post/Pre-84 ratios for standard deviations and the Post-Pre-84 differences for correlations.

Table A.10 Model simulations: Alternative shocks

technology shock reduces the cyclicality of labor productivity and wages. This is especially true for the labor supply shock case. This is why we state in the paper that including additional non-technology shocks that gain in importance relative to the technology shock would help our model generate the decrease in cyclicality of labor productivity and wages observed in the data.

APPENDIX B

SUPPLEMENTAL MATERIAL FOR "RECONCILING THE DIVERGENCE IN AGGREGATE U.S. WAGE SERIES"

B.1 Data Description

Here we describe in details the different variables used throughout the second chapter. We also provide data sources and series' IDs.

B.1.1 Macro Variables

The different macro variables used throughout the paper are:

- **Output**: Gross Domestic Product, Non-farm business, Chained-\$2005. From the NIPA tables of the Bureau of Economic Analysis (BEA). Series ID: A358RX1. We divide this series by the U.S. population (see below) to get an hours per capita measure.

- **Price deflator**: The main series we use is the Personal Consumption Expenditure (PCE) deflator, from the NIPA tables of the BEA; index, 2005=100. Series ID: A002RD3.

- **Population**: Non-civilian population, 16 years old and over; from the Bureau of Labor Statistics' (BLS) Labor Productivity and Costs (LPC) program. Series ID: LNU00000000.

B.1.2 Labor Productivity and Costs (LPC)

The Major Productivity and Costs program of the BLS produces labor productivity and costs (LPC) measures for the private-sector U.S. economy. Below we list the variables we use from the LPC dataset. All of them are available quarterly (seasonally adjusted) and annually.

- **Compensation**: Total compensation from the LPC dataset is comprised of a 'wages and salaries' component, and a 'supplements' component.[1] The 'wages and salaries' component is based on earnings data from the Quarterly Census of Employment and Wages (QCEW), previously known as the BLS ES-202 program. The QCEW is "*...a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and the State Employment Security Agencies (SESAs)...[and] produces a complete tabulation of employment and wage information for workers covered by State unemployment insurance (UI) laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program*". This represents about 98 percent of all U.S. jobs. The definition of labor earnings in the QCEW are very comprehensive. Specifically: *"Wage and salary disbursements consist of the monetary remuneration of employees (including the salaries of corporate officers, commissions, tips, bonuses, and severance pay); employee gains from exercising nonqualified stock options; distributions from nonqualified deferred compensation plans; and an imputation for pay-in-kind (such as the meals furnished to the employees of restaurants)."* See

[1] The proportion of wages and salaries in total compensation has been trending downwards in a constant way through time, from around 91% of total compensation in the mid-1960s to 80% in 2010.

http://www.bea.gov/regional/pdf/spi2005/Complete_Methodology.pdf for more information.

The 'supplements' components consists of employer contributions for employee pension and insurance funds and employer contributions for government social insurance.[2] To derive total compensation for the non-farm business sector, the LPC substracts compensation of employees working in public administration offices, in the farm sector, and in non-profit institutions and private households.[3] Moreover, the LPC imputes earnings of self-employed individuals using comparable data from workers in the CPS.

The total compensation measure we use from LPC is series ID: PRS85006063, which is in levels and not publicly available (the LPC website of the BLS only publishes the corresponding index series).[4]

- **Hours**: Total hours in the LPC database mainly comes from the Current Establishment Survey (CES) for production and nonsupervisory workers (see CES description below), supplemented by other sources to estimate hours of workers not covered by the CES. For example, LPC computes an estimate of average weekly hours for nonproduction and supervisory workers by applying a CPS-based ratio of [nonproduction & supervisory workers] / [production & non-supervisory workers] to CES production & nonsupervisory worker average weekly hours. The total hours measure we use is LPC series ID: PRS84006033. This series is in levels and not publicly available, as for the

[2]The estimates for the 'supplements' portion of total compensation come from various sources, such as the IRS, the Medical Expenditure Panel Survey, or the American Counsil on Life Insurance. The estimates are compiled by the Bureau of Economic Analysis (BEA).

[3]Note that workers employed in 'general government' are not included in the non-farm business measure, while workers in 'governement enterprises' are.

[4]We thank Shawn Sprague for supplying us with the level series from LPC.

total compensation series.[5]

- **Total employment:** We use LPC's employment series PRS85006013, which, as for compensation and hours above, is in levels.

- **Average weekly earnings:** We divide by 52 the ratio of total compensation to total employment.

- **Average weekly hours:** We divide by 52 the ratio of total hours to total employment.

- **Average hourly wage**: We compute average hourly earnings by dividing average weekly earnings with average weekly hours.

B.1.3 The Current Population Survey (CPS)

The Current Population Survey (CPS) is a monthly survey of about 60,000 households. It collects a variety of information on households' demographics and employment.[6] Since we analyze (mainly) earnings and hours in this paper, we need information on both from the CPS. However, earnings and hours questions are not asked to all CPS respondents each month. Specifically, an interviewed individual appears in the CPS for two periods of four consecutive months, separated by eight months during which the individual is left out of the survey. Between 1973 and 1978, the CPS asked all the respondents in the sample about weekly earnings and weekly hours once a year only. This data was collected in May in what is called the 'May supplements'. Starting in 1979, weekly earnings and hours questions are

[5] Further note that when reporting statistics for total hours (e.g. in Table 2, where we use total hours as a cyclical indicator), we use LPC series ID: PRS84006033 and divide it by the U.S. population to get an hours per capita measure.

