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The Great Increase in Relative Volatility of Real Wages in the United States

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Abstract:

This paper documents that over the past 25 years, aggregate hourly real wages in the United States have become substantially more volatile relative to output. We use micro-data from the Current Population Survey (CPS) 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, by contrast, account for at most 12% of the increase in relative wage volatility. Using a Dynamic Stochastic General Equilibrium (DSGE) model, we show 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, increased flexibility in wage setting is capable of accounting for a large fraction of the observed increase in relative wage volatility. At the same time, increased wage flexibility generates a substantial decrease in the magnitude of business cycle fluctuations, which suggests a promising new explanation for the Great Moderation.

Keywords: Wage volatility, business cycles, great moderation, current population survey, dynamic stochastic general equilibrium models

JEL Classification: E24, E32

1 Introduction

The 25 years prior to the current 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 U.S. output declined by more than 50% and the volatility of many other macroeconomic aggregates fell by similar proportions.[1]

In this paper, we show that the Great Moderation does not apply to one of the most prominent labor market aggregates: the average real hourly wage (or 'aggregate wages' for short). Specifically, we document the following results:

1. From 1948-1984 to 1984-2006, the business cycle volatility of the aggregate wage increased between 30 and 70 percent, depending on the filtering method and nominal deflator used.

2. As a result, the business cycle volatility of the aggregate wage *relative* to the volatility of aggregate output experienced a three- to four-fold increase over the two sample periods.

The increase in both *absolute* and *relative* volatility of aggregate wages raises several questions. First, to what extent does this increase apply to different groups of workers? Second and related, how much of the increase in volatility is due to compositional changes of the workforce; 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 such labor market changes contribute to our understanding of business cycle fluctuations in general and the Great Moderation in particular?

To answer the first and second question, we use microdata from the Current Population Survey (CPS) to construct hourly wage series for different groups of workers. We document that the increase in *absolute* volatility of the real wage is not generalized but concentrated among male, skilled and young workers. Also, there are large differences across industries, with absolute volatilities of hourly wages in many industries decreasing. However, these decreases are generally modest and thus, the volatility of real hourly wages *relative* to the volatility of aggregate output increases substantially across most of decompositions considered. We call this phenomenon the 'Great Increase in Relative Volatility of Real Wages'.

To quantify how much of the increase in the relative volatility of aggregate wages is due to increases in relative volatility of wages across different groups of workers, we develop an accounting method that allows us to decompose the increase in aggregate wage volatility into compositional changes and changes in relative volatilities and correlations. The main result coming out of this

[1] See McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) or Stock and Watson (2002).

exercise is that the large increase in relative volatility of aggregate wages is predominantly due to the increase in the relative volatility of wages of the different worker groups. Compositional changes of the labor force, by contrast, account for at most 12% of the increase in the relative volatility of the aggregate wage. This suggests that the increase in the relative volatility of aggregate wages is due to changes in the economic environment that affected wage dynamics of most groups of workers, although to varying degrees.

To address the third and fourth question, we build a small Dynamic Stochastic General Equilibrium (DSGE) model with a stylized wage setting function that allows for varying degrees of wage rigidity. We calibrate the model consistent with U.S. data and show that while changes in the importance of exogenous shock processes can have a sizable effect on the *absolute* volatility and cyclicality of aggregate wages, their effect on the *relative* volatility of wages is negligible. Similarly, structural changes to the economy that do not directly affect the labor market (e.g. a more aggressive monetary policy response to inflation) are unlikely to have a large effect on the relative volatility of wages. By contrast, more flexible wage setting is capable of accounting for a large fraction of the observed increase in relative wage volatility and simultaneously implies a substantial decrease in the magnitude of business cycle fluctuations for given exogenous shocks.[2] We confirm the robustness of our findings in the larger DSGE model of Smets and Wouters (2007) that contains many frictions and shocks. These results suggest that the hypothesis of increased wage flexibility has a lot of potential to rationalize the observed changes in U.S. labor market dynamics and at the same time provides a promising new explanation for the Great Moderation.

The hypothesis of increased flexibility in wage setting is appealing for several reasons. On the one hand, it is consistent with the documented rise in individual earnings volatility in the U.S. in the 1980s and 1990s (e.g. Gottschalk and Moffitt, 1994; Dynan et al., 2008). On the other hand, the U.S. labor market has undergone several important changes over the past 25 years that are likely to have led to increased flexibility in wage setting. Among them are the large decrease in private sector unionization (e.g. Farber and Western, 2001); the shift towards performance-pay contracts (e.g. Lemieux et al., 2008); the erosion of the minimum wage (e.g. DiNardo et al., 1996); and the increase in temporary help services (e.g. Estevao and Lach, 1999) and overtime work hours (e.g. Kuhn and Lozano, 2008). In the last part of the paper, we discuss in more detail the cases of deunionization and performance-pay. On theoretical grounds, both deunionization and the shift towards performance-pay contracts should make wages more sensitive to current business cycle conditions, thus increasing their volatility. On empirical grounds, this is confirmed by Lemieux et al.

[2] Increased wage flexibility does not render the economy immune to large business cycle shocks such as the ones experienced during the recent financial crisis. Our results suggest that the effects of these large shocks would have been more severe if wage setting had been as rigid as in the early 1980s.

(2008) who document that wages are more responsive to changes in local labor market conditions for non-union and performance-pay contracts. Furthermore, we show that the decrease in unionization and the shift towards performance-pay contracts roughly coincide with the evolution of relative wage volatility over time.

Our paper contributes to a recent literature on changes in labor market dynamics over the past decades. Most notably, Barnichon (2008), 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.[3] Gali and Van Rens (2009) build a DSGE model with labor hoarding and search frictions and find that a decrease in search frictions can account for both of these changes in labor market dynamics. Gali and Van Rens (2009) also note the increase in volatlity of aggregate wages and argue that under certain assumptions about wage setting, a decrease in labor frictions may endogenously increase wage flexibility.[4] Compared to Gali and Van Rens (2009), our paper focuses more squarely on wage volatility. In particular, we are the first to document that the increase in the relative volatility of wages is generalized across different worker groups and not due to compositional changes of the labor force. As we argue in the paper, this result is important because it suggests that the increase in wage volatility is related to structural changes in the labor market that affect wage dynamics of all groups of workers. At the same time, we uncover that increased wage flexibility is also a powerful mechanism to account for the Great Moderation.[5]

The rest of the paper proceeds as follows. In Section 2 we document the increase in wage 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 our DSGE model and simulates the effects of increased wage flexibility. Section 5 explores the decline in unionization and the shift towards performance-pay as potential sources of increased wage flexibility. Furthermore, we discuss the hypothesis put forward by Gali and Van Rens (2009) that labor search frictions have declined. Section 6 concludes.

[3] By contrast, Manovskii and Hagedorn (2009) find that labor productivity constructed from CPS data instead of aggregate data from the BLS is more procyclical and remains so even after 1984.

[4] Champagne (2007) and Gourio (2007) are two other, unpublished manuscripts that document the increase in wage volatility during the Great Moderation. The findings in Champagne (2007) provided the starting point for the present paper.

[5] Davis and Kahn (2008) suggest that greater wage flexibility may offer a unified explanation for the observed rise in income volatility and the Great Moderation. However, they do not formally investigate this conjecture.

2 Aggregate hourly wages during the Great Moderation

In this section, we document the increase in volatility of aggregate real hourly wages in the United States. We first describe the construction of our preferred measure of aggregate hourly wages and present the main results. Then, we discuss alternative aggregate wage series and show further results. For the sake of brevity, we keep the description of the data to a minimum. An appendix that is available on the authors' websites provides more detailed information and contains several robustness checks.

2.1 Data

The most comprehensive aggregate wage series in the United States comes from the Labor Productivity and Costs (LPC) program. This program is based on the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW) and covers total compensation and hours worked for about 98% of non-farm occupations. Total compensation includes direct wage and salary payments (including executive compensation); commissions, tips and bonuses; as well as supplements such as vacation pay or employer contributions to pension and health plans. Aggregate hourly wages are computed by dividing total compensation by total hours worked. To obtain real aggregate hourly wages, we deflate this measure by the Personal Consumption Expenditure (PCE) deflator from the NIPA tables. All of our results are robust to alternative deflators such as the Consumer Price Index (CPI) or output deflators. To compare our wage series with the business cycle, we use non-farm real chain-weighted GDP per capita, obtained from the National Income and Products Accounts (NIPA).

All data series are logged and filtered to extract the business cycle component. We use three different filtering methods: (i) a quarterly first-difference filter; (ii) a Hodrick-Prescott (HP) filter; and (iii) a Bandpass Filter (BP) proposed by Christiano and Fitzgerald (2003).[6]

2.2 Main results

Table 1 shows the standard deviation of output and aggregate real hourly wages for the period 1948:1-1983:4 and for the period 1984:1-2006:4, with standard errors for each estimate provided in

[6] The first-difference filter removes stochastic trends but also cuts out a substantial part of business cycle fluctuations. The HP filter is close to a high-pass filter that removes trends but leaves all other fluctuations, including high frequency fluctuations. The BP filter removes both low and high frequency fluctuations and only keeps fluctuations with periodicities between 6 and 32 quarters.

parenthesis.[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 decreased by about 60% over the two periods (i.e. the Great Moderation), the volatility of aggregate hourly wages increased substantially. The p-value of Levene's (1960) test of equal variance indicates that these changes in volatility are highly significant.[8] The different evolution of output and wage volatility is even more striking when considering relative standard deviations. As the last column of Table 1 shows, the volatility of wages relative to the volatility of output has increased by a factor of 3 to 3.5 over the two samples. These ratios are far above the changes in relative volatility observed for other macro aggregates during the Great Moderation (see discussion in Section 4).

To further illustrate the change in relative volatility of aggregate wages, we plot the volatility of output and aggregate wages over 8-year rolling windows. As the first panel of Figure 1 illustrates, the volatility of output fell precipitously in the 1980s whereas the volatility of the aggregate wage steadily increased steadily during the 1980s and 1990s. The standard error bands indicate that both of these changes are significant. As shown in the second panel, the relative volatility of the aggregate wage thus increased dramatically and significantly from the mid-1980s to the mid-1990s. Thereafter, the relative volatility of aggregate wages returns to an intermediate level that remains, however, more than twice as high than the level before the mid-1980s.

We take away two main results from Table 1 and Figure 1. First, as the volatility of output drops during the Great Moderation, the *absolute* volatility of aggregate wages increases. Second, the drop in output volatility is proportionally much larger than the increase in aggregate wage volatility. The three- to four-fold increase in the *relative* volatility of aggregate wages is thus driven to a large part by the drop in output volatility. The challenge for any theory is to explain how there can be such a marked fall in output volatility without a similar fall in the volatility of aggregate wages.

2.3 Evidence from other aggregate wage measures

The aggregate wage series from the LPC program is a very broad measure of compensation that includes not only wages and salaries but also stock options. Mehran and Tracy (2001) argue that this may provide a misleading picture of the evolution and volatility of compensation in the 1990s since these stock options are recorded when realized, not when handed out to employees. We

[7] When computing the volatility of aggregate wages or other macro variables, we drop the first and last year to improve the accuracy of the filters. Standard errors are computed via the delta method from GMM-based estimates. See the appendix for details.

[8] The largest p-value of 0.13 occurs for the first-differenced wage series. Since first-differencing filters out a substantial part of business cycle fluctuations, we attribute less importance to this exception.

thus check the robustness of our results with three other measures of aggregate hourly measures constructed, respectively, from the CPS May/MORG, the NBER manufacturing database and the Private Economy Labor Quality (PELQ) database.

As described in more detail in the next section, the hourly wage measure from the CPS May/MORG is computed from a representative sample of employed individuals and takes into account wages and salaries, overtime earnings, tips, commissions and bonuses if paid as part of usual compensation. Stock options are not included. The wage measure from the NBER database covers wages of production workers in about 450 four-digit manufacturing industries and is unlikely to be influenced by stock options either. The wage measure from the PELQ database is constructed by Dale Jorgenson and co-authors from a cross-section of CPS and Census data and also excludes stock options (e.g. Jorgenson et al., 2008). The frequency of each of these datasets is annual and spans the period 1973-2006 for the CPS, 1976-2002 for the NBER manufacturing database, and 1976-2000 for the PELQ database.