[6] For more documentation on the CPS and in particular the May / ORG extracts, see Schmitt (2003); and Roth and Feenberg (2007).

asked each month to the individuals who are at the end of a four-month rotation – the 'Outgoing Rotation Group' (ORG). Hence, from 1979 onward, one fourth of the CPS sample is asked about earnings and hours each month.[7]

Following Abraham et al. (1998) and Lemieux (2006), we use the earnings and hours information from the CPS May supplements and the ORG extracts to create an annual series of weighted average weekly earnings and weighted average weekly hours from 1973 onwards. The individual weights used in this calculation are provided by the CPS to make the resulting sample representative of the U.S. workforce.

Since sectoral coverage of the LPC and the CES series differs slightly and the LPC coverage cannot be replicated directly, we use a private non-agricultural coverage for the CPS that resembles the NIPA and CES coverage (see below); i.e. we remove from the CPS May / ORGs extracts all unemployed; self-employed; individuals under 16 years of age; all government, agricultural and private household workers; as well as former armed force personnel. For 1973-1978, the May supplements yield an average of 30,406 individual observations per year. For 1979 onward, the combination of 12 monthly ORG files yields an average of 139,230 individual observations per year.

Lastly, note that the actual CPS ORG extracts (1979-2011) we use are from the Center for Economic Policy Research (CEPR).[8] These extracts are based on the 'Merged Outgoing Rotation Groups' files ('MORGs', i.e. the ORGs, merged in annual files) compiled by the National Bureau of Economic Research (NBER). We

[7] In March of each year, the CPS also asks all invididuals in the sample about their annual labor earnings. Extending our earnings analysis using the CPS March earnings data remains to be done.

[8] See Center for Economic and Policy (CEPR) Research. 2012. CPS ORG Uniform Extracts, Version 1.7. Washington, DC. (http://www.ceprdata.org/).

use the CEPR data because the CEPR modifies the NBER MORGs to make them more user-friendly.[9] But the greatest advantage with the CEPR data is that they provide detailed documentation on the modifications and additions they make to the NBER's MORG files. We use this documentation to replicate the CEPR's adjustments for the NBER MORG extracts for the CPS May Supplement files so as to have consistent variables throughout the whole sample (1973-onwards).

- **Compensation**: Workers in the CPS May/ORG extracts report earnings in two different ways, depending on whether they are salaried or paid by the hour. Salaried workers report usual weekly earnings, defined as compensation normally received, including bonuses, overtime, tips and commissions (OTC) if paid and earned each period but excluding payments in kind, stock options, any other form of irregular bonuses, and any supplements to wage earnings. Hourly-paid workers report their usual hourly wage rate, which is not supposed to take into account OTC or any form of irregular pay, and are also asked their usual weekly earnings, as asked to salaried workers. Hence, CPS earnings contain some fraction of bonuses and OTC if paid and earned each period but no irregular form of compensation.

  To create consistent average hourly (and weekly) earnings series from this data, two issues need to be addressed. The first issue concerns topcoding of high earnings; the second issue concerns the computation of treatment of OTC earnings for hourly-paid workers.

  Topcoding concerns the fact that the CPS limits (i.e. topcodes) publicly available data of individuals with high earning to a maximum value that varies over time and depends on whether a worker reports weekly earnings

[9] For instance, the coding of some variables in the CPS survey changes through time, e.g. the variable 'education'. The CEPR ORGs are formatted such that there is consistency in each variable through time.

or the hourly wage rate. For the latter, the CPS topcodes the hourly rate at \$99.99, a threshold rarely crossed. For the former (i.e. salaried workers), the CPS topcodes weekly earnings at \$999 until 1989; \$1923 between 1989 and 1997; and \$2884 from 1998 onward. For certain years, this puts a substantial share of workers above the topcode, which may lead to earnings discontinuities around topcode changes.[10] To reduce this risk of discontinuities, we multiply topcoded weekly earnings by a factor of 1.3 before averaging across individuals. While this constant-factor adjustment is standard in the labor literature (e.g. Abraham et al., 1998; Lemieux, 2006), it does not completely eliminate the possibility of discontinuities from topcode changes. Alternatively, one can use more sophisticated adjustment methods that estimate mean earnings of individuals above the topcode from the cross-sectional distribution of earnings below the topcode. The most popular among these methods is based on the Pareto distribution which, for certain years, has been shown to provide to provide a better approximation of actual earnings in confidential CPS samples.[11] In the paper, we provide a new method to account for topcoding, by using data from Piketty and Saez (2003) on the top income earners in the U.S. See the next section of this Appendix for more details.

The second issue with creating a consistent average hourly wage series from CPS data concerns the treatment of OTC earnings for hourly-paid workers. Prior to 1994, hourly-paid workers were simply asked to report their hourly wage rate as well as their weekly earnings. With the redesign of the CPS survey in 1994, the CPS introduced an additional question on weekly

[10] This could, for example, induce spurious earnings volatility in the post-1984 sample, since all topcode changes occur after 1984.

[11] See Feenberg and Poterba (1992), Polivka (2000) and Schmitt (2003).

OTC earnings for hourly-paid workers but not for salaried workers.[12] The consequence of this additional question is a more accurate measurement of OTC earnings for hourly-paid workers starting in 1994 (see below for more discussion).[13] Due to this discontinuity in earnings reporting, the main statistics in the paper using CPS earnings data simply use the hourly wage rate times the usual hours worked as the measure of weekly earnings for hourly-paid workers. See below for more details and the treatment of OTC earnings.

- **Hours**: Hours in the CPS May / ORGs are recorded as the usual number of hours per week worked on the main job. As for compensation above, the CPS redesign in 1994 created a small consistency problem with hours; from 1994 onward, the redesigned CPS allowed respondents to indicate that their "hours vary". As a result, starting in 1994, no response for usual weekly hours is recorded for these individuals. As Schmitt (2003) notes: "*a sizeable share of workers (typically, 6-7%) chose to report that their hours vary. Since the distribution of hourly earnings for these workers may differ systematically from that of workers whose hours generally do not vary, simply excluding the group of workers whose hours vary may reduce comparability*

[12] Furthermore, the 1994 CPS redesign also affected the hours reported by individuals in the ORGs. See hours bullet point below for more information.

[13] For example, before 1994, hourly-paid workers provided their hourly wage (not incluing OTC earnings), and then were asked to provide their usual weekly earnings (supposedly including OTC earnings). Our calculations (see paper) show that workers often did not include OTC in weekly earnings and, as a result, the average difference between weekly earnings for hourly-paid workers vs. weekly earnings not including it (i.e. hourly wage rate times weekly hours) is small. Starting in 1994, the new, more precise question about OTC earnings made the hourly-paid individuals respond more precisely about their weekly OTC earnings. Confirmation of this issue comes from Polivka (2000) who concludes: "*Prior to 1994, workers identified as paid by the hour were simply asked to report their hourly rate, the number of hours they worked and then a weekly amount in addition. The repetitive process of asking these questions irked some respondents provoking statements such as, "Well, figure it out yourself." (Polivka and Rothgeb, 1993).*"

of wage series across the 1994 redesign." The CEPR CPS ORG extracts we use in this paper impute weekly hours for these individuals whose hours are missing. As a result, we use the CEPR-generated variable 'uhoursi', which is a variable created by the CEPR using the variable 'uhourse' in the NBER CPS ORG extracts ('uhourse' reports the usual weekly earnings for each individual CPS respondent in the NBER ORGs). 'uhoursi' equals 'uhourse' for the 1979-1993 period; from 1994-on, it equals 'uhourse', unless a CPS respondent answered that his hours vary. In that case, 'uhoursi' equals the hours imputation made by the CEPR.[14]

- **Average weekly earnings:** To compute average weekly earnings, we proceed differently for salaried and hourly-paid workers. For salaried workers, we simply use the weekly earnings reported under the variable 'earnwke' in the CPS ORGs extracts for the whole sample. For hourly-paid workers, our main results compute weekly earnings as hourly wage rate times weekly hours, thus omitting OTC earnings.[15]

  In the second half of the paper, we account for OTC earnings of hourly-paid workers as follows. Before 1994, weekly earnings of hourly-paid workers are computed as $\max(wage\_rate * weekly\_hours, weekly\_earnings)$; from 1994 onward, weekly earnings of hourly-paid workers are computed as $\max(wage\_rate * weekly\_hours + OTC, weekly\_earnings)$, where the term 'weekly_earnings' in the brackets refers to the usual weekly earnings variable, labeled 'earnwke' in the CPS ORGs.[16]

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[14] See Schmitt (2003) for more details on the imputation procedure.

[15] As mentioned above, to compute average weekly earnings in the CPS sample, we use a weighted average of individual weekly earnings, where the weights are individual weights provided in the CPS May / ORGs extracts.

[16] Note that between 1979 and 1988, the response of hourly-paid workers for the weekly

- **Average weekly hours:** To compute average weekly hours, we use a weighted average of the variable 'uhoursi' described above. As for average weekly earnings, the weights used are individual weights provided in the CPS.

- **Average hourly wage**: We compute average hourly wages by dividing (weighted) average weekly earnings with (weighted) average weekly hours.

B.1.4 Current Employment Statistics

The CES is a monthly survey of employment, wages and hours in the private non-agricultural establishments. The CES grew from about 166,000 to about 330,000 establishments between 1980 and 1993; and then to over 400,000 establishments in 2006. Today, the CES covers about 141,000 firms representing approximately 486,000 individual worksites. While the CES reports data for all employees as far back as 1939, it only reports earnings and hours from 1964 onwards and *only* for production workers in the goods-producing sector and nonsupervisory workers in the service-providing sector.[17]

- **Compensation**: Chapter 2 of the BLS Handbook of Methods states that: "*Aggregate payrolls include pay before deductions for Social Security, unemployment insurance, group insurance, withholding tax, salary reduction plans, bonds, and union dues. The payroll figures also include overtime pay, shift premiums, and payments for holidays, vacations, sick leave, and other leave made directly by the employer to employees for the pay period reported.*

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earnings question has been recorded under another variable in the CPS ORGs, labeled "uearnwke" See Feenberg and Roth (2007).

[17] Note that since March 2006, the CES also publishes series of weekly earnings and hours that cover all employees in the non-farm business sector.

Payrolls exclude bonuses, commissions, and other lump-sum payments (unless earned and paid regularly each pay period or month), or other pay not earned in the pay period (such as retroactive pay). Tips and the value of free rent, fuel, meals, or other payments in kind are not included."

- **Hours**: Chapter 2 of the BLS Handbook of Methods states that: "*Total hours during the pay period include all hours worked (including overtime hours), hours paid for standby or reporting time, and equivalent hours for which employees received pay directly from the employer for sick leave, holidays, vacations, and other leave. Overtime and other premium pay hours are not converted to straight-time equivalent hours."*

- **Average weekly earnings:** We downloaded the average weekly earnings series from the CES, series ID: CES0500000030. It is computed (in the CES) as the weekly average of total earnings divided by total employment.

- **Average weekly hours:** We downloaded the average weekly hours series from the CES, series ID: CES0500000007. It is computed (in the CES) as the weekly average of total hours divided by total employment.