Table 2 presents the results for the different aggregate wage series together with an annualized version of the LPC measure, both in first-differenced and HP filtered form.[9] The PELQ measure shows the largest increases in wage volatility, matching the results of the LPC measure almost exactly. The NBER manufacturing measure and the CPS measure show a somewhat smaller increase in absolute wage volatility, but their relative wage volatility still increases by a factor of 2.5 or more. We can only speculate about the reason for these differences. For the NBER measure, they may be due to the exclusive focus on production workers in manufacturing; for the CPS measure, they may be due to top-coding of large income workers who have seen a more important increase in wage volatility in the post-1984 period than the average worker (see next section). The key point remains, however, that as the volatility of output drops during the Great Moderation, the volatility of all of these wage measures remains stable or even increases slightly. As a result, the relative volatility of aggregate wages increases by a factor of 2.6 to 3.8 between the pre-1984 and the post-1984 period.

Another aggregate wage measure to consider is the Average Hourly Earnings (AHE) series from the Current Establishment Survey (CES) of the BLS. As Champagne (2007) and Gali and Van Rens (2009) document, the absolute volatility of the AHE aggregate wage measure declines substantially from the pre-1984 to the post-1984 period and as a result, its relative volatility remains roughly constant. Given the popularity of the AHE measure in both academic research and the business press, it is important to investigate this difference further. We follow Abraham et al. (1998) who document in earlier work that the AHE wage measure diverges greatly from other aggregate wage

[9] As recommended by Ravn and Uhlig (2002), we set the HP filter parameter to 6.25. We do not report BP filtered results for annual data because the BP filter requires us to cut fluctuations of 2 years or less. This would remove a potentially important part of business cycle fluctuations.

measures in terms of its trend over time. For example, whereas the aggregate wage series from the NIPA (basically our QCEW series from the LPC) increases by about 7% over the 1973-1993 period, the AHE measure falls by about 10% over the same period. Abraham et al. (1998) consider three possible explanations for this divergence in trends: (i) problems related the underrepresentation of young establishments in the CES; (ii) differences in the earnings concept used; and (iii) differences in the worker population covered. We examine to what extent any of these three possibilities can explain the very different evolution of the volatility of the AHE measure.[10]

We start with differences in the worker population covered. The AHE measure covers only production and non-supervisory workers, which account for about 80% of total payroll, whereas the aggregate wage measures from the LPC, the CPS May/MORG and the PELQ database are representative of the entire workforce.[11] It is possible that the wage volatility of the 20% of workers not covered by the AHE increases by so much in the post-1984 period that it more than outweighs the drop in wage volatility in the AHE measure. To assess this possibility, we use the CPS May/MORG data together with occupational definitions from the BLS to recreate an hourly wage series for production and non-supervisory workers, as presumably captured by the AHE measure, and an hourly wage series for the remaining private-sector workers. We find that the wage volatility of *both* of these series remains approximatively constant over the pre-1984 and the post-1984 sample period. As a result, the wage volatility of both worker groups relative to the volatility of output increases by a factor of more than 2.5. Abraham et al. (1998) further argue in their paper that employers in the CES often 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. Since wages of hourly workers and other non-exempt workers have fallen over their 1973-1993 period, Abraham et al. (1998) conclude that this difference in worker coverage provides the best possible explanation for the divergence in wage trends between the AHE measure and other wage measures. As we show in the next section, however, the relative volatility of hourly workers' wages also increases substantially in the post-1984 period. It is therefore unlikely that differences in worker population covered can explain the diverging evolution of wage volatility of the AHE measure compared to the different other aggregate wage measures.

[10] Another obvious candidate for differences in wage volatility across different wage series is measurement error. For measurement error to explain the very different evolution of wage volatility between the AHE series and the other aggregate wage series, however, it would have to be the case that the measurement error for the AHE series relative to the LPC, CPS May/MORG and PELQ measure decreased substantially. We know of no evidence that points in this direction.

[11] According to Abraham et al. (1998), the proportion of production and non-supervisory workers in total employment has remained roughly constant over the 1973-1993 period.

Second, we consider differences in earnings concepts. The AHE does not include tips and records commissions and bonuses only if earned and paid in the same period. The CPS May/MORG wage series is the closest to the AHE measure in this respect because it records commissions and bonuses only if they are part of usual earnings. This leaves tips as a difference. As Abraham et al. (1998) report, the BEA estimates tips to be a mere 0.3% of total weekly compensation in 1993. Hence, even if the volatility of tips had increased greatly, this would not explain why the volatility of the CPS May/MORG wage measure increased by such a large amount relative to the AHE wage measure.

Third, we turn to the issue of underrepresentation of young establishments in the CES. As Abraham et al. (1998) explain, the CES sample of reporting establishments was not rotated regularly for most of the sample period we consider. Hence, young establishments are typically underrepresented. Furthermore, the CES sample grew from about 166,000 establishments in 1980 to about 333,000 establishments in 1993, which is likely to have led to an increase of the proportion of young establishments in the CES sample. While Abraham et al. (1998) conclude that the effect of this expansion on aggregate wage trends is likely to be modest, it is possible that this expansion explains at least part of the difference in the evolution of wage volatility. Absent micro data on the different CES establishments, however, we cannot investigate this possibility further. The difference in the evolution of wage volatility for the AHE measure relative to the other aggregate wage measures thus remains a puzzle. Given the similarity of results across the LPC, the CPS May/MORG, the NBER manufacturing database and the PELQ database, it appears safe to conclude, however, that the increase in the relative volatility of aggregate wages is a robust feature of the data and not an artifact of some particular measurement of compensation or restriction to a narrow segment of the worker population.

3 A closer look at disaggregated data

To further investigate the increase in volatility of real hourly wages, we take the CPS data and construct wage series for different groups of workers. We first describe important details about the CPS data and then look at the evolution of wage volatility for different groups of workers. Based on these decompositions, we develop an accounting method that allows us to quantify how much of the increase in the volatility of the aggregate wage is due to increases in wage volatility of different worker groups.

3.1 CPS data

The CPS is the official household-based labor market survey in the U.S. It collects information on roughly 60,000 households about various worker characteristics. Following Lemieux (2006), we use the Dual Jobs Supplement of the CPS May extracts for the 1973-1978 period and the CPS Merged Outgoing Rotation Groups (MORG) for the 1979-2006 period to construct annual series of average hourly wages and hours of work.[12] From the total sample, we drop all unemployed, self-employed, and individuals under 16 years old. We also remove private household workers, agricultural workers, armed force personnel, and individuals with no data on either earnings or hours. For the remaining sample, we collect a direct measure of the hourly wage rate for all workers paid by the hour (i.e. 'hourly workers'). For workers not paid by the hour (i.e. 'non-hourly workers'), we compute an hourly wage rate by dividing usual weekly earnings by usual weekly hours. We then combine these hourly wage data with the appropriate CPS weights to compute a representative time series for the aggregate non-farm hourly wage rate as well as average hourly wage rates for different groups of workers as defined below.[13]

There are two important issues with the CPS data that we need to address for our time-series analysis of wages: topcoding and the 1994 redesign of the CPS. Topcoding in general may lead to biased measures of wage volatility because variations in wages of topcoded individuals cannot be taken into account. Furthermore, there have been several adjustments of the topcoding threshold over time, which may lead to discontinuities in our wage series and overstate the volatility of wage series.[14] To account for topcoding, several researchers have taken a simple adjustment rule and multiplied topcoded earnings observations by a factor of 1.3 or 1.4. Others have tried to estimate the mean above the topcode based on different distributional assumptions. The most popular among them is the Pareto distribution approach, which has been shown to provide the best approximation

[12] The MORG data is available on a quarterly basis. Since the data only starts in 1979, we do not consider the MORG data in isolation but compute annual averages from the quarterly data and combine them with the May extracts for a longer sample.

[13] Alternatively, we could have computed hourly wage series from the CPS March Supplements. The CPS March data would have the advantage that it starts in 1963 rather than 1973. However, before 1976, only weekly earnings can be computed, which is a biased measure of hourly wages if hours worked vary across weeks. Furthermore, as Lemieux (2006) argues, CPS March wage measures are subject to substantial measurement error that are not present in the CPS May/MORG data. The reason for this difference is that the CPS March collects labor earnings only on a yearly basis. The CPS May/MORG, by contrast, asks directly for the wage rate for hourly workers. This seems to yield more precise answers. For these reasons, we refrain from using CPS March data.

[14] For hourly worker, wages are topcoded at $99.99 per hour, a threshold that is rarely crossed. For non-hourly workers, weekly earnings are topcoded at $999 before 1989, $1,923 before 1998 and $2,884 thereafter. A substantial share of individuals is above that threshhold at any time of the sample.

of the actual mean in confidential CPS samples.[15] We use a battery of different topcode adjustment methods and find that our volatility results do not differ across methods. For simplicity, we thus report all of our results here for topcoded weakly earnings adjusted by a factor of 1.3.

The second important issue is the CPS redesign in 1994, more specifically the treatment of weekly overtime earnings, tips, and commissions (OTC). Before 1994, hourly workers were asked to report their hourly wage rate, without a specified question on OTC earnings. After 1994, a specific question was added to hourly workers about weekly OTC earnings.[16] The consequence of this redesign is a potential discontinuity in the wage series for hourly workers, which could lead to an overstatement of the wage volatility in the post-1984 period. To check whether this may be the case, we compute two alternative wage series for hourly workers. First, we simply drop OTC earnings after 1994. Second, we adjust the wage series for non-hourly workers before 1994 with a linear trend so as to correct for any discontinuity. In both cases, all of our results remain robust, meaning that the addition of the OTC question in 1994 for non-hourly workers does not lead to an overstatement of the volatility in CPS wages.

3.2 Wage volatility across different decompositions

We consider four different decompositions: (i) skill / gender; (ii) skill / age; (iii) skill / employment status; and (iv) skill / industry affiliation.[17] Following Krusell et al. (2000) and many others, we measure skill by years of schooling. To keep the decomposition manageable, we consider only two groups, defining a 'skilled worker' as someone with a college degree (bachelor) or more, and an 'unskilled worker' as someone with less than a college degree. The definitions of the other decompositions are described below.

For each of the decompositions, we compute an average hourly wage series and follow the same procedure as for the aggregate wage series: filter the series to extract the business cycle component; split the sample into a pre-1984 and a post-1984 period; compute the volatility of the hourly wage series both in absolute terms and relative to the volatility of aggregate output.[18] Aside from the

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

[16] For non-hourly workers, the usual weekly earnings include OTC earnings throughout the whole sample. As a result, the CPS redesign did not affect the usual weekly earnings of non-hourly workers.

[17] Given the discussion about the effects of deunionization on wage flexibility in Section 5, it would be interesting to do a decomposition along union membership as well. Unfortunately, the CPS MORG does not provide union data before 1983, and for 1981 and 1982 the CPS May contains only very few (respectively no) individuals with information on union membership. This makes it impossible to compute reliable wage series for unionized and non-unionized workers for the pre-1984 sample.

[18] All results are reported for H-P filtered data with constant 6.25 as before. We cut off the first and last year of the sample to improve the accuracy of the filter. All the conclusions are robust to alternative filters.

volatility of the hourly wage, we also report the average wage share and the volatility of the hours' share, defined, respectively, as the fraction of total earnings and total hours accounted for by a given worker group (the formal definition is provided in Section 3.3). Both of these statistics turn out to be important for the volatility accounting exercise below.

Gender / skill decomposition

Table 3 reports the decomposition for gender and skill. The first noticeable change across subsamples is the increase in the relative importance of skilled and female workers (as measured by average wage shares). Second, we observe that the absolute volatility of hourly wages increases for all but skilled female workers for which wage volatility falls slightly. Relative to the volatility of output, however, the volatility of wages increases substantially across all groups. This is especially pronounced for male skilled workers who see their relative wage volatility increase by a factor of 4.5. By contrast to the hourly wage, the volatility of hours' share decreases markedly for all groups. As a result, the *relative* volatility of hours' share increases by much less and actually falls for both male and female skilled workers.

Age / skill decomposition

Table 4 displays the decomposition for age and skill. Following Gomme et al. (2004), and Jaimovich and Siu (2008), we create three age groups: 16-29 year olds ('young workers'); 30-59 year olds ('grown-ups'); and 60-70 year olds ('old workers'). As the changes in the average wage shares show, there is a substantial shift in the workforce from young to grown-up workers between the pre-1984 and the post-1984 period. In terms of volatility, we find that the absolute volatility for all but the young skilled workers decreases. However, this increase is modest for all but the old skilled workers. As a result, the relative volatility of wages still increases strongly for all but this last group. In particular, the relative wage volatility of young skilled workers increases by a factor of 4.5. For hours' share, in turn, the picture is very similar to the gender-skill decomposition: in absolute terms, the hours' share volatility falls substantially for almost all worker groups and thus, the relative volatility remains on average more or less unchanged.[19]

Employment situation / skill decomposition

Table 5 shows the decomposition for employment status and skill, where employment status is measured by whether a worker is paid an hourly wage rate or a non-hourly salary in his main job. As for the gender / skill decomposition, the evolution of the average wage share indicates that there is a shift towards a more skilled workforce. The volatility of wages increases for all but the

[19] As a sidenote, Gomme et al. (2004) and Jaimovich and Siu (2008) document that the volatility of hours displays a U-shaped pattern with respect to age. As Table 4 shows, the same U-shaped pattern is present for the volatility of hours' share.

non-hourly unskilled group. The relative volatility of wages thus increases markedly for all worker groups. Interestingly, this increase is most pronounced for hourly unskilled workers and non-hourly skilled workers, the two opposites in this decomposition. In terms of hours' share, the situation is similar to the above decompositions: the volatility of hours' share decreases substantially and thus, its change in relative volatility is much more muted than for the hourly wage.

Industry / skill decomposition

Table 6 reports the decomposition for industry affiliation and skill. We choose a relatively detailed decomposition into 10 private sector industries and one public administration sector. The importance of the wage share for the service sector increases markedly whereas the wage share of unskilled manufacturing groups decreases. In terms of volatility, we see that the wage volatility of many groups decreases. As for the age / skill decomposition, however, this decrease in volatility is generally modest and thus, the increase in relative volatility of wages remains large for all but communications and public sector workers (both skilled and unskilled). For hours' share, the picture is reversed. Most worker groups see a large decrease in absolute volatility and thus, the relative volatility of hours' share increases only modestly on average.

We take away three stylized facts from the different decompositions. First, there are important shifts in the workforce as measured by average wage shares. Second, there are substantial differences in the evolution of wage volatility across different worker groups. The largest increases in volatility occur for male, skilled and young workers. Many other groups, especially in the industry / skill decomposition, see their wage volatility decrease. However, these decreases are relatively modest in *absolute* terms and thus, the volatility of real hourly wages *relative* to the volatility of aggregate output increases substantially for almost every worker group. This phenomenon is what we call in the introduction 'The Great Increase in Relative Volatility of Real Wages'. Third and finally, there is a more substantial decrease in the volatility of hours' share for most worker groups. As a result, changes in the relative volatility of hours' share are on average much more modest. These stylized facts are robust with respect to other decompositions that we attempted with the CPS data (details are available from the authors upon request).

3.3 Volatility accounting

An obvious question coming out of the different decompositions is how much of the increase in absolute and relative volatility of aggregate wages is due to changes in wage volatilities within the different worker groups and how much is due to compositional changes of the workforce (i.e. a shift of the workforce towards jobs with more volatile wages). To quantify these effects, we develop an accounting method that allows us to decompose the increase in aggregate wage volatility into compositional changes, changes in volatilities of hourly wages and hours' shares, and changes in correlations thereof.

By definition, the aggregate real hourly wage w_t equals the sum of average real hourly wages $w_{i,t}$ across worker groups i of some decomposition (e.g. skilled and unskilled), weighted by the respective hours shares $h_{i,t} = H_{i,t}/H_t$; i.e.

$$w_t = \sum_i w_{i,t} h_{i,t},$$

where H_t and $H_{i,t}$ denote total aggregate hours worked and hours worked by group i. Next, we let $x_{i,t} = w_{i,t} h_{i,t}$ be the 'wage component' of worker group i and compute growth rates of the above decomposition. We obtain

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

where $s_{i,t-1} = x_{i,t-1}/w_{t-1}$ denotes the 'wage share' of worker group i. Given this decomposition, we can express the variance of the growth rate of the aggregate real hourly wage as

$$V(\Delta \log w_t) = \sum_i \sum_j COV(s_{i,t-1} \Delta \log x_{i,t}, s_{j,t-1} \Delta \log x_{j,t}).$$

To make this variance decomposition operational for our accounting exercise, we assume that wage shares $s_{i,t-1}$ are approximately constant over the sample under consideration; i.e. $s_{i,t-1} = \bar{s}_i$. For each of the decompositions, we check this approximation and find the induced error to be negligible. This allows us to express the difference in aggregate hourly wage variances over two subsamples (denoted 1 and 2) as

$$\sigma^2_{w,2} - \sigma^2_{w,1} = \sum_i \sum_j \bar{s}_{i,2} \bar{s}_{j,2} \rho(x_{i,2}, x_{j,2}) \sigma_{x_{i,2}} \sigma_{x_{j,2}} - \sum_i \sum_j \bar{s}_{i,1} \bar{s}_{j,1} \rho(x_{i,1}, x_{j,1}) \sigma_{x_{i,1}} \sigma_{x_{j,1}},$$

where $\sigma^2_{w,2}$ denotes the variance of aggregate wage growth $V(\Delta \log w_t)$ in subsample 2; $\rho(x_{i,2}, x_{j,2}) = COV(\Delta \log x_{i,t}, \Delta \log x_{j,t})/\sqrt{V(\Delta \log x_{i,t}) V(\Delta \log x_{j,t})}$ denotes the correlation coefficient between wage component of group i and wage component of group j in subsample 2; and so forth for the other elements. Our objective is to decompose $\sigma^2_{w,2} - \sigma^2_{w,1}$ into (i) changes in wage shares; (ii) changes in wage volatilities across worker groups; (iii) changes in hours' share volatilities across worker groups; and (iv) changes in correlation coefficients. As the above expression shows, this is not straightforward because the different moments enter both additively and multiplicatively. Consider first the contribution of changes in wage shares versus the contribution of changes in covariances of the wage components (which captures the remaining three changes). By adding and substracting different elements, we can expand the above expression as

$$\begin{aligned}\sigma^2_{w,2} - \sigma^2_{w,1} &= \sum_i \sum_j \bar{s}_{i,2}\bar{s}_{j,2}\left[\rho(x_{i,2}, x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}} - \rho(x_{i,1}, x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}\right] \\ &\quad + \sum_i \sum_j \left[\bar{s}_{i,2}\bar{s}_{j,2} - \bar{s}_{i,1}\bar{s}_{j,1}\right]\rho(x_{i,1}, x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}.\end{aligned}$$

This decomposes the change in the variance of aggregate wages into changes in wage shares *given covariances of wage components of the first subsample* and changes in covariances of wage components *given wage shares of the second subsample.* Alternatively, we can expand the above expression as

$$\begin{aligned}\sigma^2_{w,2} - \sigma^2_{w,1} &= \sum_i \sum_j [\bar{s}_{i,2}\bar{s}_{j,2} - \bar{s}_{i,1}\bar{s}_{j,1}]\rho(x_{i,2}, x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}} \\ &\quad + \sum_i \sum_j \bar{s}_{i,1}\bar{s}_{j,1}\left[\rho(x_{i,2}, x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}} - \rho(x_{i,1}, x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}\right].\end{aligned}$$

In this way, we decompose the change in the variance of aggregate wages into changes in covariances of wage components *given wage shares of the first subsample* and changes in wage shares *given covariances of wage components of the second subsample.* Since there is no particular economic justification to prefer one expansion over the other, we take the average over the two and obtain

$$\begin{aligned}\sigma^2_{w,2} - \sigma^2_{w,1} &= \sum_i \sum_j \left[\frac{\bar{s}_{i,2}\bar{s}_{j,2} + \bar{s}_{i,1}\bar{s}_{j,1}}{2}\right]\left[\rho(x_{i,2}, x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}} - \rho(x_{i,1}, x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}\right] \\ &\quad + \sum_i \sum_j \left[\frac{\rho(x_{i,2}, x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}} + \rho(x_{i,1}, x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}}{2}\right]\left[\bar{s}_{i,2}\bar{s}_{j,2} - \bar{s}_{i,1}\bar{s}_{j,1}\right].\end{aligned}$$

This averaging over two different extremes is obviously an arbitrary choice. We find, however, that all of our robust are robust if we used instead one of the two extremes.

We are left with the decomposition of changes in covariances of wage components into changes of variances and correlation coefficients of average hourly wages and hours' shares. We can express any covariance between wage components of worker group i and j as $\rho(x_i, x_j)\sigma_{x_i}\sigma_{x_j} = \rho(w_i, w_j)\sigma_{w_i}\sigma_{w_j} + \rho(h_i, h_j)\sigma_{h_i}\sigma_{h_j} + 2\rho(w_i, h_j)\sigma_{w_i}\sigma_{h_j}$. Applying the same averaging over the two possible expansions to this expression (see the appendix for details), we obtain the following final decomposition of aggregate wage variances over two subsamples[20]

$$
\sigma_{w,2}^2-\sigma_{w,1}^2 = \sum_i\sum_j \frac{\left[\bar{s}_{i,2}\bar{s}_{j,2}+\bar{s}_{i,1}\bar{s}_{j,1}\right]}{2}\left\{\begin{array}{l}
\left[\begin{array}{l}\frac{\rho(w_{i,2},w_{j,2})+\rho(w_{i,1},w_{j,1})}{2}\left(\sigma_{w_{i,2}}\sigma_{w_{j,2}}-\sigma_{w_{i,1}}\sigma_{w_{j,1}}\right)+\\ \frac{\rho(w_{i,2},h_{j,2})+\rho(w_{i,1},h_{j,1})}{2}\frac{\sigma_{h_{j,2}}+\sigma_{h_{j,1}}}{2}\left(\sigma_{w_{i,2}}-\sigma_{w_{i,1}}\right)\end{array}\right]^{(1)}+\\
\left[\begin{array}{l}\frac{\rho(h_{i,2},h_{j,2})+\rho(h_{i,1},h_{j,1})}{2}\left(\sigma_{h_{i,2}}\sigma_{h_{j,2}}-\sigma_{h_{i,1}}\sigma_{h_{j,1}}\right)+\\ \frac{\rho(w_{i,2},h_{j,2})+\rho(w_{i,1},h_{j,1})}{2}\frac{\sigma_{w_{i,2}}+\sigma_{w_{i,1}}}{2}\left(\sigma_{h_{j,2}}-\sigma_{h_{j,1}}\right)\end{array}\right]^{(2)}+\\
\left[2\frac{\sigma_{w_{i,2}}\sigma_{h_{j,2}}+\sigma_{w_{i,1}}\sigma_{h_{j,1}}}{2}\left[\rho(w_{i,2},h_{j,2})-\rho(w_{i,1},h_{j,1})\right]\right]^{(3)}
\end{array}\right\}
$$

$$
+\sum_i\sum_j\left[\frac{\rho(x_{i,2},x_{j,2})\sigma_{x_{i,2}}\sigma_{x_{j,2}}+\rho(x_{i,1},x_{j,1})\sigma_{x_{i,1}}\sigma_{x_{j,1}}}{2}\right]\left[\bar{s}_{i,2}\bar{s}_{j,2}-\bar{s}_{i,1}\bar{s}_{j,1}\right]^{(4)}.
$$

Part (1) is the portion of the change in the variance of aggregate wages accounted for by changes in wage volatility of different worker groups; part (2) is the portion accounted for by changes in the volatility of hours shares; part (3) is the portion accounted for by changes in correlations coefficients across hourly wages and hours shares; and part (4) is unchanged from before, measuring the portion of the change in the variance of aggregate wages accounted for by compositional changes in the workforce as measured by the difference in wage shares.

The proposed accounting exercise can be implemented for the difference in *absolute* variances of aggregate wages (described above) as well as for the difference in *relative* variances of aggregate wages; i.e. $\sigma_{w,2}^2/\sigma_{y,2}^2-\sigma_{w,1}^2/\sigma_{y,1}^2$. For the latter, we simply divide each second moment term by $\sigma_{y,2}^2$ or $\sigma_{y,1}^2$, respectively. Note that this leaves the difference in wage shares unchanged, which turns out to be important for the results.