- **Average hourly wage**: The average hourly wage is computed as the ratio of average weekly earnings to average weekly hours.

B.1.5 National Income and Product Accounts (NIPAs)

The National Income and Product Accounts, produced by the Bureau of Economic Analysis (BEA), provide, among several other macroeconomic variables, detailed information on compensation of workers at the national and industry levels. Contrary to LPC, NIPAs provide compensation of employees series for the whole economy (not restricted to the non-farm business sector); moreover, the

NIPA tables provide details on the 'wage and salaries' and 'supplements' parts of total compensation (while LPC only provides information on total compensation).

To calculate non-farm business series for the variables defined below, we take total private figures from the NIPA tables and subtract total agriculture, which includes farms, agricultural services, forestry, and fishing. Note that this definition is similar to the CES' non-farm business sector, as well as our CPS non-farm business definition; however, it slightly differs from LPC's non-farm business definition (see LPC subsection above). The reason for these differences is that from the publicly-available NIPA tables, we do not have the information to replicate LPC's non-farm business sector definition. Further note that NIPA private non-agricultural series do not include an imputation of self-employed workers' earnings, hours, and employment.

- **Compensation**: Total compensation in the NIPAs is computed as the sum of 'wages and salaries' and 'supplements to wages and salaries'. As in LPC, the 'wages and salaries' portion of total compensation is based on earnings data from the Quarterly Census of Employment and Wages (QCEW), and the 'supplements to wages and salaries' is computed by the BEA.
  - The total compensation measure we use from the NIPAs is taken from Table 6.2, series ID: A033RC0.
  - The 'wages and salaries' portion of total compensation, available from the NIPAs, is taken from Table 6.3 ID: A034RC0.
- **Total employment:** Total employment series comes from NIPA Table 6.4, series ID: A4201C0. It includes all full- and part-time workers. The BEA source for employment is the QCEW.[18]

[18] The CES actually benchmarks its employment estimates each year to Census data (i.e.

- **Hours**: Total hours are taken from NIPA Table 6.9, series ID: B4701C0. Total hours include all hours worked by full- or part-time employees. It is computed (by the BEA) as total NIPA employment times average weekly hours. The source of average weekly hours is LPC and do not include self-employed workers.

- **Average weekly compensation and wages & salaries:** We divide by 52 the ratio of total compensation to total employment for average weekly compensation, and divide by 52 the ratio of total wages and salaries to total employment for average weekly wages and salaries.

- **Average weekly hours:** We divide by 52 the ratio of total hours to total employment.

- **Average hourly compensation and wages & salaries**: We divide average weekly compensation with average weekly hours to get average hourly compensation, and divide average weekly wages and salaries by average weekly hours to get average hourly wages & salaries.

B.2 Topcode adjustments: Income data from Piketty-Saez

We use the dataset on income inequality constructed by Piketty and Saez (P-S, thereafter) from IRS data first release with their seminal 2003 QJE paper and updated to 2010 since then. This dataset is available on Saez's website at: http://elsa.berkeley.edu/~saez/. P-S provide an analysis of inequality at two levels: 1) at the income level (with and without capital gains) and 2) at the wages and salaries level. Since our work focus on the wage portion of income, we will use their data on "wage inequality" instead of income inequality, because the earnings

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QCEW).

concept from the P-S wage inequality data is very similar to the earnings concept in the QCEW (detailed above).

In their wage inequality dataset, P-S provide wage shares (of total wages and salaries), average wages and salaries for the top-10% decile and numerous fractiles within the top-10%, as well as wages and salaries threshold values for these fractiles. Below, we will use these average (and thresholds) wages and salaries to estimate mean earnings for topcoded observations in the CPS data.

B.2.1 Using P-S data to estimate means above the topcode in the CPS

We use the information in the P-S dataset on *average and threshold wages and salaries* values for various fractiles within the top-10% of income earners. Then, using the proportion of CPS respondents with topcoded earnings each year in the CPS May and ORGs, we can impute a value for weekly earnings to these respondents using the P-S data. Here are the detailed steps we follow to compute the assigned weekly earnings (to topcoded earnings in the CPS May / ORGs) in each year:

1. Gather, for the years 1973 to 2009, average (nominal) annual earnings for the top-5%, top-1%, top-0.5%, top-0.1%; and gather threshold values for the 95th, the 99th, the 99.5th, and the 99.9th percentiles from P-S dataset.[19]

2. Convert these annual earnings in weekly earnings (divide annual earnings by 52).

[19] Ideally, we would like to use more precise values (i.e. that coincide exactly with the CPS densities of observations at the topcode described below) but P-S provide only these average and thresholds values for earnings.

3. Gather, from the CPS May / ORGs, the densities (%) of workers with topcoded weekly earnings in each year.[20]

4. Compute the values to assign (from the P-S dataset) in each year to the topcode earnings observations in the CPS May / ORGs.

Steps (1) to (3) are straighforward, but step (4) is more complicated. There are two main reasons why the assignation of P-S values to topcoded observations is not simple; first, the P-S average and thresholds earnings values do not correspond exactly to the densities of observations with topcoded earnings in the CPS. As a result, we need a procedure that uses some average and/or threshold fractiles values from P-S and compute an approximative earnings value to assign to CPS topcoded observations.