Tables 7 and 8 show the results of our accounting exercise, both for the change in absolute volatility of aggregate wages (i.e. $\sigma_{w,2}^2-\sigma_{w,1}^2$) and the change in relative volatility of aggregate wages (i.e. $\sigma_{w,2}^2/\sigma_{y,2}^2-\sigma_{w,1}^2/\sigma_{y,1}^2$). All results are for HP filtered data. In other words, we substitute growth rates of hourly wages and hours' shares by their respective HP business cycle component. This approximation holds extremely well.[21]

As Table 7 shows, compositional changes account for more than 100% of the increase in the absolute volatility of aggregate wages for all four decompositions discussed in Section 3.2. The contributions of changes in wage volatility, hours share volatility and correlation coefficients, by contrast, differ wildly across decompositions. This variation in results should not come as a surprise.

[20] Note that for $i=j$, $\rho(w_i,w_j)\sigma_{w_i}\sigma_{w_j}$ simplifies to $\sigma_{w_i}^2$, and $\rho(h_i,h_j)\sigma_{h_i}\sigma_{h_j}$ simplifies to $\sigma_{h_i}^2$ Hence, our variance decomposition contains both variances and correlation coefficients. The form of this decomposition is similar to the one proposed in McConnell and Perez-Quiros (2000), Kahn et al. (2002) or Stiroh (2009) for other macro aggregates. However, our decomposition is complicated by the fact that the sum of log hourly wages of different worker groups does not equal the log of aggregate hourly wages.

[21] Coen-Pirani and Castro (2008) use the same approximation in their decomposition of hours volatility.

For example, the absolute volatility of wages increases substantially for most groups of the gender / skill and the employment status / skill decomposition, but decreases for most groups of the other two decompositions. As a result, the contribution of changes in wage volatility across worker groups to the increase in aggregate wage volatility is strongly positive for the gender / skill and the employment status / skill decompositions, but strongly negative for the other two decompositions. Similar differences explain the large variations in contributions of changes in hours share volatility and correlations across the different decompositions.

The picture is very different in Table 8 where we display the same accounting exercise for the change in relative volatility of aggregate wages. Now, for every decomposition, changes in the relative volatility of wages across worker groups account for the bulk of the increase in the relative volatility of aggregate wages. Compositional changes and changes in the relative volatility of hours shares, by contrast, account for no more than 12% (in the employment situation / skill decomposition). This difference in results is due to the fact that the volatility of wages relative to the volatility of output increases strongly for almost all worker groups in each of the decompositions while the change in composition and the change in relative volatility of hours share is generally modest.

3.4 Additional evidence from individual panel data

The decompositions we consider remain averages for workers with broad characteristics (e.g. male and skilled). Hence, it could be that the documented increase in *relative* wage volatility is the result of compositional changes *within* the different worker groups considered.[22] However, starting with Gottschalk and Moffitt (1994), different papers using panel data show that income has become considerably more volatile (in absolute terms) on an individual level as well. Dynan et al. (2008) provide an extensive review of this literature and document, using data from the Panel Study of Income Dynamics (PSID), that this increase in individual income volatility (i) occurred within each major age and education group; (ii) stems to a large part from an frequency of large income changes rather than changes throughout the income distribution; and (iii) is predominantly due to increased volatility in labor earnings per hour. Jensen and Shore (2008) extend the analysis of the PSID data and find that most of this increase in income volatility can be attributed to individuals with the most volatile incomes, identified ex-ante by high income changes in the past. For the other individuals, income volatility has remained more or less constant.

[22] Unfortunately, the CPS data does not allow us to discard this possibility because the same individual appears only for two periods of four months, separated by eight consecutive months during which the individual is left out of the survey.

Our results based on CPS data are consistent with Dynan et al. (2008) and Jensen and Shore (2008) in the sense that we find substantial heterogeneity about the change in *absolute* wage volatility across the different decompositions.[23] Compositional changes within worker groups may play some role for this heterogeneity. At the same time, these panel studies report that individual income volatility has either increased or remained roughly constant. Since the volatility of output fell by about 60% during the same time period, the volatility of income *relative* to the volatility of output must have increased substantially. This is entirely consistent with the conclusions from our accounting exercise that the across-the-board increase in relative wage volatility is the main source of the increase in the relative volatility of aggregate wages. The challenge is to come up with a theory that rationalizes both the drop in the volatility of output and the relatively modest changes in the magnitude of wage fluctuations across different workers groups.

4 Wage volatility in general equilibrium

To assess the potential of different explanations for the change in relative wage volatility, we build a small DSGE model with real wage rigidity. The model is similar to the one presented in Blanchard and Gali (2007) who use it to analyze the implications of wage rigidity for optimal monetary policy. We use the model instead to first explore to what extent changes outside of the labor market are capable of generating the observed increase in relative wage volatility. Second, we consider the quantitative effects of changing the degree of wage rigidity on wage dynamics and the economy in general.[24]

The model is set in a representative agent framework. We thus see our exercise first and foremost as an account of aggregate labor market dynamics. However, the effects of changes in wage rigidity that we highlight below apply equally to specific labor markets (e.g. the labor market for skilled workers in a given industry). As such, we consider our exploration also as a general first pass at explaining why the relative volatility of wages has increased substantially for most worker groups.

[23] Given that the panel dimension is absent in the CPS data, it is difficult to compare our results further with the results from PSID studies. Since our data is topcoded (thus missing some of the increase in large income changes noted by Dynan et al., 2008), and self-employed workers (which play an important role in Jensen and Shore's 2008 analysis) are dropped, our estimates of the evolution of wage volatility are likely to be on the conservative side.

[24] Gourio (2007), in an unpublished note, proposes a similar model to analyze the effects of changes in the degree of wage rigidity. His calibration and analysis is more limited, however.

4.1 Model

Since most of the model is standard, we keep the exposition to a minimum and refer the reader to the appendix for a full description. In the following, upper-case variables denote observed macroeconomic quantities and lower-case variables denote percent deviations from appropriately transformed steady states.

The economy is populated by 3 types of agents: a continuum of identical worker-households, a continuum of identical firms and a monetary authority. Households discount time at rate β and have preferences over consumption and leisure. Period t utility is given by

$$Z_{t-1}\left[\log C_t - \frac{N_t^{1+\phi}}{1+\phi}\right], \tag{1}$$

where C_t and N_t are a composite consumption good and hours worked, respectively; Z_{t-1} is an exogenous preference shock; and $1/\phi > 0$ denotes the Frisch elasticity of labor supply. Households maximize present discounted utility by choosing consumption, hours worked, and investment in either physical capital $K_{t+1} - (1-\delta)K_t$ or nominal bonds B_{t+1} subject to the budget constraint

$$C_t + K_{t+1} - (1-\delta)K_t + \frac{B_{t+1}}{R_t^n P_t} \leq W_t N_t + R_t^K K_t + \frac{B_t}{P_t} + D_t, \tag{2}$$

where W_t, R_t^K and R_t^n are the real wage rate, the real net rental rate of capital, and the gross nominal bond return, respectively; P_t is the aggregate price level; and D_t are dividends from a perfectly diversified portfolio of claims to firms.

Each firm produces a differentiated good with constant returns to scale technology

$$Y_t = F(K_t, A_t N_t), \tag{3}$$

where A_t denotes an exogenous labor-augmenting technology shock. The different firms' goods are combined into the final composite good according to the Kimball (1995) aggregator.[25] Hence, each firm is a monopolistic competitor, maximizing profits subject to a downward-sloping demand curve.

The monetary authority sets the nominal interest rate according to the following rule

$$R_t^n = \left(R_{t-1}^n\right)^{\rho} \left(\Pi_t\right)^{(1-\rho)\theta_\pi} \left(Y_t/Y_{t-1}\right)^{(1-\rho)\theta_y}, \tag{4}$$

where Π_t denotes the gross inflation rate of the composite good's price, and Y_t/Y_{t-1} is the growth rate of aggregate output.

[25] 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 Fischer (2007).

We impose two market frictions for the determination of equilibrium allocations. First, as is common in the New Keynesian literature, we assume that price setting is staggered following Calvo (1983), with each firm facing a constant probability in any given period of being able to reoptimize its price. This implies a loglinearized New Keynesian Phillips curve (NKPC) for inflation

$$\pi_t = \beta E_t \pi_{t+1} + \kappa mc_t, \tag{5}$$

with mc_t denoting real marginal cost. The slope coefficient κ in this equation is a nonlinear function of price setting and demand parameters (see, for example, Eichenbaum and Fischer, 2007).[26]

Second, we posit as in Blanchard and Gali (2007) that real wages adjust sluggishly according to the following loglinear wage setting curve

$$w_t = \gamma w_{t-1} + (1-\gamma) mrs_t, \tag{6}$$

where mrs_t denotes the workers' marginal rate of substitution

$$mrs_t = c_t + \phi n_t. \tag{7}$$

Given this wage, firms hire labor to satisfy their optimality condition

$$w_t = mc_t + y_t - n_t. \tag{8}$$

In words, wages are assumed to be fully allocative but for some unmodelled friction, workers are not on their labor supply schedule as defined by the marginal rate of substitution. This formulation of the labor market is admittedly ad-hoc. Yet, there are several reasons for proceeding in this way. First, the simple form of the labor market allows for a straightforward analysis of the effects of increased wage flexibility. Second, the next section discusses evidence suggesting that wages indeed play an allocative role over the business cycle. Third, very similar formulations can be derived from more explicit environments; for example (i) an environment with unions that formulate wage demands according to a partial adjustment process (e.g. Blanchard and Gali, 2007); (ii) a model with unobserved ability where firms pay performance-based wages to a fraction of the workforce (e.g. Lemieux et al., 2008); or (iii) an efficiency wage setup where workers evaluate the fairness of a given wage offer by comparing it to their past wage (e.g. Danthine and Kurmann, 2009). Fourth, very similar formulations of wage rigidity are introduced in search-based models of the labor market, motivated by the same type of fairness considerations (e.g. Hall, 2005 and Shimer, 2005). These

[26] Alternatively, we could have left prices completely flexible in which case the model collapses to the RBC benchmark. None of the main results below are affected by this simplification. However, it would imply that wages and labor productivity share exactly the same loglinear dynamics, which is not the case in the data.

search-based models have many advantages compared to the present stylized model.[27] As we discuss below, however, changes in wage rigidity turn out to be as crucial for search-based models as they are for our more stylized formulation to match observed changes in relative wage volatility.

For capital markets, we keep the competitive markets assumption. The household's first-order condition for investment in physical capital is

$$c_t = E_t c_{t+1} - \beta r^k E_t r^k_{t+1} - \Delta z_t \tag{9}$$

and the firm's demand for capital is

$$r^k_t = mc_t + y_t - k_t. \tag{10}$$

Likewise, the household first-order condition for investment in nominal bonds is

$$c_t = E_t c_{t+1} - (r^n_t - E_t \pi_{t+1}) - \Delta z_t, \tag{11}$$

As is clear from both (9) and (11), the preference shock plays a similar role than a credit shock that drives a wedge between market returns and the intertemporal rate of substitution. Everything else constant, an increase in Δz_t lowers current consumption, which in turn lowers mrs_t and w_t (depending on the degree of wage rigidity γ).

4.2 Calibration

We calibrate the model to quarterly data. Except for the degree of wage rigidity γ, the different model parameters are kept constant for all simulations and are set as follows.

Calibrated model parameters

α	β	δ	$1/\phi$	κ	ρ_r	θ_π	θ_y
0.333	0.987	0.025	1.000	0.100	0.800	2.000	0.200

The values of α, β and δ are standard (e.g. King and Rebelo, 2000). The unit elasticity of labor supply is a compromise between the values suggested in the micro and macro literature. The remaining 4 parameters are calibrated in line with estimates from New Keynesian models. The value of the NKPC slope coefficient κ lies between the estimates found in limited information studies such as Gali and Gertler (1999) or Kurmann (2007) and the full-information estimates from

[27] Aside from providing a clear definition of unemployment and labor market flows, search-based models have the appealing theoretical property that wage rigidities are not necessarily inefficient. In the present formulation, by contrast, we need to appeal to unspecified costs that prevent workers and firms from renegotiating wages until the marginal rate of substitution equals marginal productivity of labor.

medium-scale macro models such as Smets and Wouters (2007). The monetary policy parameters are close to the ones estimated by Smets and Wouters (2007) for the 1957-2004 period.