Second, as mentioned above, the topcode value changes through time in the CPS; as a result, the densities of observations at the topcode change throughout the sample, especially when the topcode value changes. For example, in 1988, the proportion of observations with topcoded weekly earnings (for the whole economy[21]) was 4.17%, while in 1989 is drops to 0.45%. The same pattern is observed between 1997 and 1998, the other time the topcode value changes in the CPS: in 1997, the % of topcoded earnings is 1.50%, while in 1998 it is 0.60%. These changes in densities when the topcode values change are important because they can guide us in imputing reasonable values to the topcoded observations. For example, we assume that it is highly improbable that in 1988 (or before), more than 0.45% of individuals made above $1923/week, since in 1989, only 0.45% of

[20] Note that for simplicity, we only consider salaried workers as potential workers with topcoded weekly earnings. The reason behind this is that the topcode level for the hourly wage is $99/hour, a threshold almost never crossed throughout the sample.

[21] As specified in the paper, the whole economy sector is defined as all workers less private households and military workers (who are not asked the earnings questions).

individuals made more than \$1923/week. Consequently, even though 4.17% of individuals had topcoded earnings (topcoded at \$999/week) in 1988, we assume that no more than 0.45% is assigned a value higher than \$1923/week.[22] Let us now turn to the actual assignment procedure from the P-S dataset.

- For years where the density (%) of topcoded earnings is lower than 1%, we use wage information in P-S for fractiles within the top-1% to impute values to these topcoded observations. For example, in 1975, the density (%) of topcoded earnings was 0.21%. For this year, we assign to 0.1% of observations the top-0.1% average weekly earnings value in P-S (labelled "$P(99.9-100)$", for the average weekly earnings of the top-0.1%), and to the remaining topcoded values (i.e. 0.21%-0.1% = 0.11%) we assign the P-S average earnings value $P\,(99.5-99.9)$, i.e. the average earnings for individuals with wages between the 99.5 and 99.9 fractiles, since we do not have the exact average earnings value from P-S for those 0.11% observations. The detailed formula to compute the assigned weekly earnings in 1975 is thus:

$$\frac{0.1}{0.21} * P\,(99.9-100) \ + \ \frac{(0.21-0.1)}{0.21} * P\,(99.5-99.9)$$

- For years where the density (%) of topcoded earnings is higher than 1%, we use average earnings value for the top-1% (i.e. $P\,(99-100)$), and a weighted average of the $P95$ and $P99$ percentiles thresholds for the rest of topcoded observations (again, we proceed accordingly because we only have details on $P(95-99)$, $P95$, and $P99$ between the 95th and 99th percentiles in the

[22] Of course, this assumption eliminates the possibility of large swings in high incomes due to business cycles that would change the density of people with topcoded earnings in the CPS. The reason we make this assumption is that when we do not take into account these sharp drops in densities when the topcode value changes, we obtain unrealistically large decreases in CPS average wages in the years after the topcode value changes, i.e. a year where the density is very high (e.g. 1988), vs. 1989, when the topcode value changes.

P-S data). Take year 2005 as an example (where % topcoded earnings is 1.20%); the detailed formula to compute the assigned weekly earnings (in 2005) from P-S is thus:

$$\frac{1}{1.20} * P\,(99-100)$$
$$+\frac{(1.20-1)}{1.20} * \left[\frac{0.20}{4} * P95 + \frac{(4-0.20)}{4} * P99\right]$$

where, as above, PXX corresponds to the weekly earnings threshold for the $XXth$ percentile.

- Finally, to be consistent with our assumption above[23], between 1979-88 and 1989-97, if the density (of topcoded observations) in any year is higher than the density in the year the topcode value subsequently changes (i.e. in 1989 and in 1998), we do not assign an earnings value from P-S that is higher than the "new" topcode value in the CPS (in the year it changes). To illustrate this "rule", take an example: in 1988, the topcode density is 4.17%. We thus use the procedure described above to assign an earnings value to the top-0.45% (i.e. the density in 1989 after the topcode value changes in the CPS from $999/week to $1923/week); for the rest of the topcoded observations (i.e. 4.17% - 0.45% = 3.72%), we follow the same procedure as above *unless* the assigned topcode values exceeds $1923/week, the new CPS topcode value in 1989. In that case, we simply use a 1.3 multiplicative factor (times the CPS topcode value in 1988, i.e. $999*1.3). Therefore, the detailed formula

[23] Recall that topcode values in the CPS change two times throughout the sample, in 1989 and in 1998. We assume it is improbable that in 1988 (or before), more than 0.45% of individuals made above $1923/week, since in 1989, only 0.45% of individuals made more than $1923/week. The same analogy applies from 1989 to 1997: in these years, we assume that no more than 0.60% of individuals made above $2884/week, since this is the proportion of individuals with topcoded earnings (at $2884/week) in 1998.

to compute the assigned weekly earnings in 1998 is:

$$\frac{0.45}{4.17} * \left[\frac{0.1}{0.45} * P(99.9 - 100) + \frac{(0.45 - 0.1)}{0.45} * P\,(99.5 - 99.9)\right]$$
$$+\frac{(4.17 - 0.45)}{4.17} * 1.3 * 999$$

i.e. all observations above 0.45% were assigned \$999/week time 1.3 since the assigned P-S value found was higher than the CPS topcode value in 1989 (i.e. \$1923/week). This would mean that more than 0.45% of workers in 1988 would have earned weekly earnings above than \$1923, even though only 0.45% of CPS workers had topcoded earnings in 1989 at \$1923/week. By using a 1.3 multiplicative factor, we rule out this possibility.

B.3 Computation of Standard Errors

See first chapter's appendix above.

APPENDIX C

SUPPLEMENTAL MATERIAL FOR "BUSINESS CYCLE IMPLICATIONS OF INCENTIVE PAY IN THE LABOR SEARCH MODEL"

C.1 Data

All the data used in Tables 3.1, 3.3, 3.5, and 3.6 are in quarterly terms. Data from Figure 3.1 is taken from Champagne and Kurmann (2013a).