For the shock calibration, we also follow the literature and let the technology shock and the preference shock follow independent AR(1) processes

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

We estimate the two parameters for each process directly from the data. For the technology shock process, we use a quarterly approximation of the total factor productivity measure constructed by Basu, Fernald and Kimball (2006), which controls for variable factor utilization. We convert this measure into logarithms, subtract a linear trend and then estimate ρ_a and σ_{ε_a} by ordinary least squares (OLS).[28] For the preference shock process, we measure Δz_t as the residual from the Euler equation for nominal bonds in (11); i.e. $\Delta z_t = E_t \Delta c_{t+1} - (r^n_t - E_t \pi_{t+1})$.[29] 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.[30] As for total factor productivity, we subtract a linear trend from the obtained series of Δz_t and then estimate $\rho_{\Delta z}$ and $\sigma_{\varepsilon_{\Delta z}}$ by OLS. We limit the first observation for all data series to 1953:2 because Treasury bill rates were not market-determined until the 1951 Treasury-Fed Accord, and because we want to avoid the extreme swings in inflation during the Korean War period. The point estimates for the pre-1984 and the

[28] Substracting a linear trend implies that total factor productivity has a deterministic exponential growth rate, as assumed for example in King and Rebelo (2000). Our results are robust when we apply a higher-order detrending procedure.

[29] Alternatively, we could measure Δz_t as the residual from the investment Euler equation in (9). There are two reasons we 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 in (10). Both the real marginal cost and capital stocks are difficult to measure and thus, we have less confidence in the resulting series for the rental rate of capital than bond prices and inflation, which are directly observable in the data. 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, which would lead to a substantially smoother series for Δz_t. These investment-specific shocks do not enter into the bond Euler equation.

[30] Based on Schwarz' Bayesian Information Criterion (BIC), we select a VAR in 5 lags. The different results are robust to alternative lag specifications.

post-1984 period are[31]

Estimated driving processes

	ρ_a	σ_{ε_a}	$\rho_{\Delta z}$	$\sigma_{\varepsilon_{\Delta z}}$
pre-1984	0.9788	0.0094	0.7956	0.0033
post-1984	0.9738	0.0057	0.8951	0.0020

Both shock processes become less volatile in the post-1984 period by about 40%. This drop in volatility of exogenous driving forces is robust across many different model and shock specifications (e.g. Smets and Wouters, 2007) and provides the basis of the 'good luck hypothesis' of the Great Moderation, a point to which we return below. For the baseline calibration, we set the different shock parameters to their pre-1984 estimates and then vary them later to their post-1984 estimates.

The final parameter we need to calibrate is the degree of wage rigidity γ. Since the wage setting equation in (6) is reduced-form, we cannot calibrate it based on micro evidence. We thus set γ such that the model calibrated with the above parameter values and shock estimates for the pre-1984 period matches the standard deviation of HP filtered output. This yields a value of $\gamma = 0.85$, implying that the pre-1984 period was characterized by a substantial degree of wage rigidity.

4.3 Simulations

We compute several simulations of the model to illustrate the importance of increased flexibility in wage setting. First, we discuss how model under the baseline calibration matches salient labor market dynamics in the pre-1984 period. Second, we assess to what extent a reduction in the volatility of exogenous shocks can generate an increase in the relative volatility of wages. Third, we consider the effects of lowering the degree of wage rigidity by setting $\gamma = 0.15$ while keeping the shock processes at their pre-1984 calibration. This decrease in wage rigidity is motivated in part by direct evidence from Kahn (1997) who uses PSID data to show that the frequency of wage adjustments has increased over the past decades. Furthermore, we discuss in the next section different sources that may have led to this type of increase in wage flexibility. At the same time, neither Kahn's (1997) study nor the evidence discussed in the next section allows us to conclude that wage setting has become almost completely flexible as implied by $\gamma = 0.15$. Rather, we want to assess with this simulation the extent to which increased wage flexibility is capable of affecting labor market dynamics.[32] Fourth, we keep $\gamma = 0.15$ and adapt the shock calibration to the post-84

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

[32] Notice that the simulation results presented below change only little for values between $\gamma = 0.3$ and $\gamma = 0$.

estimates so as to assess how changes in the relative importance of shocks interact with increased wage flexibility.

While the main focus of our investigation is to quantify the potential of increased wage flexibility to generate the observed increase in relative volatility of wages, we are also interested in assessing whether our theory can replicate other prominent changes in labor market dynamics. As noted in the introduction, the Great Moderation period is also characterized by an increase in the relatively volatility of hours worked and a fall in the correlation of labor productivity with output and hours.[33] The first three columns of Table 9 document these changes. The volatility of both hours and labor productivity has increased relative to output. However, this increase in relative volatility is far smaller than the relative increase in volatility of aggregate wages. The correlation of labor productivity with output has turned from robustly positive to zero whereas the correlation with hours has turned substantially negative. A similar development applies to wages, which have become mildly negatively correlated.

Baseline calibration

Simulation 1 in Table 9 displays the second moments generated by the model for our baseline calibration with $\gamma = 0.85$ and the shock processes set to their pre-1984 estimates. As discussed above, the degree of wage rigidity is chosen such that the model matches the pre-1984 volatility of output in the data. Despite its simplicity, the model does a surprisingly good job in matching other pre-1984 data moments. In particular, the model generates a relative volatility and correlation coefficient of wages that is only slightly above the values in the data. The relative volatility of labor productivity and its correlation with output and hours are also close to their data counterparts.

Smaller shocks

We now change the calibration of the two shock processes to their post-1984 estimates while keeping all of the other parameters at their baseline values. This is the 'good luck hypothesis' of the Great Moderation, proposed by Stock and Watson (2003) or Sims and Zha (2006) among many others, which says that most of the decrease in business cycle volatility in the post-1984 period can be attributed to smaller shocks. As Simulation 2 in Table 9 shows, the smaller estimates of the two shock processes leads to a substantial fall in output volatility of about 40% as well as a fall in the cyclicality of wages and labor productivity. Hence, the 'good luck hypothesis' is quite powerful in accounting for the Great Moderation and is consistent with some of the changes in labor market dynamics highlighted by Stiroh (2009), Barnichon (2008) and Gali and Gambetti (2009). At the same time, the decrease in shock volatility in the post-1984 period leads to a substantial fall in the volatility of wages such that the relative volatility of aggregate wages hardly changes. The 'good

[33] See Barnichon (2008), Gali and Gambetti (2009) and Stiroh (2009).

luck hypothesis' on its own thus fails to account for the sizable increase in the relative volatility of wages that we observe in the data.

To understand these results, it is useful to consider a graphical illustration of the labor market. Figure 2a depicts the response of wage setting (6) and labor demand (8) to a positive technology shock in the $w - n$ space. 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. Because of consumption smoothing, this income effect is relatively modest. A high degree of wage rigidity (i.e. $\gamma = 0.85$) thus implies that wages adapt slowly and firms increase labor input (and production) by a lot, as depicted by the move to equilibrium point B. Smaller technology shocks change the absolute but not *relative* size of the shifts in the two curves. The magnitude of adjustments in w compared to n (and output) thus remain more or less unchanged.[34] Figure 3a illustrates the effect of a preference shock on labor demand and wage setting. Everything else constant, the preference shock reduces current consumption, which implies a negative income effect that shifts down the wage setting curve. Aside from negligible effects from dynamic capital adjustments (not shown here), the labor demand schedule remains unaffected and thus, the economy adjusts from point A to its new equilibrium at point B. Similar to the technology shock, smaller preference shocks result in smaller shifts of the wage setting curve. But as long as the degree of wage rigidity and the wage elasticity of labor demand remain unchanged, the relative magnitude of adjustments in w and n remain more or less 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 technology and preference shocks may have important effects on the cyclicality of wages and labor productivity. As the two figures reveal, technology shocks imply that both wages and labor productivity co-move with hours, whereas preference shocks imply exactly the opposite. 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. As Simulation 2 in Table 9 shows, this is exactly what happens in our model for the post-1984 estimates of the two shocks.

The graphical illustration suggests that similar conclusions apply for other exogenous shocks that shift either the wage setting curve or the labor demand but do not affect their respective wage elasticities. Likewise, structural changes outside of the labor market (e.g. changes in monetary policy) should have only a negligible impact on the relative volatility of wages. We assess this conjecture with the larger DSGE model of Smets and Wouters (2007) that contains several real and nominal frictions and seven different exogenous shocks.[35] We first simulate the model using the

[34] Our explanation ignores dynamic effects coming through movements in capital stocks. Since capital stocks move slowly over the business cycle and account for a relatively small part of production, these effects are negligible.

[35] Specifically, the Smets-Wouters model features sticky nominal price and wage setting that allows for indexation to

estimates for the 1966-1979 period reported by Smets and Wouters and then change the calibration of the seven exogenous shock processes to their 1984-2004 estimates (keeping all other parameters constant). The HP-filtered volatility of output drops from 1.82 to 1.26, thus confirming the 'good luck hypothesis' of the Great Moderation. At the same time, the volatility of real wages falls from 0.84 to 0.79, implying an increase in relative wage volatility from 0.45 to 0.62. While this increase is somewhat larger than for the more stylized DSGE model above, it remains far from the increase in relative wage volatility observed in the data. Furthermore, when we change the calibration of the monetary policy rule in the Smets-Wouters model from the 1966-1979 estimates to the 1984-2004 estimates, we find that the impact on the relative volatility of wages is very small.[36] We therefore conclude that the observed increase in relative wage volatility is unlikely to come from changes outside the labor market (e.g. smaller exogenous shocks or different monetary policy).

Increased wage flexibility

To assess the effects of increased wage flexibility in isolation, we reset the calibration of the shock processes in our small DSGE model to their pre-1984 estimates and reduce instead the degree of wage rigidity from $\gamma = 0.85$ to $\gamma = 0.15$. As Simulation 3 in Table 9 shows, this simple increase in wage flexibility is capable of generating a substantial increase in the relative volatility of wages. More specifically, the increase in relative wage volatility is due to a modest increase in the absolute volatility of wages (not shown) and a drop in output volatility of about 35%. Hence, the increase in wage flexibility not only leads to an increase in wage volatility but also implies smaller business cycle fluctuations. At the same time, the increase in wage flexibility leads to a counterfactual increase in the correlations of wages and labor productivity with output and hours.

As before, it is useful to consider a graphical illustration to understand the mechanisms behind these results. Figure 2b depicts the impact of a positive technology shock in a labor market with high and low degrees of wage flexibility. The low wage flexbility case (i.e. $\gamma = 0.85$) is exactly the same case than in Figure 2a; i.e. a positive technology shock shifts out the labor demand curve and the economy moves along a relatively flat wage setting curve from point A to point B. Under flexible

lagged inflation, external habit persistence in consumption, investment adjustment costs, variable capital utilization and fixed costs in production. The exogenous shocks are a TFP shock, an investment-specific technology shock, a government spending shock, a labor supply shock, an intertemporal preference shock, a price markup shock, and a monetary policy shock. We simulate a loglinearized version of the model using the DYNARE code that Smets and Wouters supply on the AER website.

[36] Clarida et al. (2000) and Boivin and Giannoni (2006) among others argue that starting in the 1980s, U.S. monetary policy has become substantially more aggressive with respect to inflation. However, estimates by Smets and Wouters (2007) contradict this result. In our small DSGE model as well as in the Smets-Wouters model, we find that changes in the monetary policy response to inflation have have only a small impact on output volatility and do not matter for the relative volatility of wages.

wages (i.e. $\gamma = 0.15$), the reaction of wages to increased labor demand is much stronger because the elasticity of labor supply and the equilibrium income effect of larger consumption now both play a more important role. Firms thus increase labor input and production by a much smaller amount and the labor market moves to point C. The equilibrium response of wages relative to the equilibrium response of hours thus increases as wages become more flexible. 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).[37]

Figure 3b depicts the impact of a positive preference shock with relatively rigid and relatively flexible wage setting. We start again at point A. Under rigid wage setting, the income effect of the preference shock is small because changes in the marginal rate of substitution exert only a limited effect on wage setting. Hence, the economy ends up at new equilibrium point B, as in Figure 3a, where wages and labor adjust relatively little. Under flexible wages, the income effect is much larger. As long as the Frisch elasticity of labor supply is sufficiently high (i.e. the wage setting curve is not too steep), the economy ends up at point C where the response of both wages and hours is larger compared to point B. Based on this condition, increased wage flexibility leads to larger movements in *both* wages and hours. Furthermore, 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).

Increased wage flexibility and smaller shocks

The above results suggest that an increase in the *relative* importance of preference shocks brings the model implications of increased wage flexibility closer to the data with respect to the cyclicality of wages and labor productivity. To assess this conjecture, we keep $\gamma = 0.15$ (as in Simulation 3) and change the calibration of the two shock processes to their post-1984 estimates (as in Simulation 2). As Simulation 4 in Table 9 shows, the change in shock processes together with increased wage flexibility leads to a substantial decrease in the correlation of wages and labor productivity with output and hours. At the same time, output volatility falls slightly below the observed volatility in the post-1984 period. Increased wage flexibility together with the decrease in shock volatilities

[37] We perform a similar exercise in the larger DSGE model of Smets and Wouters (2007) where increased wage flexibility takes to form of a higher frequency at which households can reoptimize their nominal wage (keeping everything else constant). This leads to a sizeable decrease in output volatility and a large increase in relative wage volatility, thus confirming the results of our smaller DSGE model. Details are available from the authors upon request.

can therefore account for the entire drop in output volatility during the Great Moderation. The decrease in correlations is not sufficient to match the labor market dynamics observed in the post-1984 data. Given the stylized nature of our model, this should not come as a big surprise. In particular, any additional shock that affects the marginal rate of substitution (e.g. a labor supply shock or a government spending shock) would further decrease the cyclicality of wages and labor productivity, thus pushing the model implications in the right direction.

We take away three main lessons from the simulations.

1. Changes in exogenous shock processes have substantial impact on the *absolute* volatility and cyclicality of wages and hours but they cannot account for the observed increase in *relative* wage volatility. Likewise, structural changes outside of the labor market (i.e. changes that do not directly affect the elasticity of wage setting or labor demand) are an unlikely source of large changes in relative wage volatility.

2. Increased wage flexibility makes wages more volatile relative to output, independent of the shock.

3. Increased wage flexibility in combination with a decrease in the importance of shocks that shift labor demand (e.g. technology shocks) relative to shocks that shift the labor supply (e.g. preference shocks) allows the model – despite its simplicity – to account for a surprising fraction of the observed changes in the cyclicality of different labor market variables.

5 Sources of increased wage flexibility

The U.S. labor market has undergone several important changes over the past 25 years that are likely to have led to increased flexibility in wage setting. In this section, we focus on two potential sources: deunionization and the shift towards performance-pay contracts. We first compare the evolution of these characteristics to the evolution of aggregate wage volatility. Then, we discuss theoretical and empirical work of how changes in these labor market characteristics may lead to increased wage flexibility. Finally, we discuss an alternative theory by Gali and Van Rens (2009) who argue that increased wage flexibility can be explained by a reduction in search frictions.

5.1 Structural changes in the U.S. labor market

In Figure 4, we plot the evolution of unionization and performance-pay contracts and compare the two measures to the evolution of relative volatility of aggregate wages (HP filtered, centered

8-year rolling windows). The two top panels show the different time series. The two bottom panels show scatter plots of each labor market measure against the relative standard deviation of aggregate wages. Unionization measures the fraction of individuals working under a union contract, as computed from our CPS data. The measure of performance pay, in turn, is taken from Lemieux et al. (2008) and represents the proportion of male household heads whose total compensation included a variable pay component (bonus, commission, or piece-rate) at least once during the employment relationship.

As the left panel of Figure 4 shows, unionization has decreased substantially over the past decades, from about 27% in the early 1970s to 12% in 2006, with a large part of this decrease occurring in the first half of the 1980s.[38] The decline in unionization is well-documented in the literature and is more pronounced for private-sector workers. The majority of unionized jobs are now concentrated in the public administration sector (e.g. in 2008, union density was 7.6% in the private sector compared to 37% in the public administration sector).[39] Interestingly, as we pointed out in Section 3, public administration workers are among the very few groups for which wage volatility has decreased substantially in the post-1984 period.

The right panel displays the incidence of performance-pay contracts. As for deunionization, the shift towards performance-pay contracts increases sharply during the early 1980s and continues, although at a lower pace, during the second half of the 1980s and the 1990s. The literature has suggested several underlying forces for this tendency towards compensation schemes with explicit performance clauses. Among them are better management techniques, increased competition due to lower entry barriers and globalization (e.g. Cunat and Guadalupe, 2005).

As the four panels of Figure 4 show, the different changes in labor market characteristics roughly coincide with the evolution of relative wage volatility. Both the deunionization of the workforce and the shift towards performance-pay contracts accelerates in the early 1980s as aggregate wages start to become more volatile relative to output. During the late 1980s and early 1990s, as the decrease in unionization and the increase in performance-pay contracts slow down, the relative volatility of aggregate wages stabilizes at a higher level. Finally, in the mid-1990s, there is another marked but temporary increase in the relative volatility of wages, which coincides with a further reduction in

[38] Many observers relate this fall in unionization to Reagan's negative reaction to the air traffic controller strike in 1981. For example, Farber and Western (2002) document that new certification elections dropped precipitously in the early 1980s. Other possible explanations are the change in employment towards industries where union organization is more expensive; increased competition among firms that reduce appropriable rents and thus the potential benefits of unions; and skill-biased technology change that makes union-induced wage compression more difficult to sustain. See Acemoglu et al. (2001).

[39] See See Faber and Western (2002) as well as Hirsch and Macpherson's (2003) website http://www.unionstats.com.

unionization but is not matched by a further increase in performance-pay contracts.

5.2 Consequences for wage flexibility

We now discuss how deunionization and a shift towards performance-pay contracts may map into our concept of increased wage flexibility as described by a reduction of γ in (6). Consider first the effects of a decrease in unionization. Unions typically negotiate wage contracts for several years ahead and index the contracts to inflation. As Blanchard and Gali (2007) show, such contracts with indexation lead to a staggered real wage structure that is similar in form to the wage setting equation in (6). A decrease in unionization in such an environment is equivalent to a shortening in contract length for the average worker, thus implying a fall in γ under the condition that wages of non-unionized workers are more responsive to current economic events.

A shift towards performance-pay contracts has similar consequences for aggregate wage setting provided that fixed-wage contracts are set in advance whereas performance-pay contracts are a function of observed outcomes. Lemieux et al. (2008) illustrate this implication in a simple model with ex-ante unobserved ability where firms endogenously choose between the two types of contracts depending on monitoring costs and the conditional variance of ability. Alternatively, consider an efficiency wage set-up where firms have the choice to elicit effort either through a monitoring-and-punishment scheme – i.e. the shirking story of Shapiro and Stiglitz (1984) – or by paying a fair wage such that workers reciprocate with a commensurate level of effort – i.e. the fair wage story of Akerlof (1982). According to the shirking story, incentive-compatible wages are typically a function of current variables (e.g. Danthine and Donaldson, 1990; or Alexopoulos, 2004). According to the fair wage story, profit-maximizing wages are a function of the reference (or norm) that workers consider as fair. As Bewley (2002) emphasizes in his survey on pay practices, this reference is tightly linked to past wages because *"...employees usually have little notion of a fair or market value for their services and quickly come to believe that they are entitled to their existing wage, no matter how high it may be..."* (page 7).[40] An increase in the incidence of performance-pay contracts in such an efficiency wage set-up corresponds to a move away from a fair-wage labor market towards a monitoring / no-shirking labor market where lagged wage references are no longer important. In terms of our wage-setting equation in (6), this would imply a fall in γ.

While it seems reasonable to assume that both the decrease in unionization and the shift towards performance-pay contracts increase wage flexibility on the aggregate level (i.e. a lower γ), it is not necessarily the case that these changes lead to more volatile wages in equilibrium. This all depends

[40] See Collard and De la Croix (2000) or Danthine and Kurmann (2009) for a modern macroeconomic analysis of the implications of fair wages based on a lagged wage reference.

on whether wages of workers in non-union jobs and on performance-pay contracts are more volatile than wages of their counterparts in unionized jobs and on fixed-wage contracts. This question is addressed in the study by Lemieux et al. (2008) mentioned above. Using PSID data, they show that wages are most responsive to local labor market shocks (as measured by changes in local unemployment rates) for non-union workers covered by performance-pay schemes, and least responsive for union workers who are not paid for performance. Interestingly, the exact opposite is the case for hours of work, which suggests that wages play an allocative role over the business cycle, as assumed in our model.

The evidence in this section shows that the timing of deunionization and the shift towards performance-pay contracts coincides surprisingly well with the observed increase in aggregate wage volatility. In addition, there are several theoretical and empirical arguments why this common tendency may not just be an coincidence.

5.3 Labor hoarding and smaller search frictions

In a recent paper, Gali and Van Rens (2009) explore an alternative explanation based on labor hoarding and search frictions to account for the observed changes in labor market dynamics. The main focus of their paper is on explaining the increase in the relative volatility of employment and the fall in the correlation of labor productivity with output and hours. Their hypothesis is that a decline in search frictions over the past decades has lead to a decrease in unobserved work effort variations (i.e. a decrease in labor hoarding).[41] As a result, labor productivity has become less procyclical and the relative volatility of employment has increased, as observed in the data. As long as wages are determined by Nash bargaining, however, the decline in search frictions leads to a decrease rather than an increase in the relative volatility of wages. This result justifies our decision to abstract from search frictions as a first pass: without appealing to some form of change in the wage setting process, search-based models of the labor market are equally incapable of generating the observed large increase in relative wage volatility than competitive models.

Based on this insight, Gali and Van Rens (2009) impose a wage setting process that is similar in form to ours but where the degree of wage rigidity γ is a reduced-form function of the bargaining set implied by the search friction. A decline in search frictions narrows the bargaining set and thus leads to an increase in wage flexibility. Simulations with different functional forms for γ show that under certain conditions, this mechanism may generate an increase in aggregate wage volatility as well as a modest decrease in business cycle fluctuations.

[41] This result follows readily from the assumption that effort per worker has stronger diminishing returns to production and stronger increasing disutility than employment.

Gali and Van Rens' (2009) explanation for the increase in aggregate wage volatility is very different from ours. While we argue that wage setting per se has become more flexible due to inherent changes in the way firms and workers negotiate compensation, Gali and Van Rens maintain that labor adjustments have become less costly and as a consequence, wages must have become more flexible in order to remain privately efficient (i.e. stay inside the bargaining set). From a theoretical point of view, this mechanism is appealing because it clearly spells out the frictions that have changed to make wages more flexible. From an empirical point of view, however, Gali and Van Rens (2009)' hypothesis of a decline in labor search frictions is refuted by the data. First and most importantly, their hypothesis predicts that average job finding rates have increased (smaller search costs increase the equilibrium vacancy-unemployment rate, thus leading to a higher matching probability for workers). Yet, exactly the opposite has happened in the data: since the 1950s, job finding rates in the U.S. have fluctuated around a steadily *decreasing* trend (see, for example, Figure 5 in Shimer, 2005).[42] Second, a central and in our view sensible assumption for Gali and Van Rens (2009)' explanation is that in the absence of search frictions, variations on the intensive labor margin are relatively more costly than variations on the extensive margin. This is why a decline in search frictions in their model leads to smaller variations in unobservable work effort. But by exactly the assumption, a decline in search frictions should also lead to smaller variations in hours per worker; i.e. the volatility of average hours worked relative to the volatility of output should decrease. In the data, however, the volatility of average hours worked (defined as total hours divided by employment) decreases only modestly in the post-1984 period. As a result, its volatility relative to the volatility of output increases by almost 70%.[43]

We conclude that while Gali and Van Rens' (2009) explanation based on a decline in search frictions is appealing from a theoretical point of view, its predictions for labor market flows and intensive margin adjustment are contradicted by the data. In fact, while the U.S. labor market appears to have become more flexible in terms of wage setting, it has become more rigid in terms of employment fluctuations at the extensive margin.

[42] Shimer's (2005) job finding rate is computed from unemployment data only and does not depend on vacancy data (such as the help-wanted index). Fundamental changes in what vacancy data captures are therefore not a concern.

[43] The H-P filtered standard deviations of average hours for the 1948:1-1983:4 period and the 1984:1-2006:4 periods are 0.55 and 0.49, respectively. Dividing by the corresponding output volatilities in Table 1 yields relative volatilities of 0.21 and 0.35, which represents an increase of almost 70%.