- **Output**: Gross Domestic Product, Non-farm business, Chained-$2005. From the NIPA tables of the Bureau of Economic Analysis (BEA). Series ID: A358RX1. I divide this series by the U.S. population (see below) to get a GDP per capita measure.

- **Price deflator**: The main series used is the Personal Consumption Expenditure (PCE) deflator, from the NIPA tables of the BEA; index, 2009=100. Series ID: A002RD3.

- **Population**: Non-civilian population, 16 years old and over; from the Bureau of Labor Statistics' (BLS) Labor Productivity and Costs (LPC) program. Series ID: LNU00000000Q.

The rest of the variables come from the Major Productivity and Costs program of the BLS which produces labor productivity and costs (LPC) measures for the private-sector U.S. economy.

- **Compensation**: Total compensation from the LPC dataset is comprised of a 'wages and salaries' component, and a 'supplements' component.[1] The 'wages and salaries' component is based on earnings data from the Quarterly Census of Employment and Wages (QCEW), previously known as the BLS ES-202 program. The QCEW is "*...a cooperative program involving the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor and the State Employment Security Agencies (SESAs)...[and] produces a complete tabulation of employment and wage information for workers covered by State unemployment insurance (UI) laws and Federal workers covered by the Unemployment Compensation for Federal Employees (UCFE) program*". This represents about 98 percent of all U.S. jobs. The definition of labor earnings in the QCEW are very comprehensive. Specifically: *"Wage and salary disbursements consist of the monetary remuneration of employees (including the salaries of corporate officers, commissions, tips, bonuses, and severance pay); employee gains from exercising nonqualified stock options; distributions from nonqualified deferred compensation plans; and an imputation for pay-in-kind (such as the meals furnished to the employees of restaurants)."* See http://www.bea.gov/regional/pdf/spi2005/Complete_Methodology.pdf for more information.

  The 'supplements' components consists of employer contributions for employee pension and insurance funds and employer contributions for gov-

[1] The proportion of wages and salaries in total compensation has been trending downwards in a constant way through time, from around 91% of total compensation in the mid-1960s to 80% in 2010.

ernment social insurance.[2] To derive total compensation for the non-farm business sector, the LPC substracts compensation of employees working in public administration offices, in the farm sector, and in non-profit institutions and private households.[3] Moreover, the LPC imputes earnings of self-employed individuals using comparable data from workers in the CPS.

The total compensation measure we use from LPC is series ID: PRS85006063, which is in levels and not publicly available (the LPC website of the BLS only publishes the corresponding index series). We thank Shawn Sprague for supplying us with this series.

- **Hours**: Total hours in the LPC database mainly comes from the Current Establishment Survey (CES) for production and nonsupervisory workers (see CES description below), supplemented by other sources to estimate hours of workers not covered by the CES. For example, LPC computes an estimate of average weekly hours for nonproduction and supervisory workers by applying a CPS-based ratio of [nonproduction & supervisory workers] / [production & non-supervisory workers] to CES production & nonsupervisory worker average weekly hours. The total hours measure we use is LPC series ID: PRS84006033. This series is in levels and not publicly available, as for the total compensation series.

- **Total employment:** I use LPC's employment series PRS85006013, which, as for compensation and hours above, is in levels.

- **Vacancies**: I use Regis Barnichon's (2010) vacancies index for the U.S.

[2] The estimates for the 'supplements' portion of total compensation come from various sources, such as the IRS, the Medical Expenditure Panel Survey, or the American Counsil on Life Insurance. The estimates are compiled by the Bureau of Economic Analysis (BEA).

[3] Note that workers employed in 'general government' are not included in the non-farm business measure, while workers in 'governement enterprises' are.

economy.

- **Unemployment**: Unemployment rate, seasonally adjusted, quarterly series from the Bureau of Labor Statistics, Current Population Survey. Series ID: LNS14000000Q.
- **Average weekly earnings:** I divide by 52 the ratio of total compensation to total employment.
- **Average hourly wage**: I compute average hourly earnings by dividing average weekly earnings with average weekly hours.
- **Vacancies:**
- **Unemployment rate:**

C.2 Surplus from employment

Here I describe in details how I derive the households' value of having an additional member working under each wage bargaining scenario.

C.2.1 Efficiency-wage sector

For illustrative purposes, let us assume that all workers and firms bargain over efficiency-wage contracts (i.e. $p = 0$). In that case, the household's problem becomes:

$$W(\Omega_{ew,t}) = \max_{c_t} \left\{ c_t - \left[n_{ew,t} \frac{(e_{ew,t})^{1+\eta}}{1+\eta} \right] + \beta E_t \left[W\left(\Omega_{ew,t+1}\right) \right] \right\} \tag{C.1}$$

subject to :

$$
\begin{aligned}
c_t &= \begin{pmatrix} \left[n^{ns}_{ew,t} + (1-d)n^{s}_{ew,t}\right] w_{ew,t} + \\ +(1 - \left[n^{s}_{ew,t} + n^{ns}_{ew,t}\right])b + \Pi_{ew,t} \end{pmatrix} \qquad \text{(C.2)} \\
n_{ew,t+1} &= \left((1-s)\left[(1-d)n^{s}_{ew,t} + n^{ns}_{ew,t}\right] + f_{ew,t}u_{ew,t}\right)
\end{aligned}
$$

where $u_{ew,t} = 1-(1-s)\left[(1-d)n^{s}_{ew,t} + n^{ns}_{ew,t}\right]$. As mentioned in the main text, the surpluses from employment are different whether an employed member is shirking or supplying effort level $\bar{e}$. These surpluses are found by taking the first-order conditions of $W(\Omega_{ew,t})$ with respect to $n^{s}_{ew,t}$ and $n^{ns}_{ew,t}$, respectively, subject to the budget constraint and employment evolution equation above (C.2). This yields:

$$
\begin{aligned}
\frac{\partial W(\Omega_{ew,t})}{\partial n^{s}_{ew,t}} &= W^{s}_{2}(\Omega_{ew,t}) = (1-d)w_{ew,t} - b \qquad \text{(C.3)} \\
&\quad + \beta E_t\left[W_2\left(\Omega_{ew,t+1}\right)\frac{\partial n_{ew,t+1}}{\partial n^{s}_{ew,t}}\right] \qquad \text{(C.4)} \\
\frac{\partial W(\Omega_{ew,t})}{\partial n^{ns}_{ew,t}} &= W^{ns}_{2}(\Omega_{ew,t}) = w_{ew,t} - b - \frac{\bar{e}^{1+\eta}}{(1+\eta)} \\
&\quad + \beta E_t\left[W_2\left(\Omega_{t+1}\right)\frac{\partial n_{ew,t+1}}{\partial n^{ns}_{ew,t}}\right] \qquad \text{(C.5)}
\end{aligned}
$$

where:

$$
\frac{\partial n_{ew,t+1}}{\partial n^{s}_{ew,t}} = \left(\left(1-s\right)\left(1-d\right)\left(1-f_{ew,t}\right)\right)
$$

and:

$$
\frac{\partial n_{ew,t+1}}{\partial n^{ns}_{ew,t}} = \left(\left(1-s\right)\left(1-f_{ew,t}\right)\right).
$$

Note that the surpluses from employment above are already expressed in terms of current consumption, as utility is linear. Rearranging yields:

$$W_2^s(\Omega_{ew,t}) = (1-d)w_{ew,t} - b \tag{C.6}$$

$$+\beta\left[(1-s)\,(1-d)(1-f_{ew,t})\right]E_t\left[W_2\left(\Omega_{ew,t+1}\right)\right] \tag{C.7}$$

$$W_2^{ns}(\Omega_{ew,t}) = w_{ew,t} - b - \frac{\overline{e}^{1+\eta}}{(1+\eta)}$$

$$+\beta\left[(1-s)(1-f_{ew,t})\right]E_t\left[W_2\left(\Omega_{ew,t+1}\right)\right] \tag{C.8}$$

which are equivalent to the surpluses from employment (3.11) in the main text.

Incentive compatibility constraint. For workers to exert any effort, firms must offer workers a wage that satisfies their incentive compatibility constraint. Define this constraint as the 'no–shirking condition' (NSC), expressed as $W_n^{ns}(\Omega_{ew,t}) \geq W_n^s(\Omega_{ew,t})$. Using (3.11) above, one gets:

$$\frac{\overline{e}^{1+\eta}}{(1+\eta)} \leq d\left[w_{ew,t} + \beta(1-s)(1-f_{ew,t})E_t\left\{W_n(\Omega_{ew,t+1})\right\}\right] \tag{C.9}$$

or, alternatively:

$$w_{ew,t} \geq \frac{\overline{e}^{1+\eta}}{(1+\eta)}\frac{1}{d} - \beta(1-s)(1-f_t)E_t\left\{W_n(\Omega_{ew,t+1})\right\} \tag{C.10}$$

Workers will exert the desired amount of effort $\overline{e}$ only if on the loss they would incur if detected shirking, weighted by the probability of being detected (d) is greater or equal to their disutility (in terms of current consumption) of supplying $\overline{e}$. This loss is the sum of two components: the forgone real wage value if detected shirking, plus the expected discounted value of a match in the next period. Consistent with the efficiency-wage literature (e.g. Shapiro and Stiglitz, 1984; Riggi, 2013), the no-shirking wage is higher when: (i) the level of effort to be supplied is higher; (ii) the detection probability (d) is lower; (iii) the exogenous separation rate is higher (i.e. the fact that matches have high probability of being terminated in the near future increases the incentive to shirk); (iv) the discount factor β is lower (since low value on employment next period implies lower loss if worker is detected shirking).[4]

C.2.2 Performance-pay wage sector

Again for illustrative purposes, let us assume now that all workers and firms bargain over performance-pay wage contracts (i.e. $p = 1$). The household problem becomes:

$$W(\Omega_{pp,t}) = \max_{c_t} \left\{ c_t - \left[n_{pp,t} \frac{(e_{pp,t})^{1+\eta}}{(1+\eta)} \right] + \beta E_t \left[W\left(\Omega_{pp,t+1}\right) \right] \right\} \tag{C.11}$$

subject to :

$$\begin{aligned} c_t &= (n_{pp,t} w_{pp,t} + (1 - n_{pp,t}) b + \Pi_{pp,t}) \qquad \text{(C.12)} \\ n_{pp,t+1} &= (1-s)\, n_{pp,t} + f_{pp,t} u_{pp,t} \end{aligned}$$

where $u_{pp,t} = 1 - (1-s) n_{pp,t}$. The surplus from employment (or the household's value of having an additional member employed) can be derived from the first-order condition (with respect to $n_{pp,t}$) of the household's problem (C.11) subject

[4] Another interesting comparative static is the higher the job-finding rate f_t, the higher the no-shirking wage must be. Using equation (3.11), rewrite (C.10) as:

$$\begin{aligned} w_{ew,t} \geq \; & \frac{\overline{e}^{1+\eta}}{(1+\eta)} \frac{1}{d} \\ & -\beta(1-s) E_t \left\{ f_{ew,t+1} w_{ew,t+1} - b + \frac{\overline{e}^{1+\eta}}{(1+\eta)} \left(\frac{1 - d - f_{ew,t+1}}{d} \right) \right\} \end{aligned}$$