6 Conclusion

This paper documents that the relative volatility of wages increased by a factor of 2.5 to 3.5 during the Great Moderation. Most of this increase in relative wage volatility is due to the fact that while output volatility fell by about 60% during that period, the volatility of aggregate wages remained constant or even increased modestly. CPS microdata reveals that this relative stability of wage volatility applies for many different groups of workers. As a result, the increase in the relative volatility of aggregate wages is predominantly due to the increase in relative wage volatility across different groups workers. Compositional changes of the labor force, by contrast, account for at most 12% of the increase in the relative volatility of aggregate wages.

We view these findings as an important challenge for macroeconomic modeling in general and explanations of the Great Moderation in particular. Using a small DSGE model, we show that changes in the volatility of exogenous shocks are unlikely to generate sizable changes in relative wage volatility. Similarly, structural changes outside of the labor market are unlikely to affect relative wage volatility. This puts the labor market front and center. In particular, we argue that increased flexibility in wage setting has a lot of potential to generate the observed increase in the relative volatility of wages. The main mechanism behind this increase in relative wage volatility is, as in the data, the drop in output volatility that increased wage flexibility generates. This general equilibrium effect provides at the same time a promising new explanation for the Great Moderation that has so far been unexplored.

There are many potential sources why wage setting has become more flexible over the past decades. Our model is too stylized to distinguish between different competing explanations. We argue, however, that the marked decline in private-sector unionization and the shift towards performance-pay contracts are promising candidates. In future work, it would be interesting to formally assess this hypothesis, both by exploiting disaggregate data and by evaluating general equilibrium models that incorporate more explicit theories of wage setting and labor market frictions.

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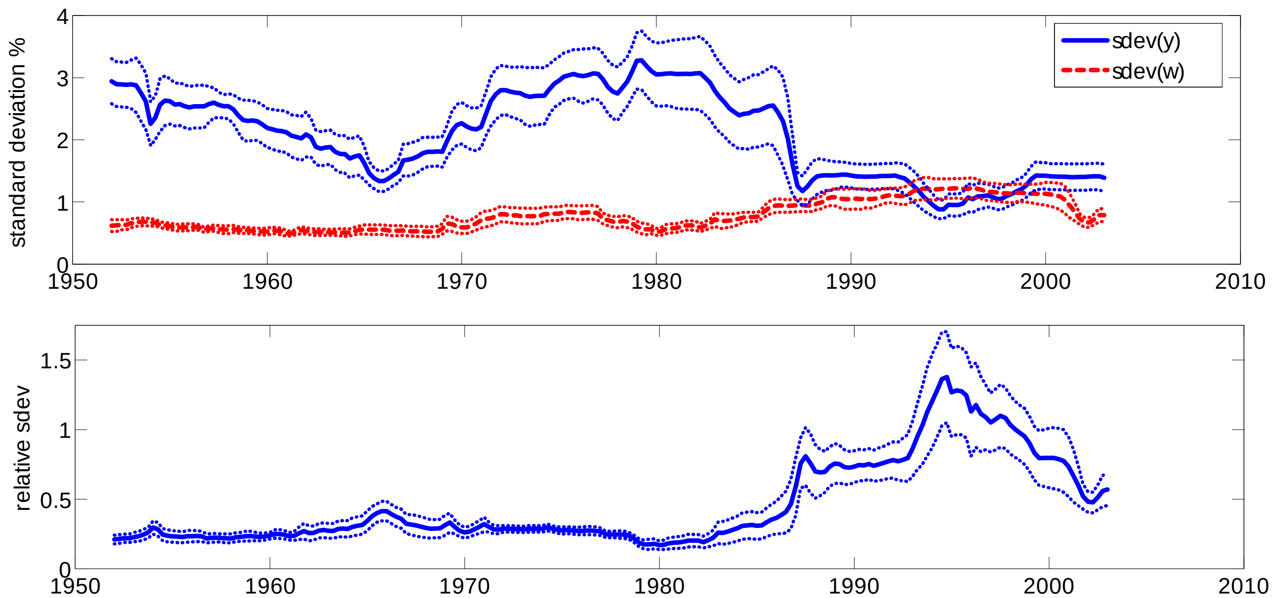
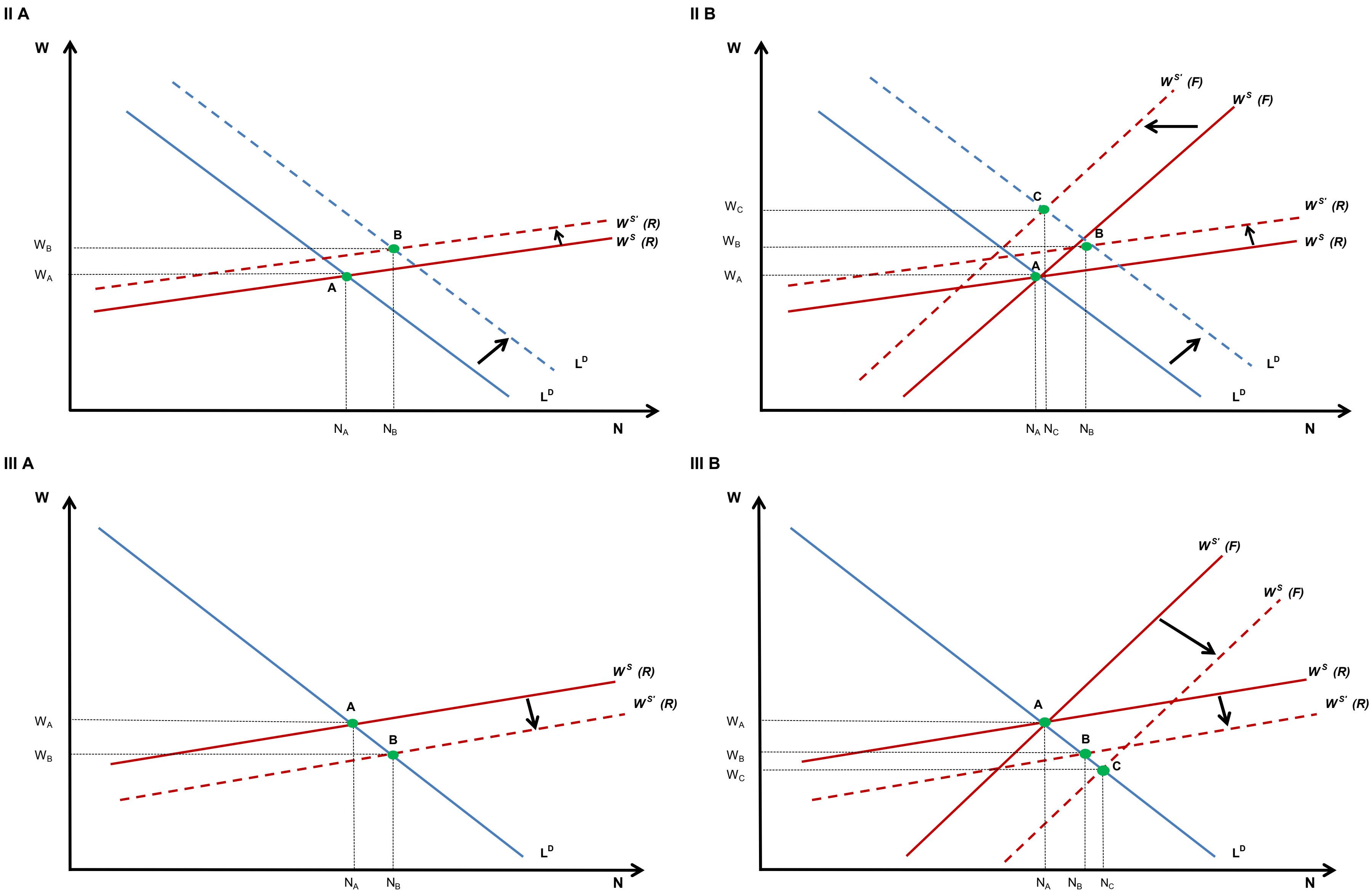


Figure 1: Rolling windows of standard deviations (upper panel) and relative standard deviations (lower panel). Dotted lines represent +/- one standard deviation bands.



Figures II & III. Wage setting rule and labor demand responses to a positive technology (Figure II) and preference shock (Figure III) shock under rigid wage setting (Panel A) and both rigid and flexible wage settings (Panel B), where *F* stands for flexible wage setting and *R* for rigid wage setting.

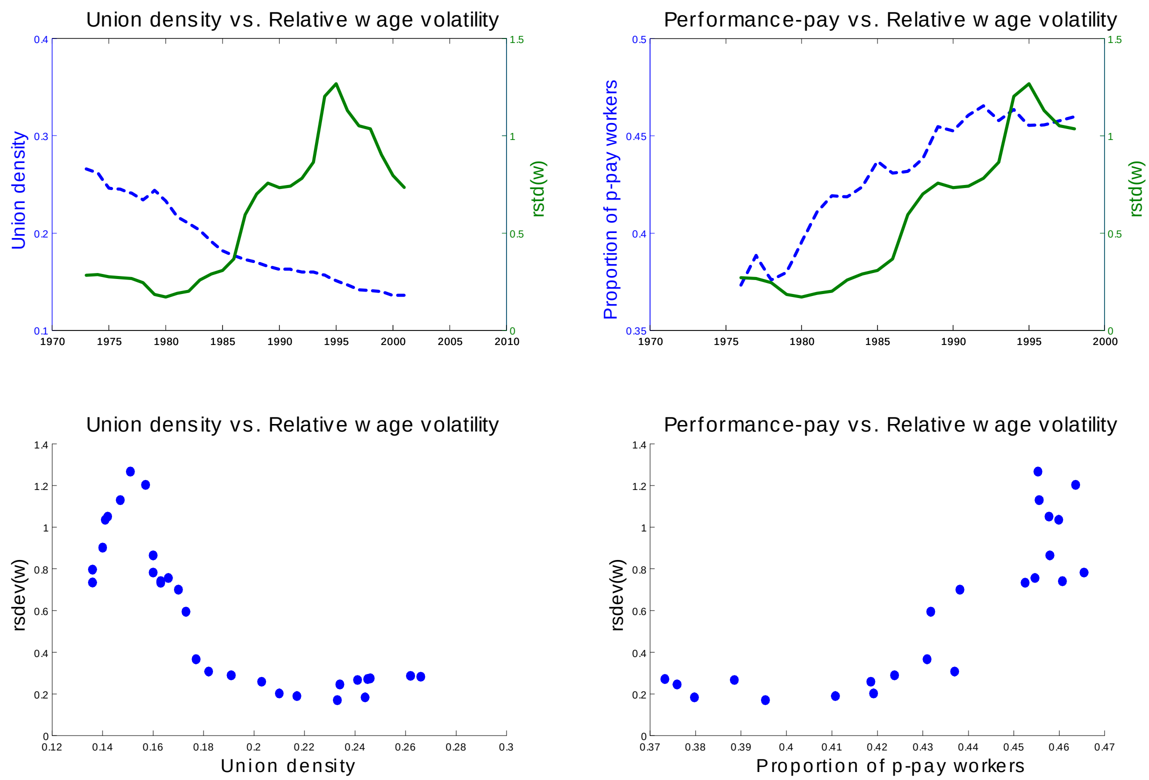


Figure 4: Evolution of union density (left) and performance-pay (right) vs. relative wage volatility.

TABLE I
Changes in Volatility

	Standard Deviation				Relative Standard Deviation		
	Pre-84	*Post-84*	*Post/Pre-84*	*p-value*	*Pre-84*	*Post-84*	*Post/Pre-84*
First-Difference							
Output	1.57	0.68	0.43	0.00	1.00	1.00	1.00
	(0.11)	(0.07)			(0.00)	(0.00)	
Wage	0.57	0.68	**1.26**	0.13	0.36	1.01	**2.92**
	(0.05)	(0.07)			(0.02)	(0.12)	
HP-Filter							
Output	2.65	1.28	0.48	0.00	1.00	1.00	1.00
	(0.21)	(0.14)			(0.00)	(0.00)	
Wage	0.63	1.03	**1.66**	0.00	0.24	0.80	**3.38**
	(0.05)	(0.09)			(0.02)	(0.12)	
BP-Filter							
Output	2.61	1.17	0.45	0.00	1.00	1.00	1.00
	(0.23)	(0.11)			(0.00)	(0.00)	
Wage	0.58	0.94	**1.62**	0.00	0.22	0.80	**3.64**
	(0.06)	(0.10)			(0.02)	(0.12)	

Notes : Total sample extends from 1948:1 to 2006:4 with split in 1984:1. Quarterly data. P-values are reported for a test of equality of variances across the two subsamples. Standard errors appear in parentheses below estimates.

TABLE II
Changes in Volatility

	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)	
Aggr. Wage (LPC)	0.99	1.49	**1.51**	0.25	0.85	**3.40**
	(0.15)	(0.23)		(0.03)	(0.18)	
Aggr. Wage (PELQ)	0.86	1.33	**1.55**	0.23	0.75	**3.26**
	(0.05)	(0.16)		(0.03)	(0.20)	
NBER manufacturing	1.57	2.20	**1.40**	0.41	1.15	**2.80**
	(0.09)	(0.34)		(0.05)	(0.25)	
CPS Wage	1.12	1.31	**1.17**	0.29	0.74	**2.57**
	(0.18)	(0.19)		(0.04)	(0.18)	
HP-Filter						
Output	2.90	1.15	0.40	1.00	1.00	1.00
	(0.19)	(0.13)		(0.00)	(0.00)	
Aggr. Wage (LPC)	0.60	0.93	**1.55**	0.21	0.80	**3.81**
	(0.08)	(0.09)		(0.04)	(0.13)	
Aggr. Wage (PELQ)	0.59	0.80	**1.36**	0.21	0.78	**3.71**
	(0.05)	(0.05)		(0.03)	(0.16)	
NBER manufacturing	1.15	1.22	**1.06**	0.40	1.09	**2.73**
	(0.14)	(0.17)		(0.05)	(0.27)	
CPS Wage	0.69	0.75	**1.09**	0.24	0.65	**2.71**
	(0.05)	(0.13)		(0.03)	(0.16)	

Notes : Total sample extends from 1973 to 2006 with split in 1984, except for PELQ wage sample that spans from 1976 to 2000, and the NBER's manufacturing database sample that spans from 1973 to 2002. Annual data. Standard errors appear in parentheses below estimates.

TABLE III
Evolution of Gender/Skill Wage Components

	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	0.50	0.38						
Wage			0.76	0.80	**1.06**	0.26	0.70	**2.69**
Hours share			0.67	0.32	0.47	0.23	0.27	1.17
Male skilled	0.20	0.24						
Wage			0.51	0.93	**1.82**	0.18	0.81	**4.54**
Hours share			1.88	0.63	0.34	0.65	0.55	0.85
Female unskilled	0.23	0.24						
Wage			0.71	0.74	**1.04**	0.24	0.64	**2.67**
Hours share			0.52	0.36	0.68	0.18	0.31	1.72
Female skilled	0.07	0.14						
Wage			1.03	0.80	0.77	0.36	0.70	**1.94**
Hours share			2.06	0.69	0.33	0.71	0.59	0.83

Notes : Total sample extends from 1973 to 2006 with split in 1984; HP-filtered, annual data.

TABLE IV
Evolution of Skill/Age Wage Components

	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	0.23	0.15						
Wage			0.96	0.99	**1.03**	0.33	0.86	**2.59**
Hours share			1.67	0.90	0.54	0.58	0.78	1.35
16-29 Skilled	0.06	0.06						
Wage			0.73	1.33	**1.81**	0.25	1.15	**4.55**
Hours share			2.75	1.25	0.46	0.95	1.09	1.15
30-59 Unskilled	0.46	0.44						
Wage			0.85	0.74	0.87	0.29	0.64	2.17
Hours share			0.43	0.36	0.84	0.15	0.31	2.10
30-59 Skilled	0.19	0.31						
Wage			0.92	0.85	0.93	0.32	0.74	2.32
Hours share			1.63	0.55	0.33	0.56	0.47	0.84
60-70 Unskilled	0.04	0.03						
Wage			1.33	1.07	0.80	0.46	0.92	2.02
Hours share			3.17	1.41	0.45	1.10	1.23	1.12
60-70 Skilled	0.01	0.012						
Wage			2.76	1.38	0.50	0.95	1.19	1.25
Hours share			7.05	3.03	0.43	2.43	2.63	1.08

Notes : Total sample extends from 1973 to 2006 with split in 1984; annual data, HP-filtered.

TABLE V
Evolution of Education/Employment Status Wage Components

	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	0.43	0.39						
Wage			1.01	1.22	**1.21**	0.35	1.06	**3.03**
Hours share			1.45	0.45	0.31	0.50	0.39	0.78
Hourly, skilled	0.03	0.07						
Wage			1.71	1.86	**1.09**	0.59	1.61	**2.73**
Hours share			3.79	2.03	0.53	1.31	1.764	1.34
Non-Hourly, unskilled	0.30	0.23						
Wage			1.08	0.83	0.77	0.37	0.72	**1.93**
Hours share			1.52	0.84	0.55	0.53	0.73	1.38
Non-Hourly, skilled	0.24	0.31						
Wage			0.59	0.77	**1.30**	0.20	0.66	**3.27**
Hours share			1.86	0.70	0.38	0.64	0.61	0.95

Notes : Total sample extends from 1973 to 2006 with split in 1984; annual data, HP-filtered.

TABLE VI
Evolution of Skill/Sectors(11) Wage Components

	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	0.01	0.01						
Wage			2.48	1.70	0,69	0.86	1.52	1.77
Hours share			8.86	4.18	0.47	3.06	3.74	1.22
Construct unskilled	0.06	0.05						
Wage			1.45	0.97	0.67	0.50	0.87	1.74
Hours share			3.84	1.90	0.50	1.33	1.70	1.28
Manuf-D unskilled	0.14	0.10						
Wage			0.84	1.01	1.20	0.29	0.90	3.11
Hours share			3.47	1.19	0.34	1.20	1.07	0.89
Manuf-ND unskilled	0.08	0.06						
Wage			0.79	1.23	1.55	0.27	1.10	4.02
Hours share			1.82	1.11	0.61	0.63	0.99	1.58
T&U unskilled	0.06	0.06						
Wage			1.414	0.91	0.65	0.49	0.82	1.68
Hours share			2.65	1.27	0.48	0.92	1.14	1.24
Comm unskilled	0.02	0.01						
Wage			2.22	1.29	0.58	0.76	1.15	1.51
Hours share			5.742	3.14	0.55	1.98	2.81	1.41
Whole T unskilled	0.04	0.03						
Wage			1.26	0.91	0.72	0.44	0.81	1.86
Hours share			3.11	2.00	0.64	1.07	1.79	1.67
Retail T unskilled	0.09	0.09						
Wage			1.15	1.00	0.87	0.40	0.90	2.26
Hours share			1.36	0.72	0.53	0.47	0.64	1.36
FIRE unskilled	0.04	0.04						
Wage			1.19	0.99	0.84	0.41	0.89	2.16
Hours share			3.16	1.66	0.52	1.09	1.48	1.36
Services unskilled	0.13	0.15						
Wage			0.46	0.69	1.50	0.16	0.62	3.88
Hours share			1.41	0.73	0.52	0.49	0.65	1.34
Public unskilled	0.05	0.04						
Wage			1.13	0.61	0.54	0.39	0.55	1.41
Hours share			4.34	2.04	0.47	1.50	1.82	1.22
MinOilGas skilled	<0.01	<0.01						
Wage			6.21	3.87	0.62	2.14	3.46	1.62
Hours share			11.05	8.26	0.75	3.81	7.39	1.94
Construct skilled	0.01	0.01						
Wage			2.36	1.74	0.74	0.81	1.56	1.91
Hours share			3.68	3.03	0.82	1.27	2.71	2.13
Manuf-D skilled	0.03	0.04						
Wage			1.50	1.25	0.83	0.52	1.12	2.16
Hours share			2.99	2.25	0.75	1.03	2.02	1.95
Manuf-ND skilled	0.02	0.02						
Wage			1.56	1.18	0.76	0.54	1.07	1.98
Hours share			5.66	2.43	0.43	1.95	2.17	1.11
T&U skilled	0.01	0.02						
Wage			2.10	2.12	1.01	0.73	1.90	2.61
Hours share			5.94	2.24	0.378	2.05	2.01	0.98
Comm skilled	<0.01	0.01						
Wage			4.54	2.15	0.47	1.57	1.93	1.23
Hours share			9.27	3.32	0.36	3.20	2.97	0.93
Whole T skilled	0.01	0.01						
Wage			1.22	1.57	1.29	0.42	1.41	3.35
Hours share			7.35	2.66	0.36	2.54	2.38	0.94
Retail T skilled	0.01	0.02						
Wage			2.99	1.93	0.64	1.03	1.72	1.67
Hours share			3.93	1.75	0.45	1.36	1.57	1.16
FIRE skilled	0.02	0.04						
Wage			1.16	1.20	1.03	0.40	1.07	2.67
Hours share			4.10	1.91	0.47	1.41	1.71	1.21
Services skilled	0.12	0.17						
Wage			1.09	1.01	0.92	0.38	0.90	2.40
Hours share			2.22	0.54	0.24	0.77	0.48	0.63
Public skilled	0.02	0.03						
Wage			2.02	0.96	0.48	0.70	0.86	1.23
Hours share			3.60	1.93	0.54	1.24	1.73	1.39

Notes: Total sample extends from 1973 to 2002 with split in 1984; annual, HP-filtered data. 10 industries and 1 public administration sector.

TABLE VII
Relative Volatility AccountingAcross Different Decompositions

Decomposition	Gender/ Skill	Age/ Skill	Emp Status/ Skill	Industry(22)/ Skill
CPS wage	100.00 %	100.00 %	100.00 %	100.00 %
Changing s_i	2.57 %	0.34%	11.98%	1.29 %
Changing σ(hourly wages)²	96.51 %	84.22%	99.54%	76.97 %
Changing σ(hours shares)²	-3.97 %	-5.18%	2.2%	-1.35 %
Changing correlations	4.89 %	20.62%	-13.73%	23.09 %

Notes : Total sample extends from 1973 to 2006 with split in 1984 (Except for Industry(22)/Education, which stops in 2002). HP-filtered data. Employment status stands for hourly paid or non-hourly (salaried) workers.

TABLE VIII
Volatility Accounting (absolute) Across Different Decompositions

Decomposition	Gender/ Skill	Age/ Skill	Emp Status/ Skill	Industry(22)/ Skill
CPS wage	100.00 %	100.00 %	100.00 %	100.00 %
Changing s_i	113.57%	117.78%	292.61%	114.13%
Changing σ(hourly wages)²	132.72%	-71.64%	254.93%	-72.82%
Changing σ(hours shares)²	-176.24%	-137.75%	-129.75%	-119.30%
Changing correlations	29.95%	191.61%	-317.80%	177.99%

Notes : Total sample extends from 1973 to 2006 with split in 1984 (Except for Industry(22)/Education, which stops in 2002). HP-filtered data. Employment status stands for hourly paid or non-hourly (salaried) workers.

TABLE IX
Model Simulations

	US Data			Simulation 1	Simulation 2		Simulation 3		Simulation 4	
	Pre-84	*Post-84*	*Relative*	*γ = 0.85 and Pre-84 shock*	*γ = 0.85 and Post-84 shock*	*Relative*	*γ = 0.15 and Pre-84 shock*	*Relative*	*γ = 0.15 and Post-84 shock*	*Relative*
σ(*y*)	2.56	1.28	0.50	**2.52**	**1.69**	**0.67**	**1.58**	**0.63**	**1.16**	**0.46**
σ(*n*)/σ(*y*)	0.78	1.15	1.47	0.85	0.95	0.65	0.59	0.69	0.83	0.98
σ(*w*)/σ(*y*)	0.24	0.80	3.33	**0.43**	**0.45**	**1.05**	**0.79**	**1.84**	**0.84**	**1.95**
σ(*y/n*)/σ(*y*)	0.49	0.59	1.20	0.40	0.42	1.05	0.69	1.73	0.67	1.68
ρ(*y,w*)	0.36	-0.14	-0.50	0.52	0.34	-0.18	0.73	0.21	0.45	-0.07
ρ(*y,y/n*)	0.65	0.01	-0.64	0.54	0.32	-0.22	0.82	0.28	0.57	0.03
ρ(*n,y/n*)	0.21	-0.50	-0.71	0.16	-0.10	-0.26	0.22	0.06	-0.12	-0.28

Notes : All moments are H-P filtered. US data spans from 1953:2 to 2006:4. The 'Relative' column denotes the Post/Pre-84 ratios for standard deviations and the Post-Pre-84 differences for correlations.