The shorter time it takes to get a job back after being fired, the higher the incentive to shirk.

to (C.12) ;

$$\frac{\partial W(\Omega_{pp,t})}{\partial n_{pp,t}} = W_2(\Omega_{pp,t}) = w_{pp,t} - b - \frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + \beta E_t \left\{ W_2\left(\Omega_{pp,t+1}\right) \frac{\partial n_{pp,t+1}}{\partial n_{pp,t}} \right\} \tag{C.13}$$

where:

$$\frac{\partial n_{pp,t+1}}{\partial n_{pp,t}} = \left(\left(1-s\right)\left(1-f_{pp,t}\right)\right).$$

Rearranging yields:

$$W_2(\Omega_{pp,t}) = w_{pp,t} - b - \frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + \beta\left[\left(1-s\right)\left(1-f_{pp,t}\right)\right] E_t\left[W_2(\Omega_{pp,t+1})\right] \tag{C.14}$$

which represents the household's value, in terms of current consumption, of having one additional member employed. Equation (C.14) is equivalent to (3.16) in the main text.

C.3 System of equations

Here I list the system of equations of the model, including the firm-specific equations and aggregate identities.

1. Aggregate vacancies:

$$v_t = pv_{pp,t} + (1-p)v_{ew,,t}$$

2. Aggregate job searchers:

$$u_t = pu_{pp,t} + (1-p)u_{ew,,t}$$

3. Segment-specific matching function (for $i = ew, pp$):

$$m(v_{i,t}, u_{i,t}) = v_{i,t}^{\sigma} u_{i,t}^{1-\sigma}$$

4. Aggregate matching function:

$$m(v_t, u_t) = v_t^{\sigma} u_t^{1-\sigma}$$

5. Segment-specific employment evolution (for $i = ew, pp$):

$$n_{i,t+1} = (1 - s)\, n_{i,t} + f_{i,t} u_{i,t}$$

6. Aggregate Employment:

$$n_t = p n_{pp,t} + (1 - p) n_{eff,t}$$

7. Aggregate unemployment rate:

$$urate_t = 1 - n_t$$

8. Segment-specific job-finding rate (for $i = ew, pp$):

$$f_{it} = \frac{m(v_{i,t}, u_{i,t})}{u_{i,t}}$$

9. Segment-specific job-filling rate (for $i = ew, pp$):

$$q_{i,t} = \frac{m(v_{i,t}, u_{i,t})}{v_{i,t}}$$

10. Segment-specific market tightness (for $i = ew, pp$):

$$\theta_{i,t} = \frac{v_{i,t}}{u_{i,t}}$$

11. Aggregate job-finding rate:

$$f_t = \frac{m(v_t, u_t)}{u_t}$$

12. Aggregate job-filling rate:

$$q_t = \frac{m(v_t, u_t)}{v_t}$$

13. Aggregate market tightness:

$$\theta_t = \frac{v_t}{u_t}$$

14. Efficiency-wage:

$$\begin{aligned} w_{ew,t} \quad &= \quad \xi \left[E_{t-1} \left\{ \frac{y_{ewt}}{n_{ew,t}} \right\} + (1-s) E_{t-1} \left\{ \frac{\kappa}{q_{ew,t}} \right\} \right] + (1-\xi) \frac{\overline{e}^{1+\eta}}{(1+\eta)} \frac{1}{d} \\ & \quad -(1-\xi) \left[\beta(1-s)(1 - E_{t-1} \left\{ f_{ew,t} \right\}) E_{t-1} \left\{ [W_n(\Omega_{ew,t+1})] \right\} \right] \end{aligned}$$

15. Surplus from employment, under efficiency-wage scenario:

$$W_n(\Omega_{ew,t}) = w_{ew,t} - b - \frac{\overline{e}^{1+\eta}}{(1+\eta)} + \beta(1-s)(1-f_{ew,t}) E_t \left\{ W_n(\Omega_{ew,t+1}) \right\}$$

16. PPay wage:

$$w_{pp,t} = \xi \left[z_t e_{pp,t} + (1-s) \kappa E_{t-1} \left\{ \theta_{pp,t} \right\} \right] + (1-\xi) \left[\frac{e_{pp,t}^{1+\eta}}{(1+\eta)} + b \right]$$

17. Effort condition, PPay:

$$e_{pp,t}^{\eta} = z_t$$

18. Production function, efficiency-wage firm:

$$y_{ew,t} = z_t n_{ew,t} \overline{e}$$

19. Production function, PPay firm:

$$y_{pp,t} = z_t n_{pp,t} e_{pp,t}$$

20. Aggregate Output:

$$y_t = p y_{pp,t} + (1-p) y_{eff,t}$$

21. Vacancy-creation condition (for $i = ew, pp$):

$$\frac{\kappa}{q_{i,t}} = \beta E_t \left\{ \frac{y_{i,t+1}}{n_{i,t+1}} - w_{i,t+1} + (1-s) \frac{\kappa}{q_{i,t+1}} \right\}$$

22. Aggregate average effort (or effort per worker):

$$e_t = p \frac{n_{pp,t}}{n_t} e_{pp,t} + (1-p) \frac{n_{ew,t}}{n_t} \bar{e}$$

23. Aggregate average wage:

$$w_t = p \frac{n_{pp,t}}{n_t} w_{pp,t} + (1-p) \frac{n_{ew,t}}{n_t} w_{ew,t}$$

24. Aggregate resource constraint:

$$y_t = c_t + \kappa v_t$$

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